Valuing natural amenities and flood risk: a hedonic house price approach

by

Tom Gillespie, B.A., M.Econ.Sc.

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J.E. Cairnes School of Business and Economics

The National University of Ireland Galway

Supervisors

Dr. Stephen Hynes

Dr. Ronan C. Lyons

Dr. Tom McDermott

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Abstract

Environmental amenities play a key role in determining where people choose to live. Understanding the dynamics of preferences for environmental amenities is crucial for managing how a population co-exists with the landscape around them by informing sustainable planning in an environmental context. Identifying these preferences requires an estimation of people's willingness to pay for environmental amenities. These underlying prices are not always revealed explicitly through markets and therefore non-market values must be uncovered in some cases to reveal the full extent of how people value the environment. Studying housing markets can help reveal peoples' willingness to pay for environmental goods and services. The methodology for revealing people’s environmental preferences through the use of housing market data is known as the hedonic house price method and forms the basis of this thesis.

The thesis applies the hedonic house price method to estimate implicit prices related to blue space and green space amenities, but also the dis-amenity of exposure to flood risk, in an Irish context. Advantage is taken of a large (>2million raw observations) dataset of sale and rental listings in Ireland, from 2006 to 2018, and also a complementary sub-sample of transaction prices with highly detailed dwelling characteristics, sourced from the *daft.ie* property website. Such a large amount of variation, combined with a wide-ranging robustness strategy based on the use of spatial fixed effects, improves identification by minimising omitted variable bias, a pervasive issue in the hedonic house price literature. This research also takes advantage of access to environmental data that is of the highest level of detail available in Ireland. Novel measures of environmental views are developed and help identify the aesthetic value of the environment as well as the recreational value which is identified using proximity metrics. Aesthetic measures are also employed as controls in analysing the competing relationship between coastal flood risk and sea views.

As well as chapters on relevant literature, data, and methodology, there are three empirical chapters that apply the hedonic house price methodology included in this thesis: The first empirical chapter is related to coastal "blue space" amenities where the willingness to pay for coastlines by type and views of the sea is estimated. A novel and continuous measure of sea views is developed using 3D GIS viewshed simulation. The second chapter looks at how flood risk and flood events affect house prices in Ireland, and is a logical follow on from a focus on preferences for blue space exposure. The wide temporal range of the housing data allows for the before and after effect of the release of flood risk information, the construction of flood defences, and the occurrence of a flood event to be accounted for in the hedonic house price models. The third chapter is focussed on the willingness to pay for urban "green space" in Ireland. The purpose of these econometric and methodological investigations is to advance the understanding and modelling of individual preferences associated with housing decisions. This in turn should enable more informed policy decisions regarding the preferences for coastal and urban green space management, and future planning for flood risk which is projected to increase in future as a result of climate change.

Declaration of work

I, **Tom Gillespie**, certify that the Thesis is all my own work and that I have not obtained a degree in this University or elsewhere on the basis of any of this work.

Signed: ______________________ Date: 31/03/2021

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Finally, I would like to thank my parents, Paul and Deirdre, and my brother Fintan, for their years of support and encouragement.

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List of Abbreviations

AFA: Areas of Further Assessment

BDD: Border Discontinuity Design

BER: Building Energy Rating

CBD: Central Business District

CFRAM: Catchment Flood Risk Assessment Management

CLC: CORINE Land Cover

CORINE: Co-ORdinated INformation on the Environment

CSO: central statistics office

CVM: Contingent Valuation Methodology

DC: Discrete Choice

DEM: Digital Elevation Model

DSM: Digital Surface Model

ED: Electoral District

EEA: European Environment Agency

EPA: Environmental Protection Agency

EU: European Union

EUA: European Urban Atlas

FE: Fixed Effect

GIS: Geographical Information System

GNI: Gross National Income

GS: Green Space

GUI: Golf Union of Ireland

LiDAR: Light Detection and Ranging

LM: Local Market

LUZ: Larger Urban Zones

MLDT: Mayor et al. (2009)

MWTP: Marginal Willingness To Pay

NPWS: National Parks and Wildlife Services

OLS: Ordinary Least Squares

OPW: Office of Public Works

OSi: Ordinance Survey Ireland

OV: Omitted Variable

OVB: Omitted Variable Bias

PFRA: Preliminary Flood Risk Assessment

PPR: Property Price Register

RMSE: Root Mean Square Error

RP: Revealed Preference

SA: small area

SD: Standard Deviation

SE: Standard Error

SEAI: Sustainable Energy Association of Ireland

SFE: Spatial Fixed Effects

SP: Stated Preference

TCM: Travel Cost Method

UGS: Urban Green Spaces

UN: United Nations

UQR: Unconditional Quantile Regression

WTA: Willingness To Accept

WTP: Willingness To Pay

1 Introduction

What is the use of a house if you haven't got a tolerable planet to put it on?

— Henry David Thoreau (Sanborn, 1894), Familiar letters

1.1 Background to the research

Understanding the dynamics of people's preferences for environmental amenities has been a major challenge for economists for more than half a century. These preferences underpin social norms and translate into policies which govern our relationship with the environment around us. It is widely accepted that we are at a critical juncture with respect to humanity's relationship with the rest of the earth's systems (IPCC, 2018). Global-scale social and economic processes such as growing populations, expanding global consumption, and rapid urbanisation are putting natural systems under increasing pressure. This view is informed by scientific consensus and is magnified by a growing social concern for the deteriorating state of the environment. The Intergovernmental Panel on Climate Change tell us that unless global warming is limited to 1.5 degrees above pre-industrial times, the world faces extreme weather events, food shortages, wildfires, dying coral reefs, droughts, floods and poverty for hundreds of millions of people as a result of climate change (IPCC, 2018). Also linked to climate change is the loss of species and habitats, which, according to the United Nations-backed Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services, is as much of a threat to human life (IPBES, 2019). Given the alarming context of this new global epoch now known as the Anthropocene, it is becoming increasingly important to better understand people's preferences and behaviours with respect to the environment. Accurate estimates of the economic value that people assign to various environmental goods and services can play a crucial role in determining effective policy to mitigate the negative environmental externalities associated with our collective behaviours and consumption patterns, and hence improve quality of life.

Estimating a value for these environmental goods and services, or the costs of environmental hazards, is difficult to do as their prices are not always revealed explicitly through market-based transactions (Winkler, 2006). Environmental goods and services are generally classed as public goods as they are non-rival and non-excludable. Determining their economic value is therefore part of the broad topic of research known as non-market valuation (Haab and McConnell, 2002). These techniques have been used in important policy decisions including determining the compensation liability in cases such as the Exxon Valdez oil spill of 1989 (Cohen, 1995) and the deep-water horizon oil spill in 2010. Exxon settled out of court a fine of $1 billion, which was partly justified by the use of non-market valuation techniques, one of the largest fines ever handed down for natural resource damages. Cost-benefit analyses of (for example) infrastructure projects can be grossly misguided if the non-market values of environmental goods and services are not properly identified and incorporated (Martín-López et al., 2014; Leemans and De Groot, 2003). Given the context of rapid urbanisation and paralleled bio-diversity loss, research in this field has important implications at this moment in time.

In practice, non-market valuation techniques translate people's preferences for environmental goods and services into a monetary value known as their *Willingness To Pay* (WTP). Estimating people's willingness to pay for scarce environmental goods and services, even if non-definitive or lower-bound, can create a link between their allocation and protection via instruments of targeted taxation (property tax) or appropriate fines and compensations if damaged or destroyed, as in the example illustrated above. There are also economic costs associated with the natural environment such as those that arise from environmental hazards, for example wild fires, earthquakes, and floods. Improving insights into people's WTP to avoid natural hazards has important real world implications for policies related to urban development, public health, immigration, and distributional concerns. Understanding how flood risk is perceived and priced, informs policies aimed at adapting to climate change, as well as estimating the likely future costs of climate change.

Putting a value on an environmental good may seem like objectifying nature for human benefit (Harvey, 1996, p. 156), but despite being occasionally framed as such, it can help decisions on balancing the "ecosystem services" of the natural world. It is however a common misconception that the goal is to put a price on the good itself; rather, it aims to value the benefits to individuals and societies that result from the environmental good. These values are essential in decision making policy when weighing up the costs and benefits of economic growth versus environmental conservation. Put bluntly, without an estimate of these values, the benefits are treated either as worthless or infinite, and thus untouchable.

1.2 Specific focus

In the thesis, three broad categorisations of environmental amenities/dis-amenities in Ireland will be examined: blue space amenities, urban green space amenities and the dis-amenities associated with flooding hazards.

1.2.1 Coastal "Blue Space" Amenities

The first is related to coastal "blue space" amenities in the context of their aesthetic value as well as their recreational value. Proximity to, and views of, water – especially the sea – is associated with many positive measures of physical and mental wellbeing, from higher levels of vitamin D to better social relations (Mitchell and Popham, 2008; MacKerron, G. and Mourato, S., 2013; Gascon et al., 2015; Dempsey et al., 2018). Blue spaces can be exposed to socio-economic pressures such as pollution, rezoning or access restrictions. It can therefore be argued that knowledge of the benefits from blue spaces needs to be integrated in spatial development and management policies (TEEB 2011). Approximately 40% of Ireland's population live within five kilometres of the coastline, but when considering a European classification, over 90% of the island is considered a coastal zone (Tsakiridis et al., 2019).

This chapter (chapter 5) focuses on the WTP for coastal amenities. Based on a thorough literature review in section 2.4.2 it is unique in the literature of coastal valuation in that it attempts to estimate implicit prices for separate categorisations of the coastline (beaches, sand/shingle zone, and cliffs). It also contributes to the limited literature on estimating the aesthetic value of the coastline using a continuous measure of sea views. Novel measures of sea views are developed and a methodological approach to reduce computational intensity is outlined. This methodological contribution addresses a common issue with measuring environmental aesthetics on large scales and samples. Schaeffer and Dissart (2018) analyse 328 peer-reviewed articles between 1974 and 2013 on environmental amenities. One of their conclusions is that few papers attempt to measure environmental views. They say this is regrettable "since perception of the local environment comes first and foremost through people's gaze" (Schaeffer and Dissart, 2018).

Chapter 5 has four goals: firstly, to develop a novel continuous measure of sea views based on 3D GIS simulation; secondly, to elicit aesthetic, as well as recreational values for the coastline based on the hedonic house price model and compare the magnitudes of these effects directly; thirdly, to compare the price and rental effects of coastal amenities; and, lastly, to analyse how the price effects of "picture" and "playground" amenities changes over the housing market cycle and the price distribution.

1.2.2 Floods

The second focus (chapter 6) of the thesis relates to the dis-amenity associated with flood hazards. Flood risk is one of the most pervasive natural risks and is estimated to affect 15% of the world's population. One billion people in 155 countries are exposed to flood risk (JRC 2017). With the prospect of climate change, rising sea levels and the potential for more intense rainfall events are expected to increase flood risk in many locations. Alongside changes in flood risk associated with climate change, projections of the future costs of flooding depend heavily on assumptions about increases in future exposure to flood risk. For example, projections of changing exposure to flood risk indicate a near ten-fold increase between 2005 and 2050, from US$6 billion to US$52 billion (Hallegatte et al., 2013). Recent flooding in Ireland has been costly too, with roughly €1bn, or close to €800 per household, in insured losses over the period 2000-2014. Moreover, the Irish government has committed to spending large sums on flood relief schemes: the 68 schemes in the analysis cost €226.6 million in total, with an additional €1 billion of planned public expenditure, or roughly 0.5% of national income, on flood relief schemes over the next 10 years (OPW, 2018). The scale of the projected increase in losses associated with increasing exposure underlines the importance of the extent to which flood risk is taken into account in private decisions. Moreover, these costs are often borne, at least in part, by taxpayers in the form of various subsidies to flood risk (including subsidised insurance, flood relief schemes and disaster assistance).

The availability of a wide range of data relating to floods in Ireland allowed for four main questions to be asked: Can a price discount for dwellings at risk of flooding be cleanly identified? How do flood events affect house prices? How does the construction of flood defences affect house prices? Does flood risk affect either end of the housing market differently, and what are the implications if so?

The use of a survey also allows an understanding of actors in the housing market's perceptions and awareness of flood risk. It asks about the appropriate price discount for dwellings at risk of flooding, a form of stated preference WTP estimate that is then compared to the findings of the hedonic analysis.

1.2.3 Green space

In a similar vein to blue spaces, urban green spaces are the subject of WTP investigation in chapter 7 of the thesis. Efforts to plan liveable neighbourhoods that facilitate public health, well-being and social connectedness can benefit from information about the valuation homebuyers place on various local amenities. Many of these spaces are in urban areas, and more will be in the future as urbanisation continues to occur around the world. Ireland has experienced some of the most rapid recent urbanisation in Europe (Ahrens and Lyons, 2019), so it is a useful place to study the valuation of urban amenities. This study estimates the value placed by homebuyers on urban green space, which includes managed urban parks, tree cover, and more natural settings, including woodlands. These amenities can offer not only direct utility benefits, which may be captured in housing market outcomes, but also indirect positive externalities including benefits to biodiversity, local air quality, ambient noise reduction and carbon sequestration.

This study focuses on WTP for the direct benefits of green space to households. It does this by examining the impact that urban green space amenities have on the sale price of housing, using a dataset of almost 40,000 real estate transactions in Dublin during the period 2010-2018. The present study updates and extends the estimates provided for Ireland by Mayor et al. (2009; hereafter MLDT), using not only more up-to-date transactions, but also higher-resolution information on urban green space and a richer set of controls, most notably for unobserved spatial factors.

1.3 Methodological Approach

There are numerous methods of estimating WTP for non-market goods. These can be broadly classified into two categories: stated preference techniques and revealed preference techniques. Whereas stated preference techniques rely on asking people to consider hypothetical scenarios in a survey framework, revealed preference techniques estimate people's WTP through their behaviours in related real-world markets. The primary methodology for estimating willingness to pay/avoid environmental amenities/dis-amenities, in revealed preference studies, is the hedonic house price model.

The hedonic house price model is based on the understanding that a house is composed of a bundle of individual characteristics, each of which has an implicit price. The market price of the house is determined by the sum total of the individual parts. Rosen (1974) established the theoretical framework for the hedonic method, which has been widely used in economic studies to analyse the impact of particular characteristics on property prices. Use of the hedonic technique allows the calculation of the implicit price of a particular attribute's contribution to the total value of a property, as perceived by the purchaser of the property. Put simply, the price difference between houses that have different levels of environmental quality, keeping constant all other characteristics, reflects the marginal WTP for the different level of environmental quality. The hedonic house price method is one of the most widely used (if not *the* most used: Schaeffer and Dissart, 2018) non-market valuation techniques for estimating WTP for environmental goods and services. This is largely due its economically intuitive premise and the growing availability of housing data and spatial environmental data. However, it is not without its drawbacks.

1.3.1 Omitted variable bias and robust identification

Progress made in the state of the art of the hedonic house price methodology, given its prolific use in the literature, has given rise to a growing concern about misspecification of the hedonic house price function, which can severely undermine its ability to identify WTP. Of primary concern is the fact that due to the spatial distribution of housing there are empirically unidentifiable spatial processes that are likely correlated with the amenity of interest and hence will lead to omitted variable bias (OVB) (Bishop et al., 2020). For example, coastal flood risk is likely correlated with proximity to coastal amenities such as beaches or sea views. If these blue space amenities are not accounted for in model specifications it may positively bias the estimated negative effect of the flood risk towards zero. Although the OVB problem in this example can be overcome with the inclusion of representative metrics of sea views and beach proximity, there are likely to be unmeasurable spatial processes present also. In the current literature a robust hedonic study must minimise the risk of OVB by implementing a research design that sufficiently isolates exogenous variation in the amenity of interest.

Bishop et al. (2020) outline the best practices when it comes to the implementation of a hedonic house price study for estimating WTP for environmental quality. The thesis uses a robust identification strategy for minimising OVB which is in-line with their findings and recommendations. For reasons outlined in Section 2.3.1.2, the use of spatial fixed effects (SFE) is the general strategy employed here for reducing OVB and improving identification. This is in contrast to another broad strand of literature which uses parametric spatial econometric approaches through the use of spatial weights matrices. Spatial econometric approaches such as the spatial error model or the spatial lag model have numerous criticisms and are not suited to large datasets such as the data used in this research (see section 2.3.1.2 for more detailed discussion and also Von Graevnitz et al., 2015). Here a number of strategies are used to identify whether OVB is an issue. They include:

1. OVB sensitivity analysis by varying the level (four levels) of spatial fixed effect while reporting robust and clustered error terms.
2. Testing a border discontinuity research design.
3. Using spatio-temporal fixed effects.

Other robustness strategies specific to each empirical chapter are also outlined in more detail in subsequent chapters. Based on the results of these robustness strategies, one can be reasonably confident that the WTP estimates generated are causal, reliable, and unbiased.

Implementing these strict robustness strategies is enabled by large data allowing for rich within variation thereby facilitating identification at smaller and smaller geographic scales, reducing OVB (Abbott and Klaiber, 2011).

1.4 Proliferation of data

In recent years, hedonic studies have benefitted immensely by the proliferation of data. This allows questions to be answered that couldn't be tackled because sufficiently detailed data was unavailable. Kuminoff et al. (2010) reviewed 69 hedonic house price studies related to willingness to pay for environmental amenities from 1996 - 2006. They found only 22% of studies had samples greater than 10,000 observations. They also found that only 9% of studies used a countrywide sample. Since 2006 there has been an increasing number of related studies with large sample sizes (>100,000) (Bishop et al., 2020). The data used in this study are in the large sample cohort of new studies with some additional unique features that sets them apart from other housing datasets (see next section).

1.4.1 Housing data

The housing data used in the thesis come from three extremely rich datasets, comprising a total of over one million observations of sales and rental listings from the real estate website *daft.ie*, with complete coverage for Ireland over the period 2006-2018, supplemented by a directly comparable dataset of nearly 40,000 sales transactions in Dublin over the period 2010-2018. Detailed dwelling characteristics such as size and type are included along with date of listing and location of listing. Compared to other housing datasets used in hedonic studies, as well as its size, it is distinctive in several respects:

1. It has estimated coverage of over 90% of all listings in the Irish market.
2. It contains like-for-like data across both sale and rental segments.

3. It includes text of the advertisement for the sale or rent of a property, which can be used to mine phrases related to the dwelling characteristics (“garden”, “parking”, “views”, etc).
4. It contains a directly comparable (to the sale and rental listings dataset) sub-sample that includes transactions data as well as highly precise and thorough dwelling characteristics (more detail in Section 3.2.2).

Although the *daft.ie* listings data do not include final transaction prices, it is shown that through the use of the directly comparable sub-sample (number 4 above) that list prices are an appropriate proxy for transaction prices (sections 5.3.2 and 6.3.4.3). With the exception of Lyons (2013a)[1] which used a smaller sample of the *daft.ie* data, this analysis is the first time these data have been used for a hedonic house price study of environmental amenities.

1.4.2 Environmental data

The relationship between house prices and local environmental goods and services forms the basis of the thesis. The quality of data that represents the environment can be as important as the quality of data representing housing when attempting to identify house price effects. The thesis takes advantage of environmental data with the highest detail available in Ireland. In terms of blue space analysis, it uses the highest resolution nationwide digital elevation model (10m) and a sub sample of LiDAR data (0.5m) to generate a continuous measure of sea views. Access to the OSi’s (Ordinance Survey Ireland) coastal categorisation data was given which is also the most granular data available. In the floods analysis there are three types of data: Scientifically assessed flood risk (CFRAM and PFRA maps), Flood events, and flood defences. These data are sourced from the OPW (Office of Public Works) and are the most comprehensive available in Ireland in relation to floods. The three types of floods data have a temporal dimension that is within the time frame of the housing

[1] The following papers have used the daft dataset for other housing economics analyses: Hyland et al., 2013; Pilla et al.,2019; Lyons, 2015; Lyons 2013a/b

data[2] which helps isolate exogenous variation by identifying a before and after effect on house prices. The green space analysis sources data from the European Urban Atlas (EUA), and PRIME 2 from the OSi which is the highest resolution vector data available in Ireland. Linking these housing and environmental data for the first time legitimises the originality of this research and the research design speaks to the amount of work which was undertaken for data cleaning, linking and analysis.

1.5 Policy goals

As outlined previously, having reliable estimates of WTP for environmental goods is crucial for informing policies related to how a population co-exist with the environment around us. The thesis attempts to answer a number of more specific questions related to policy decision-making particular to each of the three studies. These are categorised as follows:

- Blue space
    - Can property taxes appropriately reflect the value added from blue space amenities?
    - Are these values concentrated in particular segments of the housing market?
    - If the aesthetic value of blue spaces is greater than the recreational value, should coastal developments taper away from the coast in terms of building height?
    - How do the rental effects compare to the sale effects?
- Floods
    - What is the aggregate effect of flood risk on Irish housing wealth?
    - How effective are flood information provision policies at creating a price signal and hence deterring development and migration to

[2] Flood risk maps were not available in Ireland before their release in 2010, which is in the middle of the range of housing data (2006-2018). Flood defences and flood events also have a before and after component largely within the time frame of the housing data also.

flood risky areas, thus reducing exposure to floods and associated future costs?
    - Do flood defences effectively eliminate the discount associated with flood risk? If so does this encourage development in flood risk areas based on expectations of future defence strategies?
    - Does flood risk affect different ends of the price distribution and if so what does that mean for future allocations of flood defences?
    - What are people's perceptions and awareness of flood risk in Ireland (informed from survey data)?
- Green space
    - What is the minimum valuation placed on Dublin parks by residential property markets?

1.6 Structure of the thesis

The structure of the thesis is as follows.

Chapter 2 contextualises the research in terms of the preceding theory and literature as well as the current state of the art in related studies. It firstly introduces the concept of "value" and how this concept has developed into subcategories in a non-market setting such as use and non-use values. Non-market valuation techniques under the headings of stated and revealed preference are briefly outlined which leads into the hedonic house price model and why it is preferred for the thesis. The chapter then outlines the theory which underpins the hedonic house price method. Finally, a comprehensive literature review is given for the three areas of study: blue space, floods, and green space.

Chapter 3 describes in detail the data used for the research with focus on the housing and environmental data used. It then focuses on the more specific data used for each of the three empirical studies.

Chapter 4 outlines the methodological approach to the research. It starts with a recap of the general empirical specification of a hedonic model developed in detail in Section 2.3. Section 2 of chapter 4 sets out the GIS methodology used to generate various environmental metrics. There is detailed focus on the methodology used to compute view metrics. The rest of the chapter outlines the research design and computation of variables for each of the three studies.

Chapter 5 to 7 contains the detailed results and conclusions of each of the three studies. The structure of each sub-chapter is systematic: it opens with a contextualised introduction which refers back to the literature, data, and methodology chapters in the thesis, followed by a quick recap of the empirical specification which is mostly homogenous across the three studies in terms of its specification and control variables. Results follow and each are specific to the study with different sets of specifications and robustness strategies. Each chapter finishes with discussion, limitations, policy implications, and areas of further work.

Chapter 8 concludes the thesis with further broad policy recommendations, a discussion of the limitations of the methods applied and some thoughts on avenues for future research in the area.

1.7 Thesis outputs

1.7.1 List of working papers:

Gillespie, T., Hynes, S. and Lyons, R.C., 2019. *Picture and Playground: Valuing Coastal Amenities* (No. tep0518). Trinity College Dublin, Department of Economics.

Gillespie, T., Lyons, R.C. and McDermott, T.K., 2020. *Information Matters: Evidence from flood risk in the Irish housing market* (No. tep1620). Trinity College Dublin, Department of Economics. (Submitted to Economic Journal. Current status “under review”)

Gillespie, T., Lyons, R.C. and McLaughlin, F., 2019. *The impact of green space on Irish property values*. Environmental Protection Agency working paper.

Dempsey, S., Devine, M.T., Gillespie, T., Lyons, S. and Nolan, A., 2018. Coastal blue space and depression in older adults. *Health & place*, **54**, pp.110-117. (published)

1.7.2 List of presentations:

Gillespie, T. Lyons, R. 2017. "Picture vs Playground: Valuing Coastal Amenities". RSA annual conference. Trinity College Dublin, June 2017

Gillespie, T. 2017. "Picture vs Playground: Valuing Coastal Amenities" GIS centre's annual research seminar. NUIG, June 2017

Gillespie, T. 2017. "Picture vs Playground: Valuing Coastal Amenities". 8th Annual Marine Economics and Policy Research Symposium. Glenlo Abbey Hotel, Galway December 2017

Gillespie, T. McDermott, T. 2018. “Information Matters: Evidence from flood risk in the Irish housing market”. Whitaker Ideas Forum seminar. NUIG, February 2018.

Gillespie, T. 2018. "Picture vs Playground: Valuing Coastal Amenities". Environmetrics forum. Marine institute, Galway. April 2018.

Gillespie, T. 2019. "Picture vs Playground: Valuing Coastal Amenities". 7th Workshop on non-market valuation. Marseilles, July 2019.

Gillespie, T. 2018. “Information Matters: Evidence from flood risk in the Irish housing market”. The 10th Annual Marine Economics and Policy Research Symposium. November 2019

Gillespie, T. 2017. "Picture vs Playground: Valuing Coastal Amenities". “Value of the local environment for health and wellbeing: planning implications”. ESRI, Dublin January 2020.

1.7.3 List of report inputs

EPA report:

Gillespie, T., Hynes, S., Lyons, R.C., Lunn, P.D., Lyons, S., Terence, J., McElvaney, E.M., Moore, K., Murphy, M., Choisdealbha, Á.N. and Nolan, A., Research on Aspects of Ireland’s Environment, Consumer Behaviour and Health: ESRI Environment Research Programme 2016-2018.

Daft.ie report on sea views:

https://www.daft.ie/blog/coastal-costs-buyers-pay-up-to-32-more-for-a-sea-view/

Floods articles:

https://www.rte.ie/brainstorm/2020/0114/1107355-how-can-we-deal-with-rising-sea-levels-and-increased-flood-risk/

Inshore Ireland Vol 15 nr 1 Spring 2019 “Rising waters, falling prices: flood risk and the Irish housing market” Gerry Flynn DOI: https://issuu.com/inshoreirelandpublishing/docs/inshore_ireland_vol_15_nr_1_spring_

1.7.4 Contributions to papers derived from thesis

A number of papers have been written up from the thesis. While the thesis is my own work, my supervisors are co-authors on these papers. Prof Stephen Hynes was co-author on the blue space working paper and helped with the direction of the study as well with analytical suggestions; Dr Ronan Lyons was co-author on all three working papers and gave direction and assistance with the theoretical and technical considerations needed to produce the work and results; Dr Thomas McDermott co-authored the floods working paper and advised on literature and identification strategy. While not one of my thesis supervisors Finn McLaughlin co-authored the green space working paper that derived from the thesis as he assisted with the literature review therein.

In all three working papers that resulted from this thesis, the author of the thesis was the first author and principal investigator and undertook all research design, data analysis, literature reviews and writing duties.

2 Non-market Valuation

2.1 Value theory

2.1.1 The Economic Concept of Value

The previous section frequently refers to “value”, as it is a crucial element of the thesis and economics more generally. It is an especially important term in the field of environmental economics and requires an intricate understanding. Therefore, it would be prudent to start with an outline of its etymology and conceptual development. For Aristotle, value was intrinsic to the natural end an item serves whereas for Locke, Hume and Smith, the true value of an item is associated with its long-run costs of production (Sewall, 1901). The modern concept of economic value on which the non-market valuation is based can be attributed to Dupuit (1844) and Marshall (1879). According to Dupuit (1844), the `maximum sacrifice expressed in money which each consumer would be willing to make in order to acquire an object' provides `the measure of the object's utility'. Dupuit was in fact the first to identify the downward-sloping demand curve as a representation of a declining marginal utility schedule and as an expression of the consumer's marginal willingness to pay - i.e. the monetary value of his/her marginal utility (Hanemann, 2006).

Thirty years after Dupuit, Marshall independently formulated a similar argument, based on more formal analysis. Whereas Dupuit (1844) merely asserted that the demand function viewed with price as a function of quantity is the marginal WTP, Marshall formally derived this as a mathematical implication of utility maximisation. Marshall (1879) defined the economic measure of satisfaction as `that which a person would be willing to pay for any satisfaction rather than go without it'. The difference between what the individual pays for and what he/she is willing to pay was defined by Marshall as `consumer's rent' in 1879 and `consumer's surplus' in 1890.

Marshall's work postulated a cardinal, or broadly speaking, measurable utility function, which he assumed could be aggregated. According to Hanemann (2006), `Marshall himself came to be troubled that his use of the demand curve to measure consumer's surplus was inexact and relied on the assumption of a constant marginal utility of income'. In fact, Marshall emphasized that when consumer's surplus was calculated from an aggregate demand function, the resulting aggregation of values neglects the fact that `a pound's worth of satisfaction to an ordinary poor man is a much greater thing than a pound's worth of satisfaction to an ordinary rich man' (Marshall, 1890). For Marx, "[use values] constitute the material content of wealth, whatever its social form may be." (Marx, 1867, p. 2).

With the advent of the ordinal utility revolution in economics, Marshall's ideas `appeared hopelessly out-dated and irrelevant'(Hanemann, 2006). In fact, it was not until the 1970s that `the Dupuit-Marshall concept was recognized as being fully consistent with modern, ordinal utility theory and susceptible of rigorous empirical measurement' (ibid.). This was a result of a number of important contributions, beginning with the work of Hicks in the 1930s.

Hicks (1939) showed that Marshall's analysis, including his definition of consumer surplus, could be expressed precisely in terms of ordinal utility using indifference map analysis. But since indifference curves are not directly observable, Hick's findings, while deemed an important theoretical breakthrough, were not considered of practical value. Thus, Marshall's welfare definitions were still not measurable in practice. This changed however with the development of duality theory, and in particular the publication of Hurwicz and Uzawa (1971), which presented `theoretically rigorous yet practical numerical procedure for identifying the specific utility function underlying any given system of demand equations that satisfies the formal requirements of modern ordinal utility theory' (Hanemann, 2006). Thus, given a suitable demand function, it was now possible to derive a theoretically consistent and rigorous estimate of the Dupuit-Marshall measure of the economic value (ibid.).

A number of other important contributions should also be noted. While the concept of WTP was advanced by Dupuit, Marshall and Hicks, Henderson (1941) suggested a new welfare measure, based on the concept of willingness to accept (WTA). Hicks then considered the relationship between WTP and WTA for the case of a price change, showing that they differ due to an income effect (Hicks, 1942, 1943, 1946). Importantly, Willig (1976) showed that the result from Hurwicz and Uzawa (1971) could be used to show that, under certain conditions, the difference between WTP and WTA in the case of a price change for a market good is small. The final breakthrough of significance in the area came with Maler (1971, 1974) who formally showed how the WTP and WTA concepts of value could be extended to consider nonmarket goods and services. This work provided `a formal justification for the field of nonmarket valuation, including the monetary evaluation of the natural environment' (Hanemann, 2006).

Given this evolution of the concept of economic value, it is today generally accepted that the economic value of an item can be measured by how much money an individual is prepared to exchange for it. Furthermore, economic value is not limited to marketed goods and services but can be extended to environmental and recreational goods.

2.1.2 Non-market values and valuation techniques

Environmental resources have different types of values. These values can be divided into use and non-use values. These two main categories reflect the economic understanding that goods and services are deemed as beneficial through the utility ascribed to their usage and/or knowledge of their existence from an anthropocentric view. Consequently, the value of an environmental resource such as a beach may be measured through the magnitude of use and non-use values enjoyed by people.

2.1.2.1 Use values

When people derive utility from the actual usage of a resource, then that resource is considered to have a use value. Use values stem from the enjoyment derived from usage or consumption of a resource. People are generally willing to pay to enjoy this value or willing to accept payment to forego its availability for their usage. Conversely, people may be also willing to pay to avoid dis-amenities and their associated costs, such as flood risk, which is considered in more detail in the thesis. Use values can be divided into two categories of: direct use and indirect use values.

Direct use values involve the in-situ use of a resource to benefit people and might include sea swimming or walking in a city park. These direct use values may be consumptive (e.g. drawing drinking water from a river) or non-consumptive (e.g. bird watching) (Edwards-Jones, Davies, & Hussain, 2000). While there is no definitive agreement on the categorisation of direct use values, consumptive use tends to reduce the quantity or quality of the resource being consumed whereas non-consumptive use does not necessarily decrease quality or quantity. There are some beneficial functions derived from some resources that are not directly used; these are the indirect use values (Barbier, 1993).

2.1.2.2 Non-use values

The notion of non-use values was first introduced by Krutilla (1967) in his paper on the conservation of environmental resources. The motivation for non-use values may come from people's altruistic nature, their bequest desires and/or just their knowledge that a certain environmental resource exists as influenced by their spiritual or philosophical motives. Altruistic value is the value placed on a resource by people because they derive some satisfaction from preserving that resource for others such as people in another location. Bequest value is the satisfaction that individuals derive from knowing that a resource will be preserved for use by future generations. In contrast to altruistic and bequest values, existence or intrinsic value relates to the utility derived from simple knowledge of the existence of a particular environmental asset. Krutilla (1967) argued that there are many people who are willing to pay for the satisfaction of knowing that a wilderness area remains even though they would never want to visit it. This existence value may be drawn from the satisfaction of knowing a natural resource is preserved for itself and not as a function of any human use (Edwards-Jones et al., 2000). Motivations for such existence may also include stewardship, whereby individuals feel some responsibility for the resource or have a feeling of concern for an asset such as an endangered species (Bateman et al., 2002). Individuals who harbour existence values for a resource are assumed to be willing to pay for the preservation of that particular resource.

Non-use values are non-exclusive, thus they are unlike use values which may have multiple uses that are exclusive or non-exclusive. A value placed on the existence of a nature park is considered a public good due to its non-exclusive nature and vulnerability to exploitation (Plourde, 1975). Therefore, some people may be willing to pay for the existence of a unique nature resource that would otherwise be destroyed for competitive private economic activities.

Freeman et al. (2014) outlines a more technical distinction between use and non-use values. Assuming an individual has a preference ordering over a vector of market goods, $\boldsymbol{X}$, and some non-market resource, q. Here, q is taken to be a scalar measure of some characteristic of the environment, such as sea views or the value of some parameter of water quality. The notion that the total value of the resource q is not solely tied to the purchase of a complementary market good can be captured by assuming that the individual's direct utility function takes the form:

$$U = T[u(\boldsymbol{X}, q), q]$$

In this case, the non-marketed resource q enters utility in two distinct places, first by interacting with the marketed commodities, $\boldsymbol{X}$, and second on its own. The key feature of this functional form is that the marginal rates of substitution among the marketed goods, which dictate their observed consumption levels, are independent of this second role of q. Thus, information on $\boldsymbol{X}$ provides no information on this portion of preferences. (Freeman et al., 2014)

2.1.2.3 Option value

Apart from use and non-use values described above, economists have also identified option value as another form of value for resources. Option values may be either demand-side option values or supply-side option values. Demand-side option value is the value placed on a good or service by people because they want to have an option to consume it at a future time, where consumption is uncertain (Weisbrod, 1964). Consequently, demand-side option value can serve to reduce future use value, as the future value is weighted by the uncertainty of the consumption. Such people may never exercise their option. In a case where consumption is certain, option value may arise from the uncertainty of future supply; this is termed supply-side option value. Bishop (1982) noted that when the future provision of a good or service is uncertain, people may be willing to pay over and above its use value to secure its supply in the future.

Another definition of option value is that from Boardman et al. (2011) who defined option value as the difference between option price and the expected consumer surplus. Option price is what individuals would be willing to pay in uncertain circumstances. It is estimated by the sum of option value and expected consumer surplus in the absence of uncertainty. Option price may be viewed as an ex ante welfare measure because individuals value a resource without knowledge of contingencies that might occur (Boardman et al., 2011). A simpler explanation was given by Pearce et al. (2006, p. 10): option price is the maximum willingness to pay for something in a risky world and where there is uncertainty on what the outcomes will be. The correct way to value the benefits of a resource/policy in circumstances involving risk is to sum the ex-ante amounts that the affected individuals would be willing to pay to preserve it (Bishop, 1982). The willingness to pay values may be elicited from the relevant individuals using stated preference techniques.

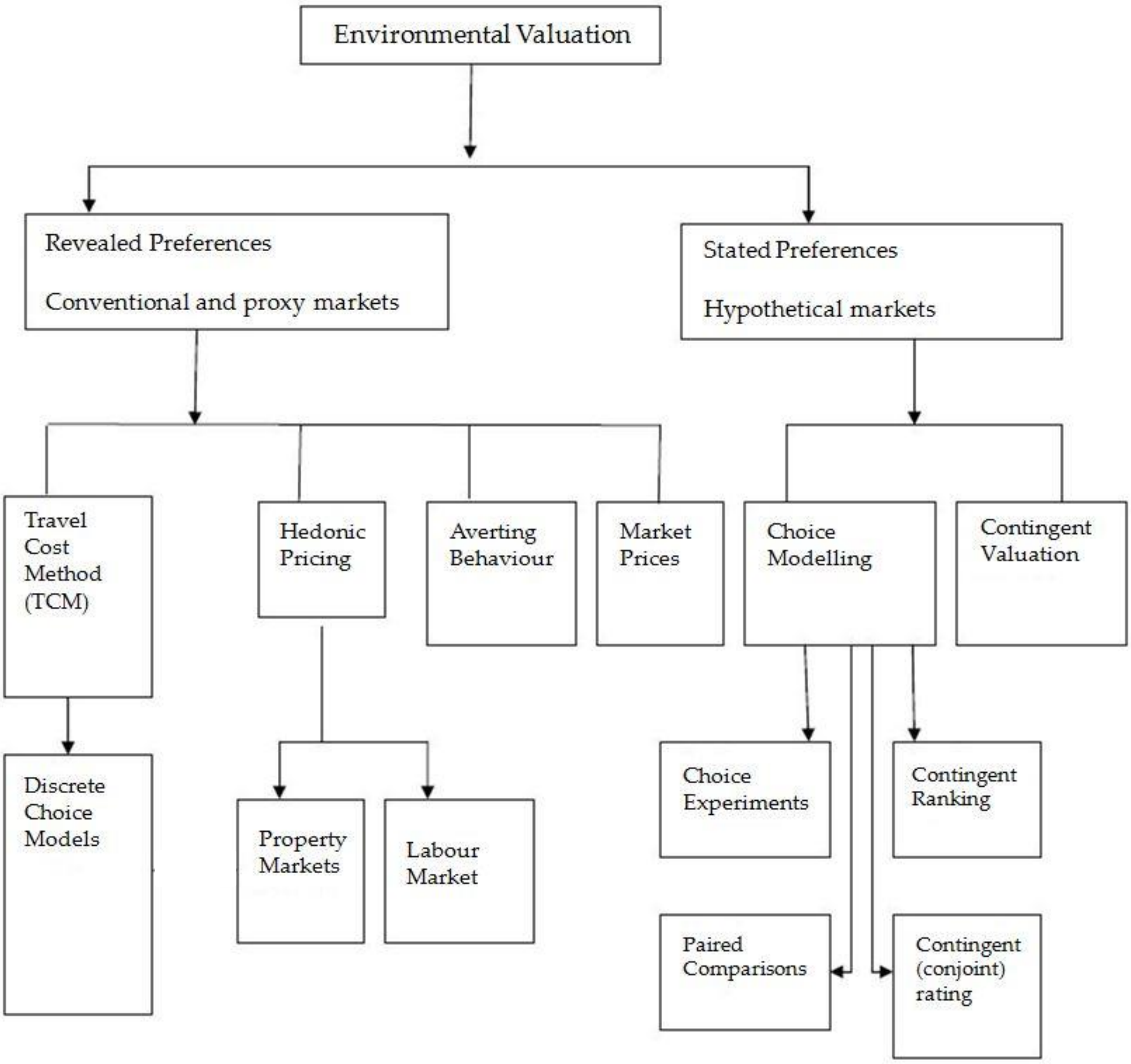
It is possible that people who derive some use-values from an environmental resource may somewhat harbour some level of non-use or option value for the same resource. The sum of all these values gives the resource's total economic value which is discussed in Bateman et al. (2002).

2.2 Economic valuation techniques

Different types of values may be estimated using either stated or revealed preference techniques. To date, various non-market valuation techniques have been developed and used to estimate economic values of environmental amenities. An overview of these non-market valuation techniques can be found in the writings of Freeman (2003a; 2003b) and Pearce et al. (2006). These methods may be divided into two main categories of stated and revealed preference techniques.

Stated preference (SP) techniques elicit people's values for goods/services from their stated responses to questions asked by analysts (Pearce et al., 2006). Because they rely on the use of surveys, stated preference techniques can be used in more applications than revealed preference techniques. Stated preference methods such as contingent valuation method may be used to estimate people's willingness to pay to access, say, a park or potential future improvements in the park or even existence values for the park. In contrast, revealed preference (RP) techniques use actual observed market choices in the real world to deduce people's underlying preferences to estimate their value for non-marketed resources (Freeman, 2003a). Thus, revealed preference methods can only be applied ex post while stated preference methods have an added advantage of being able to be used in ex ante analyses, as well as for estimating non-use values. The methodologies most suitable for valuing environmental amenities are shown in Figure 2.1. (Figure 2.1 has been adapted from Hynes (2005)).

Figure 2.1 Classification of environmental valuation methods:



2.2.1 Stated Preference Methods

Stated preference methods have two major classes of elicitation techniques that could potentially be used to analyse preferences for environmental amenities. The first type, contingent valuation, measures the value of a change from the status quo to some other state of the world. The second, the Discrete Choice (DC) experiment technique, involves the respondent choosing the preferred option from a number of scenarios in which elements of the attribute bundle describing the good are varied. The benefit of using SP techniques is that they are capable of capturing both use and non-use values, however they suffer from hypothetical biases.

2.2.1.1 Contingent Valuation

The contingent valuation method (CVM) was the first approach to directly ask people to state their value of a non- market good. The technique was first suggested by Ciriacy-Wantrup (1947), and first applied by Davis (1963) to estimate the benefits of game hunting in Maine, USA. Direct non-market valuation techniques such as CVM and DC experiments does not rely on actual market data to produce welfare estimates but rather produces estimates based on people's inferences or choices in a survey. The value elicited through CVM is dependent on the nature of the hypothetical or simulated market conveyed to the respondents. The CV method normally consists of three major parts namely: (a) the scenario or description of the policy or program by which the good/service is going to be provided; (b) the value elicitation mechanism; and (c) the socio, economic, demographic and environmental factors that could potentially influence the value placed by individuals (Mitchell and Carson, 1989).

One major limitation of CVM, however, is that it is only capable of considering the value of one hypothetical change or scenario.

2.2.1.2 Discrete choice experiments

In a DC experiment, respondents are given a hypothetical setting and are asked to choose their preferred alternative among several competing alternatives. Each alternative is differentiated by the levels of the attributes. Experimental design theory can be used to construct the hypothetical choice task. In DC experiments, it is possible to infer respondent's marginal rate of substitution between the attributes. Inclusion of a monetary attribute enables the respondent's WTP to be indirectly obtained for either an alternative in its entirety or for a non-monetary attribute, that is its marginal WTP or implicit price. The choice task includes the competing alternatives and usually a status quo or `choose none' option. This ensures that respondents do not make a forced choice and hence is similar to real market purchasing decisions.

2.2.2 Revealed Preference Methods

Revealed preference methods are also known as quasi-market-based methods. The behaviour of individuals in the market leaves data traces that may be analysed to deduce the individual's implicit preferences for non-marketed goods and services such as an environmental resource (Taylor, 2003). These data may be revealed by the premium (discount) individuals pay (receive) when they buy properties with access to an environmental amenity, or the cost they incur from traveling to an environmental amenity. The former is analogous to the hedonic house price method, and the latter to the travel cost method.

2.2.2.1 Travel Cost Method

The travel cost method (TCM) is a method by which the consumer's preferences for environmental amenities are estimated on the basis of the travel cost incurred in relation to enjoying the benefit of a natural resource. Taking green space recreation as an example; people at a particular park site pay an implicit price for using the site through the costs associated with visiting that particular site. Because people visit a site from different origins, the relation between differences in implicit price and travel behaviour can be utilized to analyse the demand for the park site. A person will choose to visit a site if the enjoyment or value of going to that site is at least as high as the travel expense.

The TCM is attractive as a non-market valuation tool as it mimics the more conventional empirical techniques used by economists to estimate economic values based on market prices. It cannot however deal with future changes that might occur in response to a change in the natural resource amenity being offered. The TCM can only calculate the current use value of a recreational site.

2.2.3 Why choose hedonics?

In the context of the thesis, the alternative methods outlined above for valuing non-market goods may be an appropriate methodological approach for valuing beach sites or green spaces (Loomis and Santiago, 2013. Lo, 2012). However, given the data available, aesthetic views and flood risk could be more appropriately valued using house prices. For that reason, the hedonic house price model was considered to be the best approach to estimating WTP for blue space and green space amenities, and also WTP to avoid flood risk. However , in the flood risk analysis the results of a CVM question asked of prospective home buyers is also presented to provide additional information on the type of person willing to pay to avoid flood risk, and their stated level of WTP, as a comparison to the estimated WTP from the hedonic analysis.

2.3 Hedonic Theory

The hedonic pricing method is one of the dominant revealed preference methods that has been used to estimate non-market values for environmental resources. This method assumes that an individual's utility from a good is a function of the characteristics of that good. Empirical work on the hedonic pricing method for housing prices is based on Lancaster's (1966) seminal paper on consumer theory and Rosen's (1974) seminal paper on product differentiation. It was argued in these two papers that the price of an attribute of a good is a function of the observed prices of heterogeneous goods and the attributes associated with such differentiated goods. The use of this approach is consistent with the hedonic premise that goods are valued for their utility bearing attributes and that people choose goods with combinations of characteristics that yield the highest utility. The approach also assumes that the property market is in equilibrium such that buyers' bids interact with sellers' offers to determine equilibrium property prices and thus the implicit prices of the different property attributes.

To estimate the value of a non-market good, the hedonic property price model assumes that when buyers or renters choose a house as their home they are making a decision to purchase a bundle of characteristics. The hedonic price model is commonly used to estimate the implicit prices paid for non-market attributes that are bundled with houses that are traded in a market. This model has been used extensively for analyses of economic impacts of changes in environmental quality on residential property values.

Consumers or buyers must be able to perceive the different qualities or quantities of an attribute so they can adjust their market behaviour with changes in that attribute. The hedonic model will not be useful in assessing the value of changes in quality/quantity of a given non-market resource where consumers are not able to perceive differences in quality or quantity (Grafton et al., 2008).

The relationship between the value of a property and its characteristics is expressed in the form of a hedonic price function. To elicit preferences, house buyers will be used to explain the underlying theory for the hedonic price model, however, the same analogy could be applied to house renters. This relationship between the price of a house and its characteristics is generally stated as follows (for example in Freeman (2014) and Taylor (2003)):

$$P = f(Z) \tag{2.1}$$

Where: P is the house selling price;

Z is a vector of characteristics, *z1, z2,… , zn*, of the house

Equation 2.1 models equilibrium transactions of willing sellers and buyers. It is assumed that sellers and buyers are aware of the heterogeneous attributes which come with each property. These attributes are made up of the different house structures, neighbourhood, and environmental characteristics that come with each location. Characteristics of the buyer and seller of a property are not included in the hedonic price regression (Taylor, 2003). The equilibrium hedonic price function is determined by the interaction of utility maximising buyers/renters, and profit-maximising sellers/landlords. Therefore the optimal house bundle is defined by a function where marginal bids and marginal offers are equal to the marginal prices for house attributes. A home buyer or renter would choose a residential house (Z) which maximises their utility (equation 2.2), subject to their budget constraint (equation 2.3), expressed as:

$$U = f(x, z_1, z_2, \dots , z_n; \alpha) \tag{2.2}$$

$$y = x + P(z_1, z_2, \dots , z_n) \tag{2.3}$$

where:

1. U is the individual’s utility from the property;

2. z_i are the various characteristics ($z_1, z_2, \ldots, z_n$) of the residential house;
3. x is a numéraire good, representing all other goods the individual spends their income on;
4. $P(z_i)$ is marginal price for attribute z_i; y is the individual's income; and
5. α are demographic characteristics that vary across individuals

The first order conditions are satisfied for the consumer problem by equation 2.4, which sets the marginal rate of substitution between one of the property characteristics (z_i) and the numéraire good (x) equal to the marginal price for the characteristic, $P(z_i)$. The equation that characterises a solution for the optimal level of the characteristic z_i and the numéraire good (x), can be written as:

$$\frac{\partial U/\partial z_i}{\partial U/\partial x} = \frac{\partial P(Z)}{\partial z_i} = P(z_i) \tag{2.4}$$

The left-hand side of equation 2.4 gives the marginal rate of substitution between z_i attribute and the numéraire good. The middle-part represents the implicit marginal price, which is equivalent to $P(z_i)$. This implicit marginal price is the additional amount that must be paid by an individual to secure a housing bundle with characteristic z_i at a specified level, all other things being equal (Freeman, 2014). For example, with an improvement in environmental quality, then the partial derivative reveals the marginal price and therefore the marginal willingness to pay for that improvement in environmental quality.

A consumer's marginal willingness to pay a price for different quantities of a good, given their budget constraint, may be viewed as their optimal bid for the different characteristics of that particular good (Rosen, 1974). The bid function represents the individual consumer's willingness to pay for a given property, Z, as one or more of its characteristics are changed, while utility (u) and income are held constant. The bid function (θ) may be represented as follows:

$$\theta = f(Z, u, y; \alpha) \tag{2.5}$$

Equation 2.5 traces out how a consumer's optimal bid varies as a given characteristic, z_i, changes, with utility and income and other characteristics held constant. The marginal bid with respect to a given z_i will equal the marginal rate of substitution between z_i and the numéraire good x. As shown in equation 2.6, the necessary conditions for utility maximisation are that the marginal bid a consumer places on z_i must equal the marginal price of that characteristic.

$$\frac{\partial(Z;u,y)}{\partial z_i} = \frac{\partial P(Z)}{\partial z_i} = P(z_i) \tag{2.6}$$

On the other side of the market, there are landlords who must choose if and when to sell or rent a house based on prevailing market conditions. These sellers will seek to maximise their profits given the cost of production, and the prevailing market prices. The costs of production will vary for each seller depending on the production costs they have to incur to produce a developed residential property, Z. Their cost function may be given as:

$$C = f(H, Z; \beta) \tag{2.7}$$

Where: H is the number of units of Z (i.e. residential properties) that the landlord offers sell or rent and β are the characteristics of the individual landlord.

Therefore a seller of a given residential property, Z, who is facing an exogenous equilibrium price schedule $P(z_i)$, will seek to maximise profits, Π, as follows:

$$\Pi = H \; x \; P(z_i) - \; C(H, z_i, \beta) \tag{2.8}$$

Equation 2.8 is essentially a deduction of costs from revenues to determine profits. The seller's decision to offer a residential property Z for sale, may be represented by a set of offer functions:

$$\phi = f(Z, \Pi; \beta) \tag{2.9}$$

The offer function, ϕ, identifies the amount of money a seller is willing to accept for a house with characteristics z and still make profit Π. In a similar pattern as for buyers' bid functions, the offer functions trace out the marginal offers by a seller such that the offers are equal to the market price $P(z_i)$. The optimised bid and offer functions will occur at tangency with the marginal price. The interaction of buyers' bid functions and landlord's offer functions for a differentiated good in a competitive market will determine the hedonic price. Thus, the hedonic model is based on the theory that the implicit price $P(z_i)$ of an attribute z_i, is equal to the consumer's marginal willingness to pay for that attribute $\theta(z_i)$.

Under the hedonic theory, buyers are not able to move to a higher utility by choosing a product with different characteristics, similarly sellers cannot increase profit by changing the quantity or type of house they offer. However, bid functions will be expected to change as income changes.

The use of data on property prices and attributes to establish a hedonic price function and therefore the estimation of the implicit prices of characteristics is referred to as first stage analysis. The second-stage analysis involves the use of the implicit prices estimated in multiple and separate first-stage analyses to estimate the demand functions for the characteristics of the commodity (Taylor, 2003). The first-stage to modelling preferences using the hedonic price technique is sufficient for answering questions at the margin (Ham et al., 2012). At the minimum, hedonic analyses are useful if they provide empirical evidence that the price of a heterogeneous market good reflects the level of some environmental good embodied in it, even if the price is zero (Leggett and Bockstael, 2000). The results of first-stage analysis address questions such as what magnitude, sign, and statistical significance an additional unit increase in an attribute quality/quantity will add to the value of a property.

Welfare analysis requires that the first-stage implicit prices are converted to money values and aggregated over the affected community (Brucato et al., 1990). The aggregated monetary amount gives the estimated welfare impact on the community and may be used for welfare analysis. When a change in an environmental attribute is localised and marginal, the estimated change in sales price, resulting from the change in the attribute, is the measure of net-benefits or total willingness to pay across all properties that receive the attribute change (Taylor, 2003). Depending on the goals of the study, the expected moving costs may be considered and subtracted from the net benefits to estimate welfare impacts. Given the many variables and assumptions involved in the estimation of the hedonic price function, there are a number of issues that must be considered and addressed in a first-stage analysis. These issues are discussed in subsequent sections.

2.3.1 Technical considerations

2.3.1.1 Functional form

Subsequent to assembling data on the dependent and explanatory variables, the researcher needs to decide on the functional form of the hedonic price method. Different functional forms have been used in hedonic property valuation models. These include: linear, quadratic, double-log, semi-log, inverse semi-log, exponential and Box-Cox transformation.

Adapted from Taylor (2003) and Sakia (1992) The functional form has mainly been empirically derived. Past hedonic price studies have argued that the functional form which yields the best fit of the data is the one that should be selected (for example Rosen (1974)). Cropper et al. (1988) investigated the functional form issue in hedonic price models using simulations. Their study demonstrated that when all housing attributes are observed without error, the more complicated functional forms such as quadratic, quadratic Box-Cox are better estimators of the implicit price. The same study found that if some independent variables are not observed or are replaced by proxies, then simpler forms such as the linear, semi-log or linear Box-Cox perform relatively better than the complex forms. More recently, this widely held view that simpler functional forms are generally better has been questioned and tested. Kuminoff et al. (2010) carried out an empirical Monte Carlo study to find out whether omitted variables seriously undermined the hedonic pricing method's accuracy using data for Wake County, North Carolina US. In this case the more flexible specifications such as the quadratic Box-Cox and log-log outperformed the simpler specifications that had dominated empirical practice for over two decades. The semi-log specification is the most frequently used in the literature (Netusil et al., 2014). In the thesis using a box-cox transformation would not be appropriate for continuous variables with a large number of zero valued observations as is the case with the sea view metric developed in Section 4.2.2 and 4.3.2. The use of semi-log models is advantageous as it offers convenient interpretation of coefficients. For a semi-log model with a log dependent variable and a linear independent variable, the implicit price for the independent variable is a product of the estimated coefficient and the mean or median house price. However, if the independent variable is a dummy, the implicit price is the exponential value of the coefficient minus one, then multiplied by the average or median house price (Halvorsen and Palmquist, 1980; Ham et al., 2012). Categorical variables can reduce the linear restrictions of the hedonic house price function by allowing it to be to be free from a pre-specified functional form.

2.3.1.2 Mitigating omitted variable bias via spatial fixed effects

According to Tobler (1970, p. 236), "everything is related to everything else, but near things are more related than distant things". The spatially based relations between properties and/or suburbs require consideration when the hedonic pricing model is used to explain property values. Omitted variable bias (OVB) is a pervasive issue in Hedonic house price modelling and there are many methods used in the literature to try and minimise its influence on identification (see Anselin et al., 2010). There are many unobservable spatial processes that can influence the price function of housing and the onus is on the researcher to outline a strategy for minimising this issue in a hedonic study. The literature is generally split into two principal methodologies for minimising the effect of unobserved spatial processes: spatial econometrics approaches involving the use of spatial weights matrices (such as the spatial error model of the spatial lag model); and the SFE approach which uses spatially delineated geographical entities. Kuminoff, Parmeter, and Pope (2010) show that the spatial fixed effect strategy can mitigate omitted-variable bias and improve the accuracy of estimates for MWTP in both linear and non-linear specifications of the hedonic price function. There is a trade off in the use of SFE: using geographically smaller units of SFE minimise omitted variable bias at the expense of variation, therefore larger datasets are more suited to the SFE approach. Spatial econometric approaches are less suited to larger datasets as computing spatial weights matrices can quickly become computationally intense with larger numbers of observations and in such cases random within-sampling is used at the loss of the full potential of available variation.

Von Graevenitz and Panduro (2015) argue that the spatial econometric models such as the spatial lag model and the spatial error model are not suited to hedonic analysis. The former implies spillovers between prices and therefore a spatial multiplier in the marginal prices that households pay for an attribute (LeSage and Pace, 2009). Only the interpretation of the spillover as a purely informational effect is consistent with the interpretation of the hedonic function describing a market in equilibrium. The spatial error model assumes that omitted spatial processes causing correlated residuals are uncorrelated with the regressors included in the model. This is unlikely to hold if the regressors include spatially varying characteristics. Because location varies only in two dimensions, spatial variables tend to be correlated with each other (Von Graevenitz and Panduro, 2015). Nevertheless, there is a lively debate in the literature over the best strategies for reducing OVB and spatial dependence, with Luc Anselin (for example Anselin, 2013a/b) being one of the main protagonists for the spatial econometrics approach. The large data available for this research, and the spatial nature of the variables of interest, such as sea views, suits the fixed effects approach.

In the thesis the approach used to minimise the influence of omitted spatial processes is the use of SFE. These are employed for two reasons. The first is that the sample size is relatively large and therefore is more suited to the use of SFE as outlined above. The second reason is that there are a number of geographical scales of SFE available to choose from in the data and hence it is easier to find an appropriately sized geographical unit which minimises omitted variable bias while maintaining a statistically acceptable amount of within variation. Having a range of SFE to choose from also allows for spatial sensitivity analysis to check for OVB. As a robustness check and as recommended by Von Graevenitz and Panduro (2015), each study reports the estimation of the primary model using all four available levels of SFE. Observing the sensitivity of the estimated coefficient on the variable of interest to changes in the level of spatial fixed effect can give an indication as to whether there is some omitted spatial process influencing the variables of interest.

Remaining spatial correlation in the error term can be accounted for by clustering errors at the level of SFE used to avoid overestimating significance levels. Robust standard errors improve on regular standard errors because the resulting inferences are asymptotically valid when the regression residuals are heteroskedastic, as they almost certainly are when regression approximates a nonlinear conditional expectation function (Angrist and Pitschke, 2008). Housing prices are unlikely to be independent across observations. Prices in the same area tend to be correlated due to the similar levels of amenities and characteristics. If areas can be reasonably identified whereby it is assumed that there is no within explanatory variation due to clustering, then clustering standard errors at the level of spatial fixed effect can correct for serial correlation as long as the number of clusters is sufficiently large. The exact number is difficult to quantify. Angrist and Pitschke (2008) report that studies that cluster at state-level in America have sufficient variation to apply clustering with confidence. In most of the preferred specifications in this thesis, the number of clusters exceeds 51 (number of North American states), and therefore the researcher is confident that clustering the error terms should correct any serial spatial correlation in the housing data.

2.3.1.3 Listings vs transactions prices

A concern about using listed sale and rental prices is that they may systematically deviate from the final, transacted, sale and rent price. Although listings prices are reported as a valid substitute for real transaction prices (Hyland et al., 2013; Malpezzi, 2003), there are relatively few studies that evaluate the amount of deviation from transaction prices. Faller et al. (2009) investigate the differences between listed and transaction prices for Northrhine-Westphalia, Germany. They found that on average the offers are 8% above the actual transaction prices. However, including controls for housing characteristics did not turn out to be an explanation for the observed differences. Significantly smaller gaps are found for urban locations and during market expansions, with marginal explanatory power for some housing characteristics (Henger and Voigtländer, 2014).

More generally, systematic mis-pricing of housing characteristics has been found to be very costly to the seller (Knight, 2002; Merlo and Ortalo-Magne, 2004), which is in line with theoretical models of seller behaviour (e.g. Knight et al., 1994). It increases time on the market and reduces the final transaction price. Both effects make it more likely that measurement errors (differences between listing and transaction prices) are unrelated to housing characteristics. This is confirmed by, among others, Knight et al. (1994) and Semeraro and Fregonara (2013) who analyse listed prices and the respective transaction data. Both studies find that coefficients changed only slightly when moving from listed to transacted prices. Three out of four coefficients for housing characteristics in Knight et al. (1994) were statistically equal across regressions, although all t-values were greater than six. The only exception is the variable 'living area' where the change of coefficients was statistically significant, but small.

In an Irish context the lag between the date of listing and the registration of a transaction price can sometimes be months after mortgage approval and legal procedures. As such the actual date of transaction can lag behind the market, whereas a listed price reflects the market value at that moment in time.

2.4 Literature review for empirical chapters

2.4.1 Methodological approach

A systematic and comprehensive literature review was undertaken to grasp the state of the art in the relevant areas of research specific to each empirical study. This approach is based on the guidelines provided by Stanley et al. (2013) for meta-analyses but also applicable in this context. Studies were collected using a systematic search of the EconLit database hosted on ProQuest. Further studies were added to the bulk list from the citations provided in the studies traced on EconLit. Relevant studies were identified using the following search criteria and narrowed by relevant subject:

1. Blue space:
   (Coast OR Sea* OR View* OR "Blue Space") AND (Propert* OR Hous* OR Resident* OR "Real Estate" OR "Hedonic")*
   Date of search: February 2021
   Hits: 988
   Earmarked for relevance: 21
   Included in review: 15
2. Floods:
   (Flood OR Inundat* OR Hurricane* OR Storm*) AND (Propert* OR Hous* OR Resident* OR "Real Estate" OR "Hedonic")*
   Date of search: February 2021
   Hits: 1,265
   Earmarked for relevance: 33
   Included in review: 16
3. Green space:
   ("Green Space" OR "Urban Green Space" OR Park) AND (Propert* OR Hous* OR Resident* OR "Real Estate" OR "Hedonic")*

Date of search: February 2021

Hits: 2,413

Earmarked for relevance: 47

Included in review: 19

2.4.2 Blue Space literature

2.4.2.1 Sea view valuation

Studies of waterfront property have found high premiums for ocean views. Benson et al. (1997) divided 397 residential property sales in Point Roberts, Washington into four views and found premiums ranged from 10% for a partial ocean view to 32% for an unobstructed ocean view and 147% for ocean frontage. Benson et al. (1998) examined a larger data set of 7,503 residential property sales in Bellingham, Washington from 1984 to 1993. The authors found a hierarchy of view premiums with direct lake frontage earning the highest premium of 126% compared to a full ocean view that commanded a price premium of almost 60% and a mountain view of less than 10%. An innovative element in this study was the inclusion of distance interaction variables to measure the proximity of an ocean view to the water: the authors found that the ocean view premium diminished with distance. Benson et al. (2000) provided similar conclusions. They examined 6,949 sales of single-family homes from 1984 to 1993 in Bellingham, Washington and found that all ocean view properties, as one category, commanded a price premium of 25.9%. They also found that the relative value of a view increased over the time period studied due to changes in the supply/demand dynamic. Other studies (Plattner and Campbell, 1978; Bourassa, Hoesli, and Sun, 2006) have shown that properties with water views appreciate at a higher rate than non-view properties.

Bond et al. (2002) found a similarly significant water view premium in their study of 190 homes on Lake Erie. Their hedonic model estimated a premium of almost 90% for a home with a view of Lake Erie compared to a home without a view. However, their study did not differentiate between different views or neighbourhood categories.

A GIS-based study of water views in New Zealand was conducted by Samarasinghe and Sharp (2008). Their study was composed of 2,243 transactions of residential properties in Auckland during 2004. Their hedonic tests examined type of views and scope of views in two different models. They found a hierarchy of views with price of water views decreasing by 18% at a distance of 500 metres away compared to a home on the coast, while wide water views cost 43% less at a distance of 500 metres. The authors attempted to deal with spatial dependency by the inclusion of several spatial variables including distance to the CBD, although they do not report spatial autocorrelation statistics.

Wallner (2014) uses GIS techniques to develop four view measures for a database of 24,491 Sydney, Australia home sales in 2008. Using a continuous variable for water views that measures the number of square kilometres of visible water surface area, the average water view is found to add 6.8-12.7% to a property's value. Water views in the top 5th percentile are found to increase property values 18.2-34.7%. For an angular diameter measure of water views, the maximum water view adds 59.4-107.0% to value. Compared to a binary (0-1) view variable for the same sample, the GIS measures improve out-of-sample prediction accuracy. As pointed out by the author, however, GIS measures cannot identify trees, telephone poles and other "idiosyncrasies" that can only be captured with an on-site inspection of a property.

Baranzini and Schaerer (2011) use GIS techniques to construct a continuous measure of view using LiDAR data around a 1km radius of each dwelling in the ~13,000 sample of rentals in Geneva, Switzerland. They account for natural environments which includes green space as well as blue space in the form of Lake Geneva, but also build space which includes the area of built environments that can be seen. They find statistically significant rent premiums associated with views as high as 57%.

Yamagata et al. (2016) generate a continuous measure of ocean views using LiDAR data in the city of Yokohama, Japan. They account for non-linear price functions of sea view using a spatial multilevel additive regression model. Their estimations were not as conclusive on the premium associated with sea views compared to previous studies.

2.4.2.2 Market Cycles

The first paper to estimate view values over time was Benson et al. (1998) (previously mentioned in Section 2.4.2.1). Results show that view premiums in percentage terms rose during the late 1980s, a period of growing demand and rising prices in the local market. For example, the percentage impact of an unobstructed ocean view (not controlling for distance) rose from 50% in 1984 and 1986 to roughly 60% from 1988 to 1993. During a period in which overall house prices are rising faster than the rate of inflation, even a constant percentage view premium implies an increase in the real price of a view. When the percentage premium is rising, that implies an even larger increase in the real view price. Thus findings of this study are consistent with the theory that prices of housing attributes with a relatively inelastic supply, such as view amenities, are likely to move with the housing cycle. During the same time period (1984-93), estimated elasticities for dwelling square footage remained relatively constant.

In another paper using transactions for coastal New Zealand, Bourassa et al. (2005) examine view values over time (1986-1996) in three cities: Auckland, Christchurch, and Wellington. Using housing attribute data that includes a binary variable for water view and a variable measuring distance from the coast, the authors estimate a hedonic model for each of eleven years for each city. Estimated percentage price impacts suggest that the premium for a water view varies over time, as well as across cities. When evaluated at the real mean sales price, estimated percentage impacts imply real prices for water views that move roughly with the local housing cycle, at least for Auckland and Christchurch. View premiums are found to be inversely related to the scarcity of views across cities, lowest in Wellington, the city with the fewest water views, and highest in Christchurch, the city with the most water views.

Hansen et al. (2013) found that given a relatively inelastic supply of locations with coastal water views, the price of a water view is likely to rise during housing market upturns and fall during downturns. Using 25 years of data and more than 20,000 home sales for Bellingham, Washington, they used the hedonic methodology to estimate water view premiums over different phases of the housing cycle. Views are differentiated both by scope and by distance from the water. Their results show real dollar premiums associated with water views move with the housing cycle, rising when housing demand and overall market prices increase and falling when the overall price of housing declines. In addition, the relative value of a view fluctuates as well (Hansen et al. 2013).

In contrast to these studies, Lyons (2013), using a smaller sample of the dataset used in this study (*daft.ie* sales listings 2006-2012), found strong evidence of counter-cyclical amenity pricing including coastal amenity. Seventy location specific characteristics were used in this research, with coastline, rivers, lakes, urban green space and forests being represented as environmental amenities. Over 50 % (26 out of the 48 amenities with statistically significant effects) exhibited counter-cyclical amenity pricing as the price of the characteristic increased during the market bust. The values for environmental amenities such as coastline, lakes, rivers and green space increased during the crash period, implying that the housing market exhibited a “property ladder” effect. For example, the premium enjoyed by a property 100m from the coast compared to one 1km away increased from 3.4% to 4.4% between bubble and crash. The author states that under normal circumstances, the individual prefers to reward access to amenities. However, during a bubble, the relative price of low amenity properties is pushed up due to a concern for lack of property. During the bubble, households were willing to pay the costs associated with longer commutes, whereas during the crash, preferences change as the capital gains decrease (Lyons, 2013).

Fernandez and Bucaram (2019) study the heterogeneity of implicit prices for various environmental amenities across submarkets and over the market cycle, in Auckland, New Zealand. They find a premium of 5.1% for beaches in the upper end of the price distribution but a discount of 2.1% in the lower end of the distribution using unconditional quantile regressions. They also show pro-cyclical price effects for beach amenities. They conclude that any planning decision involving expanding or enhancing environmental amenities should consider the market segment affected.

2.4.3 Floods literature

There are a number of papers on flood risk and property prices. Beltran et al. (2018), provide a review of this literature and meta-analysis that includes 37 studies published between 1987 and 2013. They find widely varying results, with estimates of the flood risk premium ranging from -75% and +61%. Results of their meta-analysis suggest the price differential for properties exposed to fluvial flood risk ranges between -7% to +1%.

The existing literature suffers from a number of problems, particularly related to identification, and estimates appear highly sensitive to context (Beltran et al. 2018). Various papers compare values of properties located in hazard risk zones to those located elsewhere, controlling for a range of property characteristics (e.g. MacDonald et al. 1990 [flood risk], Bin et al. 2008 [flood risk], Nagawaka 2007 [earthquake risk]). However, such studies depend on the strong assumption that hazard risk is exogenous, conditional on a set of other observable house price determinants (as argued by Bosker et al. 2018).

A recent contribution by Bosker et al. (2018) uses a border discontinuity design to more cleanly identify the effect of flood risk on property values in the Netherlands, where flood risk and defences are both prominent (€1.1bn spent annually). They find that house prices are on average 1% lower in places at risk of flooding, suggesting that perceived flood risk is higher than official protection levels.

A large body of literature, in contrast to the above, tests the effects of one-off events, such as floods, on property values. A common finding in this literature is significant flood risk discounts after flood events, but that these effects on property values fade over time, e.g. Bin & Polasky (2004), Bin & Landry (2013 J), Atreya et al. (2013), Lamond, Proverbs, & Hammond (2010). A similar finding in Gallagher (2014) shows a spike in demand for flood insurance following flood events (at the county level in the US), which declines with time since the flood.

These studies exploit the timing of disaster events, which is more plausibly exogenous, (often in a difference-in-difference set up) to identify effects on risk perceptions. However, as noted by Bosker et al. (2018), this strand of the literature identifies how people's risk perceptions change following a recent flood event. They do not identify risk perceptions (or willingness to pay to avoid risk) per se.

These findings showing updating of flood risk perceptions following flood events suggest incomplete information on existing flood risk.

In a recent contribution, Pilla et al. (2019) compare directly the effects of assessed risk versus a large flood event, for the case of Dublin after the 2011 floods. They find evidence that flood events had bigger impact than assessed flood risk, which reinforces the idea that actors in property markets are not always well informed about flood risk.

Ortega and Taspinar (2018) show a large discount on properties damaged by Sandy, which declines over time… but also a growing discount (following Sandy) for properties located in the flood zone that were not damaged -- evidence of learning or updating of risk perceptions. Their findings contrast somewhat with the short-lived effects of flood events on risk perceptions observed elsewhere. However, they argue that extreme events (such as Sandy) may lead to a more persistent updating of beliefs about risk.

Gibson and Mullins (2020) look at three separate flood risk signals on housing prices in New York: A flood insurance reform act; the hurricane Sandy flood event; and the updating of FEMA flood risk maps. They found discounts for the first two effects although they were not statistically significant. For updating of the flood risk maps the effect was larger for properties not affected by hurricane Sandy (-11%) than for properties inundated by the hurricane (-2.9%). They develop a parsimonious theoretical model to investigate the price mechanisms that allows decomposition of their reduced-form estimates into the effects of insurance premium changes and belief updating. Their results suggest the new maps induced belief changes comparable to those from insurance reform (Gibson and Mullins, 2020).

Hino and Burke (2020) use a panel set-up, exploiting the updating of flood risk maps in the U.S., to identify the flood discount. Their findings suggest that housing markets in the U.S. do not fully price flood risk in the aggregate. The results in the thesis are complementary to these (and Bosker et al., 2018) recent contributions, given that it estimates the flood discount for undefended properties (as well as the effect of installing new defences). Market responses to information updating are also analysed, and present evidence suggesting that markets continue to under-price flood risk, even following the release and widespread availability of highly detailed scientific risk assessment.

The findings in the thesis are also relevant for the literature discussing flood defences and the policy issues arising. In their Nobel Prize-winning contribution, Kydland & Prescott (1978) highlighted the issue of moral hazard, in settings where taxpayers bear some of the costs of flooding. Indeed, Husby et al. (2014) show that flood defences built after major flooding in the Netherlands in 1953 had a positive effect on long-run population growth in protected areas. In short, where market signals are weak, there may be a tendency towards over-exposure to flood risk.

2.4.4 Green space literature

The relationship between green space and housing prices is the subject of a large and rapidly growing literature. Kestens et al. (2004) is an early contribution. Using a dataset of 11,200 transactions in Québec city, Canada, they find that a 10% increase in mature trees within 100m of a property adds 1% to its value, while above-average lawn areas also add value in the suburbs (although not near the central business district). They find that while water increases property values, woodland within 1km decreases them.

Since the work of Kestens et al. (2004), other authors have found similar positive effects of green space on property values in a number of other cities, including: Jinan (Kong et al., 2007) and Wuhan (Jiao & Lu, 2010) in China; Adelaide in Australia (Hatton et al., 2010); and Los Angeles (Conway et al., 2010, and Saphores & Li, 2011), Portland, Oregon (Donovan & Butry, 2010, and Netusil et al., 2010) and Minnesota (Sander et al., 2010) in the USA. In all papers, the exact measure of green space varies and can include woodlands, parks, plazas/greens, lawns, and street trees. In a number of cases, there are limits to the results, or importance differences. For example, Saphores & Li (2012) find a difference for an individual property between the positive impact of trees in a neighbourhood and the usually negative effect of trees within the site.

Based on the literature search criteria outlined above, the following studies examine the relationship between green space and property values in Europe. These include two studies relating to Denmark, looking at Aalborg (Panduro & Veie, 2013) and Copenhagen (Panduro et al., 2018). Panduro & Veie (2013) use data on nearly 13,000 transactions of both houses and apartments in Aalborg, 2000-2007 and eight different types of green space, including agricultural fields and churchyards. They find that accessible and/or highly-rated green space is rewarded in the housing market. Panduro et al. (2018) use data on nearly 9,000 transactions of apartments in Copenhagen, 2007-2011, and focus on proximity to and density of high-quality green space. An additional hectare of park within 1km is associated with an increase in rent of 0.33%, up to roughly 60ha, while increasing proximity to the nearest park by 100m is associated with a 3% increase in rents.

Czembrowski & Kronenberg (2016) used data from Lodz, Poland, covering over 9,000 apartment sales 2011-2013. While they find that the impact of various green space categories is consistent across empirical specifications, the effect is greatest for the largest forests and parks. Franco & McDonald (2018) use data on nearly 12,000 two-bedroom apartments transacted in Lisbon, Portugal after 2007 and measures of vegetation and urban greenness. They find that a square-kilometre increase in tree canopy increases property values by 0.2% – but that this effect depends on the composition of green space in the neighbourhood green composition.

The most closely related research to this study is Mayor et al. (2009), hereby referred to as MLDT, who use a dataset of nearly 7,000 geocoded transactions in the Dublin market 2001-2006 and the 2000 CORINE dataset to capture green space. As with other researchers, they were interested in the effect on prices of both density of green space and proximity to it. They find that a 10% increase in green spaces (or park area) within 200m of a dwelling increases its price by 9% (and by 7.0% if within 2km). Due to statistical issues of multicollinearity, the authors reduce the specific parks of interest from 22 to 5 and find that only one, the Phoenix Park, has a positive impact on prices nearby – one other (Tymon Park) has a negative effect.

In summary, there is empirical evidence across a range of cities supporting the hypothesis that proximity to and density of green space has a positive effect on housing prices nearby. Nonetheless, the studies summarised above contain a range of nuances to this headline finding, including differential effects by dwelling type and, more consistently, by green space type. Large, well maintained, urban green spaces are most likely to add value to properties nearby, while certain categories (such as cemeteries) rarely have a positive price effect.

2.4.5 Summary

Based on the literature review of related studies several gaps have been identified that the empirical work in this thesis can speak to and address.

There are numerous studies that have estimated the effect of proximity to and exposure of the coastline on housing prices. A positive price premium for proximity to coastlines is a common finding but fewer studies attempt to create continuous measures of sea views due to the difficult and complex GIS work involved. Continuous measures are based on: area of sea that can be seen (Wallner, 2014; Yamagata et al.,2016); angle of view breadth (Samarasinghe and Sharp, 2008; Baranzini and Schaerer, 2011); and subjective scales of sea view quality (Benson et al. 1997 & 1998)). Some studies look at beach width as having an effect on housing prices (Gopalakrishnan et al. 2011), but no studies identified in the literature review looked at the separate effect of different types of coastline on housing prices.

A growing body of research analyses the effect of floods on housing prices. Extensive research has looked at the effect of flood events (Bin & Polasky, 2004; Bin & Landry, 2013; Atreya et al., 2013; Lamond, Proverbs, & Hammond, 2010; Ortega and Taspinar, 2018; Pilla et al., 2019) and designated flood risk zones (Beltran et al., 2018a; MacDonald et al., 1990; Bin et al., 2008; Bosker et al., 2018). Flood defences have also been investigated (Beltran et al., 2018b) but no study identified incorporated all of the above dimensions at once. Beltran et al. (2018a) also note the lack of proper controls for blue space amenities when estimating the effect of coastal flood risk, especially sea views. This is an important consideration in the context of this thesis.

The literature on urban green space and housing prices is large and generated the most number of relevant studies, of the three topics, in the literature review for this thesis. In Ireland, there has only been one attempt to estimate the value of urban green spaces but it did so using a limited dataset. Access to more detailed data with greater variation would provide an important policy contribution in an Irish context on the subject of urban green space management and planning.

More generally, the literature on the effects of environmental amenities on rents is quite limited and no studies identified in the literature review combine data on listed price, transacted price, and rents for equivalent markets.

3 The Data

3.1 Study area

The Republic of Ireland constitutes the study area in the analysis[3]. Ireland is an island nation with a small open economy and is part of the European Union. It has a population of 6.5million; 553,000 of which live in its capital, Dublin. In the timeline of the sample period used in the thesis it experienced an economic boom known as the "Celtic Tiger" which gave rise an over inflated property market fuelled by cheap credit. The financial crisis of 2008 lead to a deep recession and housing prices fell by over a half in the period from 2008-2012. It has since experienced a recovery which has led to the rise of housing prices and rents above and beyond their pre-2008 levels. Ireland has the highest share of population living in houses in Europe at 92.5% compared to the EU average of 57.6% (Eurostat, 2016). The capital city, Dublin, and its greater county area is the focus of more specific model specifications and data.

The climate of Ireland is mild, moist and changeable with abundant rainfall and a lack of temperature extremes. Irelands coastline is approximately 1,448km long and approximately 40% of Ireland's population live within five kilometres of the coastline, but when considering a European classification, over 90% of the island is considered a coastal zone (Tsakiridis et al., 2019).

3.2 Housing data

3.2.1 Listings data

The housing data used in the thesis come from two sources. Firstly, a national dataset of real estate listings from the property website *daft.ie*, the leading real estate website in Ireland is used. The *daft.ie* listings dataset is long, covering the period

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[3] The housing and environmental data therefore does not extend beyond the boundaries of Northern Ireland.

from early 2006, at the height of a property boom, through to the end of 2018. It also offers breadth, covering the national market in its entirety, and depth, with an estimated coverage of over 90% of all listings in the Irish market. The dataset is also rich, in terms of the information available for each listing, including dwelling attributes such as type and number of bedrooms and bathrooms, and an estimate of its location. The full *daft.ie* archive used in the thesis includes over 800,000 residential sale listings between 2006Q1 and 2018Q4.

Key property-level attributes for inclusion in a hedonic housing price model include the property's type and size. In the data is distinguished between apartments and houses dwelling types, with apartments further segmented between duplexes and regular apartments. For houses, there are additional distinctions in the data between terraced, semi-detached, detached and bungalow houses. These distinct property types are captured in the regressions using categorical variables.

Floor area (in square metres) is not a widely used size metric by consumers in Ireland and consequently, the majority of sale listings do not include this information[4]. To capture a property's size in the listings data, indicator variables are included for number of bedrooms (one to five) and for number of bathrooms (one to seven) relative to number of bedrooms. The sale transactions dataset includes floor area in exact square metres, based on information from official energy efficiency assessments of each individual dwelling, as well as other attributes including its year of construction and the number of floors in the dwelling.

Included in the sales dataset, hereafter referred to as the *sales listings* dataset, are:

1. List price
2. Date of listing

[4] Generally actors in the housing market judge advertised size by number of bedrooms/bathrooms, and the appearance in photos. Ideally I would have a square meter measure for each listing as it does have a significant effect, but there are no property datasets in Ireland that include it. It is however available from BER certificates in the transactions sub-sample and also from PRIME 2 building outline data.

3. Number of bedrooms/bathrooms
4. The type of dwelling
    a. Apartment
    b. Bungalow
    c. Duplex
    d. Flat
    e. House
        i. Detached
        ii. End-of-terrace
        iii. Semi-detached
        iv. Terraced
        v. Townhouse
    f. Site
    g. Studio.
5. Location accuracy (see below)
    a. Area level
    b. Building level
    c. General estate
    d. Street level
    e. Unmatched
    f. Village
6. Phrases from text of ad: "double glazed", "jacuzzi", "garden", "views", etc (Full list of phrases in Blue Space Appendix, Table A 2 and Blue Space Appendix, Table A 3.
7. *Daft.ie* generated areas (more in methodology chapter)
    a. Micro market
    b. Local market

The listed rentals dataset is similar to the sale listings dataset, in that it is sourced from *daft.ie*, with nationwide coverage from 2006-2018, and with similar dwelling attributes included. Rental price is aggregated up to an annual level allowing for weekly and monthly rent collection periods to be synchronised. There are 637,000 observations (2006-2018) in the rental listings dataset.

Included in the *rental listings* dataset are:

1. Rental price (standardised to annual rent)
2. Date of Listing
3. Number of bedrooms/bathrooms
4. Number of single beds

5. Type of dwelling
    a. House (no sub breakdown as in sales listings)
    b. Flat
    c. Apartment
6. Location accuracy (as above)
7. Mod cons and other rental features (microwave, parking, garden, etc. More in Data appendices)
8. Phrases from text of ad (as above)
9. *Daft.ie* generated areas (as above)

In addition to detailed systematic information on dwelling attributes such as size and type, a large number of other attributes were also available in the dataset, including those mined from the text of the ad[5], for example relating to the age or condition of the property; more details are provided in Blue Space Appendix, Table A 2 and

Blue Space Appendix, Table A 3**.**

A limitation of the listings dataset is, by its nature, that it does not contain the ultimate transaction price. The use of listed prices is well established in the literature, however. In Ireland, listed prices are based on estate agent assessment, rather than an owner's valuation; estate agents have local market knowledge, including the price of properties recently transacted in the area. Research exploring the relationship between list and transaction prices in Ireland during this period finds a strong correlation between the two, once hedonic methods are used, both over time and across space (Lyons 2019).

The data are then cleaned to remove outliers and/or errors in size/price. Any sales listings with prices outside of the range of €30,000-€2million were dropped from the analysis; as were listings outside the range of 1-7 bathrooms and 1-5 bedrooms.

[5] As I did not have access to the text of every advertisement, the process of mining phrases from the text of the advertisement was done in-house by *daft.ie*.

Listings locations are also cleaned for errors. Only listings that are within the republic of Ireland are included, this is done using GIS software by selecting points based on their location within a coastal and political border (Northern Ireland) outline of Ireland derived from OSi coastline data and CSO (Central Statistics Office) ED outlines. X & Y coordinates are included as well as fields for latitude and longitude. In circumstances where the x/y fields were blank they were replaced with the transformed latitude and longitude using GridInQuest software from the OSi. Due to the reliance on location precision for the various analyses, only listings with building level accuracy were included, as well as a small subset of listings that included Eircodes and therefore could be mapped with high precision.

Excluding dwellings that are either outliers or errors in size and price and restricting to those mapped to the exact building reduces the sales dataset to 426,035.

The reduction in the sample caused by the "building-level accuracy"-only condition is significant (45% reduction) and would alert the researcher to issues related to sampling bias. One possible bias would be the ratio of urban to rural listings within the sample compared to the actual ratio of urban /rural residential properties. Rural addresses are more likely to be inaccurately geocoded to xy locations, given their sometimes vague address fields, therefor there could be a bias toward urban listings in the *daft.ie* sample. To investigate this potential bias, the listings samples used in the preferred specifications of Chapter 5 and Chapter 6 were compared to the total population of residential Eircodes in Ireland. Floods Appendix, Table A 2 gives the breakdown of the sales and rentals listings, by urban/rural split, and by preferred specification. This urban/ rural ratio of listings is compared to the same ratio of urban/rural[6] residential Eircodes in Ireland, in the same geographical sample as the preferred specifications.

[6] The designation of urban/rural is based on the CORINE "discontinuous urban fabric" GIS classification.

Discrepancies between samples are reported in the table. For the floods analysis there is effectively a 0% discrepancy between the sales and rental listings sample of properties and the actual population of residential properties in Ireland. This is encouraging as identification in the floods analysis is unlikely to be affected by a sampling bias. The discrepancies are somewhat larger for the blue space (<10km from the coastline) samples: 4% and 7% for sales listings and rental listings, respectively. While the blue space sales listings vs blue space Eircode discrepancy is fairly minor (4%), the equivalent rentals discrepancy can be explained by the fact that there is a larger turn-around of rental properties in urban environments due to proximity to central business districts.

The listings datasets have at least four substantial features of value, compared to the transactions dataset. Firstly, they offer like-for-like data across both sale and rental segments, something unique in the flood discount literature. Secondly, the long time-span allows the estimation of flood risk discounts before and after the release of new information on flood risk, and also to analyse market cycles relative to the value of blue space amenities. Thirdly, they cover all markets across the country, rather than just the largest urban market. Lastly, the larger size of the two datasets, relative to transactions, allows for greater within-unit variation. In addition to the greater accuracy of the prices measured, the transactions dataset offers greater precision of location as well as some additional important control variables.

3.2.2 Transactions data

To complement the listings dataset, a supplementary dataset of housing transactions taking place in Dublin, Ireland (the largest city in Ireland) is also used. The underlying data relate to property transactions, recorded on Ireland's official Residential Property Price Register (PPR).[7] This register is a comprehensive database

[7] The data are available at www.propertypriceregister.ie (last accessed July 2020).

of all property transactions in Ireland since 2010, based on transaction tax returns made by solicitors. The register only contains the property's address as entered by the solicitor, the date of its transfer, its contractually agreed price, whether the dwelling is newly built, and whether the price is a full market price or not (i.e. whether the transaction is arm's length).

In order to accurately map these transactions, and to add the dwelling characteristics needed for hedonic housing price regressions, transactions for Dublin were mapped to Ireland's official Eircode dwelling-level identifiers. This was undertaken by *daft.ie*, using an iterative process of automatic scripts, reviewed manually to ensure accuracy[8]. Successful matches between the PPR and Eircodes enabled the identification of the exact dwelling, based on its location. Dwelling characteristics were added using Eircode matches with the database of Building Energy Ratings (BERs), which is maintained by the Sustainable Energy Authority of Ireland (SEAI). In accordance with EU regulations, since 2007 for new dwellings, and since 2009 for existing dwellings, it has been mandatory for all dwellings sold to have a standardised energy rating, on a scale from A1 to G. The only exceptions are for protected structures, although in some instances these will still have BERs for marketing purposes. BER certificates include rich property-level information entered by registered assessors, including the age, exact floor area in square metres, type of the dwelling, and number of storeys, as well as a variety of attributes used to calculate its overall energy rating, such as glazing and fuel type.

These PPR-BER matches were then reviewed for timing also. Where the date of the BER was either a month after the transaction, or a year before, this match was excluded as in either case the property attributes measured in the BER may differ

[8] This was necessarily a difficult task due to the old system of addresses in Ireland and the lack of requirement for solicitors to include Eircodes in the Property Price Register.

from those reflected in the PPR, due to renovations. PPR-BER matches through Eircodes form one transactions-level dataset, the 'double match' transactions dataset. An additional 'triple match' transactions dataset was also constructed, containing those properties that are on PPR, BER and *daft.ie* databases (as measured by their Eircodes). To do this, the *daft.ie* database was also mapped to Eircodes. This enables important robustness checks, including both a direct comparison between the properties included in both datasets and the inclusion in specifications of transactions prices of all property-level information available from *daft.ie*. Of 108,005 transactions at full market price in Dublin 2010-2018, it was possible to match 71,850 to an Eircode, and 64,432 to a BER cert matching the timing criteria. This is the 'double match' transactions dataset. Of these, a total of 39,789 were additionally matched to *daft.ie* listings, the 'triple match' transactions dataset used as the baseline sale transactions dataset in the thesis.

Included in the Transactions dataset:

1. Property Price Register (PPR)
    a. Transacted price
    b. Date of sale
    c. New or second-hand dwelling
2. Building Energy Ratings (BER)
    a. Floor area (m^2)
    b. Stories
    c. Building age
    d. Insulation type
    e. Window glazing
    f. Heating fuel type
    g. Water efficiency
    h. Space efficiency
    i. % low energy lights
3. *Daft.ie*
    a. Same variables as previous listings section

As the transactions dataset is underpinned by Eircodes there is no need for a location accuracy variable as location accuracy for Eircodes has the highest level of confidence.

3.3 GIS data

The relationship between the housing market and the surrounding environments underpins this research. The link between the housing dataset and its environments is based on the coordinates for each listing. From these coordinates link the housing dataset to a wide range of spatial data from a wide range of sources for the purposes of necessary econometric controls and for variables of interest.

Exposure to local environments can be measured in various ways using GIS software, the most common of which is using proximity measurements. ArcPRO software was used to calculate Euclidian distances from each listing to various spatial data in point, polygon, or polyline format. This was done using the near tool. Where listings were within the boundaries of a polygon of interest a select and/or spatial join tool was used.

3.3.1 Baseline spatial controls

A range of local amenities was considered that could potentially influence house prices and included in the baseline hedonic regression as control variables. The selection of these amenities/dis-amenities was based on a priori expectations, data availability and previous hedonic house price studies. A list of the spatial features selected as baseline controls is given in Table 3.1 and their descriptive statistics per empirical chapter is given in Blue Space Appendix A and Floods Appendix A. Distance measures were translated into categorical distance variables in the hedonic regressions to allow for non-linearity of the implicit price function.

Table 3.1: Spatial features used for baseline controls

Spatial Feature	Description	Spatial data type	A priori effect on price	Type of measurement	Source
Socio-economic features					
Major road network	Motorway/Primary road/secondary road	line	Positive or Negative	Distance	OSi
Central Business District	Centre of Dublin, Limerick, Cork, Waterford,	point	Positive	Distance	Drawn
Primary school		point	Positive	Distance	OSi
Post-primary school		point	Positive	Distance	OSi
Neighbourhood quality					
% with degree	Small area statistics from 2011 census	polygon	Positive	% of population within	CSO
% unemployed	Small area statistics from 2011 census	polygon	Negative	% of population within	CSO
Other features					
Power lines	Overhead power lines	Line	Negative	Distance	OSi
Golf courses		point/polygon	Positive	Distance	GUI
Mixed forest		Polygon	Positive or Negative	Distance	OSi
Deciduous forest		Polygon	Positive or Negative	Distance	OSi
Conifer forest		Polygon	Positive or Negative	Distance	OSi
Nature Reserve		Polygon	Positive	Distance	OSi
Canals		Line	Positive	Distance	OSi
Rivers		Polygon/line	Positive or Negative	Distance	OSi
Lakes		Polygon	Positive	Distance	OSi
Coast	Coastline not within transitional water body	Line	Positive	Distance	OSi
Transitional Waters	Transition from freshwater to marine conditions.	Polygon	Positive	Distance	EPA
Views (see methodology Section 4.2.1)					
Sea	% of sea area visible from total 360° view area to horizon & “views” mention in ad text	Raster	Positive	% Share	Osi/Dempsey et al. 2018
River	<75m from river polygon/line & "views" mentioned	Polygon/line	Positive	Distance/view dummy	OSi/*daft.ie*
Lake	<75m from lake polygon & "views" mentioned	Polygon	Positive	Distance/view dummy	OSi/*daft.ie*

3.4 Blue space data

GIS data was separated into two distinct categories: 'Playground' data and 'Picture data. 'Playground' data refers to the recreational potential of a coastal amenity and therefore consists of various different types of coastlines, using proximity based metrics, whereas 'Picture' variables refer to the aesthetic nature of the coastal amenities and measured in terms of their visual impact.

3.4.1 'Playground' data

The focus of this research is on the impact of both recreational and aesthetic coastal amenities on housing market outcomes. To capture recreational amenities, firstly, the coast of Ireland is split into three different but not necessarily mutually exclusive categories in addition to general coastline itself: coastal sand/shingle, designated beaches, and cliffs.[9] The sources of the data on coastal categories were Ordnance Survey Ireland (OSi) and, for cliffs, the National Parks and Wildlife Services (NPWS). Closer proximity to these coastal categories implies a higher potential for associated recreation. Euclidean distance to nearest category was generated for each listing.

- **Coastline:** The high-tide watermark (outside of a transitional water body) was used as an indicator of the coastline, as it is the most objective measure of the furthest inland frontier where the sea ends.
- **Coastal Sand/Shingle:** This classification of coast accounts for almost 78% of the coastline of Ireland. This broad classification includes rocky reefs, boulders, shingle and sand. Many small coves/tidal flats with beach-like qualities are amalgamated into this classification.

[9] Features located within transitional water bodies were not included. As these are not entirely mutually exclusive, the percentages of the coastline types add up to greater than 100%, for example, beaches located under cliffs. Similarly, a small fraction of the coastline is none of the four categories. In section 5.3.4, the study also examines the potential effect on prices of Blue Flag beaches, data for which comes from the Environmental Protection Agency (EPA) and *An Taisce*.

- **Beach:** The OSi's classification of a beach is one which has sand above the high tide line. This classification means that some sites that are effectively used as recreational beaches are classified as "sand/shingle" by the OSi. Just over 10% of the coastline is classified as beach.
- **Cliffs:** Cliffs provide recreational and aesthetic value in the forms of cliff walks and look-out points. There is also the possibility of a negative price effect from being too close to a cliff face as a result of a structural threat from coastal erosion. 25% of the Irish coastline is classified as cliffs.

3.4.2 'Picture' data

In order to generate metrics for picture variables, topographical data is needed. 10-meter resolution vector data in the form of contour lines was the highest resolution data available nationwide in Ireland. This was sourced from the OSi under the national mapping agreement. These contour lines had to be converted to raster format, necessary for viewshed analysis in ArcPRO.

3.4.2.1 National 10m DEM

The topo-to-raster tool was employed for the conversion of contour lines to a raster Digital Elevation Model (DEM). The tool allows the combination of other physical geographical features represented by vector data such as lakes, streams, and coastline in order to more accurately represent the topography close to these features that may not be well represented by the contour lines. This operation had to be done in a tiled nature as processing time increased exponentially for areas larger than approximately 8,000km^2. This split Ireland into 20 different overlapping sections and the tool was run individually on each section. All sections were joined into one DEM using the mosaic tool at the end. Raster pixels beyond the coastline were automatically assigned *no data.* To allow for viewshed projections into the sea, the DEM was extended 30km out from the coastline at a default elevation of zero. This was done using the raster calculator tool. The final output from this process was a 10-meter resolution DEM raster of the Republic of Ireland with a 30 km buffer out to sea with a zero elevation. Forestry polygons from OSi data were converted to 10m sized rasters and added as extra elevation to the DEM to account for view-blocking forestry[10].

This model of Ireland assumes a smooth landscape without buildings, individual trees and other potential objects which may block a property's view. In order to generate more robust estimates of view, LiDAR data was obtained for a sample area.

3.4.2.2 LiDAR data

LiDAR, which stands for Light Detection and Ranging, is a remote sensing method that uses light in the form of a pulsed laser to measure ranges (variable distances) to the Earth. It is much more detailed digital surface data generated from low flying plane surveys. It includes buildings and trees etc, and therefore gives a more realistic viewshed output at the expense of more intense computer processing. LiDAR data was obtained from the Office of Public Works (OPW) as a 2 meter resolution DSM for a smaller sample of Ireland[11]. The OPW originally generated this data for the purposes of coastal flood risk assessment, as such the sample is mainly confined to low elevation areas which are close to the coastline and hence most at risk to coastal flooding. The areas covered by LiDAR for this study include Galway city, and the coastline on the east coast from Dalkey in Dublin north to the border with Northern Ireland (see Blue Space Appendix, Figure A 2). Areas of LiDAR were merged together using the mosaic tool and 0 elevation sea areas were added using the raster calculator tool. This sub-sample was used for the purposes of a robustness check of the sea view metric developed in the Section 4.2.1.

[10] Technically this means that the raster used is a Digital Surface Model (DSM).
[11] LiDAR data is not widely available in Ireland and is costly to obtain, hence why a smaller sample than desired was used.

3.5 Floods data

The principal source of information related to flooding in Ireland is the Office of Public Works (OPW), the principal agency with responsibility for flood risk management in Ireland. Data was provided from the OPW on scientifically assessed risk, on past flood events, and on flood defences, as detailed below.

3.5.1 Flood risk

In the early 2010s, the Irish government began publishing new flood risk maps, to comply with EU Directive 2007/60/EC, which requires all member states to assess and manage flood risk. Preliminary Flood Risk Assessment (PFRA) maps were published in 2011 and made widely available by early 2012 with the launch of myplan.ie, a central repository for spatial information related to planning. While the most detailed map resolutions were not provided online at this point, individual dwellings could still be identified as being within the risk zones (see PFRA map example in Floods Appendix, Figure A 3), thus representing an information shock in terms of newly available information on officially assessed flood risk for the entire country. Previous to the release of the PFRA maps in 2011, there were no detailed maps available on flood risk in Ireland. This preliminary mapping exercise was used to identify Areas of Further Assessment (AFAs). The 300 AFAs identified became the focus of more detailed engineering analysis, risk assessment and extensive public consultation (see Floods Appendix, Figure A 1,). According to the OPW, approximately 80% of the dwellings at risk of flooding in Ireland are within an AFA. The geographic distribution of flood risk is illustrated in Floods Appendix, Figure A 7.

The flood risk maps that is used in the analysis come in the form of high resolution flood polygons depicting both fluvial and coastal flood risk zones at three levels of risk probability. For fluvial flood risk, these levels are 0.1% (1-in-1000 year flood), 1% (1-in-100 year flood), and 10% (1-in-10 year flood); for coastal flood risk, the low and high risk categories are the same, but the middle category is 0.5% (1-in-200 years). To identify the effect of being within a flood risk area, a categorical variable based on a dwelling's location with respect to the officially assessed flood risk zones, is defined as follows: a base (excluded) category greater than 500m from any flood risk zone; categories for intervals of 500-200m, 200-100m, and 100-0m from any flood risk zone; within the low-risk zones but not medium/high risk; and lastly, one combining medium and high risk zones. This latter category is described as 'flood risk' in headline results. A distinction between dwellings at risk of flooding but protected by flood defences, and dwellings at risk of flooding and not protected by flood defences is also made. The distinct categories of risk in the data allows for the estimation of the effects of exposure to risk of different severity, as well as proximity to those risks.

3.5.2 Flood defences

The OPW also provided polygon data related to 68 existing flood defence schemes completed between 1996 and 2017. Attributes include the date of completion, spatial extent of protection, whether the defence was permanent or demountable, and the cost of each scheme[12]. The categorical variable capturing flood risk, described above, was interacted with flood defences to enable an empirical examination of the flood discount before and after the construction of a flood defence and to ensure that the estimate of the flood discount is based on dwellings at risk of flooding and not protected by flood defences at the time of their listing or sale. In addition to a control group (dwellings more than 500m away from any flood risk), this gives ten categories of treatment by flood risk and defences. Descriptive statistics for these categories are in Table 3.2, for sale listings, sale transactions and rental listings datasets, described previously in Section 3.2.

[12] Dates of the announcement of the schemes, and hence an indicator of expectations behavior, were unfortunately not available. Although in the time between announcement and completion the properties would still be at risk.

Table 3.2: Frequency of flood risk and defence variables

Flood risk and defences measure		Sales Listings	Sales Transactions	Rentals Listings
No flood defences	More than 500m away	98,390	21,122	163,480
	500m-200m away	84,938	9,004	136,869
	200m-100m away	40,521	3,576	70,146
	<100m from low risk	47,538	4,414	97,633
	Inside low risk	6,773	741	23,302
	Inside medium/high	5,289	296	19,032
After flood defences	500m-200m away	54	24	104
	200m-100m away	20	3	81
	<100m from low risk	388	60	1,327
	Inside low risk	762	297	2,390
	Inside medium/high	209	106	412
Total		284,882	39,643	514,776

Note: The table shows the frequency of observations for each of the 11 categories of exposure to flood risk and flood defences, as described in the text, for three samples: sale listings (2006-2018), sale transactions (2010-2018) and rental listings (2006-2018).

Flood events

The data on flood events are drawn from an extensive archive of historical flooding in Ireland, compiled by the OPW. Information in the archive is drawn from various sources, such as reports by local authorities, engineers' reports, newspaper articles, and photos. This archive is the most comprehensive and complete collection of data on past flood events available in Ireland, with new information verified and checked for duplication before addition to the archive. Location and timing information from this archive is extracted. The vast majority of reported flood events include point location and peak flood time, while flood polygons (showing areas inundated) are available for a relatively small number of events. The dated flood points were defined based on a named location in the report related to the particular flood, while polygon flood event data were compiled using aerial photography. The dataset contains a total of 1,947 dated flood points and 84 dated flood polygons dating from 1763 to 2016.

The fact that the majority (~95%) of the flood events are in point format and not polygons representing flood inundation is a cause for concern. However, actors in the Irish housing market are working off the same data when considering where to live. Therefore, the underlying preferences might be best modelled in this way, where assumption of flood inundation is based on proximity to a flood event point.

Given that most of the flood events data are in point format, indicators for dwellings affected by each event based on the distance of the dwelling from the event, as well as the timing of the event are constructed. Two distance categories are made: dwellings within 100m of a flood event (or within a flood event polygon), and dwellings between 100m and 250m from a flood event. Only the most recent flood event, relative to the date of sale or listing, in the 100 (or 250) meter radius was used[13]. The time since the most recent flood within a 100 (or 250) meter radius of a dwelling was modelled as a categorical variable of which there were four categories: >30 years since a flood, 10-30 years, 2-10 years, and <2 years, with a base of no flood event recorded. With a reference category of no recorded flood event within 250m of a dwelling, this gives 10 measures of treatment by flood event, details in Table 3.3 below.

[13] Due to the added dimensions of modelling multiple floods and the associated demand on variation, the most recent flood of the 5 nearest flood points was the criteria used.

Table 3.3: Frequency of flood event variables

Flood events measure		Sales Listings	Sales Transactions	Rentals Listings
Flooding within 100-250m of dwelling	None	269,726	37,216	463,904
	More than 30 years	302	41	2,277
	10-30 years	2,425	318	8,848
	5-10 years	2,614	522	6,568
	2-5 years	2,523	468	6,110
	Less than 2 years	1,291	167	5,779
Flooding within 100m of dwelling	More than 30 years	1,665	293	5,023
	10-30 years	2,460	329	8,359
	5-10 years	907	140	3,924
	2-5 years	686	118	2,297
	Less than 2 years	283	31	1,687
Total sales		284,882	39,643	514,776

Note: The table shows the frequency of observations in each of the 11 categories related to exposure to past flood events, as described in the text, for three samples: sale listings (2006-2018), sale transactions (2010-2018) and rental listings (2006-2018).

3.5.4 Survey data

An online survey on actors in the housing market's perceptions and awareness of flood risk in Ireland was carried out in June 2019. The survey was hosted on *daft.ie*, the most popular property website in Ireland, with a link to the survey in the strapline of the home page for approximately 3 weeks in June 2019. The survey attracted a total of 837 respondents.[14] There was no mention of floods in the title or description of the survey to avoid self-selection of respondents with a particular interest in the topic, with the aim of gaining insight on actors in the housing market's perception and knowledge of flood risk. The full list of survey questions is included in Floods Appendix C: Survey.

In brief, the survey included a range of non-flood-related questions, including standard demographic questions, such as the respondent's age, gender and education, their reason for visiting the site, and questions on the budget and risk aversion of the respondent. Of those who indicated their age, the median response was the 40-44 age bracket (n=552), while of those who indicated their gender, 57% were female (n=525). Out of 837 respondents, 36% said they were interested in buying a property and 26% said they were interested in renting a property. (full survey in Floods Appendix C: Survey)

Further questions asked about the locations/markets of interest, and the importance of location characteristics, including amenities like green space and schools and dis-amenities like the crime rate. Flood risk was listed as one of these dis-amenities and additional questions (which followed later in the survey) asked respondents about their awareness of information about flood risk and of the availability of flood risk information, their concern about and experience of flooding, their perception of flood defences, and their willingness to pay to avoid flood risk.

3.5.4.1 Willingness to pay to avoid flood risk

A willingness-to-pay style question was included in the survey, relating to people's perception of flood risk discounts on property values. Each respondent was randomly assigned one of six versions of the question. The six versions were based

[14] Some respondents left questions blank, such that there are not 837 responses for every question in the survey. There were also some questions on the survey that only appeared in logical sequence depending on the answer to the previous question.

two versions for each of three levels of flood risk (0.1%, 1% and 10%), where one version for each level of risk included an illustration of the risk in terms of the probability of being flooded over the course of a 30-year mortgage. Two of the six examples (the other four are identical but at the 0.1% and 10% level of risk) are given below, with the additional text in italics (added here for clarity):

1. "Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a flood risk zone, with a 1% (one in a hundred) chance of flooding per year and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price do you think the house in the flood risk zone should be?"
2. "Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a 1% (one in a hundred) flood risk zone, *roughly similar to a 25% chance of being flooded at least once over the course of a 30-year mortgage*, and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price do you think the house in the flood risk zone should be?"

The wording was carefully considered in order to convey to the respondent that the question is asking about how *they* would behave given the choice. Nonetheless a limitation of this approach would be that the respondent may interpret the question in such a way that their answer pertains to a wisdom of the crowd's type answer. They may respond with the view that they are being asked about how the majority of people would behave in such a scenario as opposed to their own behaviour. Pilot versions of the survey on small focus groups (n=10) revealed that people interpreted in the former sense – their own behaviour – as opposed to the latter – everyone else's behaviour, however.

Results from this question are reported in Section 6.4.4.

3.6 Green space data

The focus of this element of the research is on green space amenities. To measure these in the Dublin area, the European Urban Atlas (EUA) of the European Environment Agency (EEA)was used which provides land use and land cover data for European major cities with more than 100,000 inhabitants. This data is generated using satellite imagery and machine learning for identifying features. For the GIS analysis data on urban green spaces (UGS) from the EUA including information on the land use classes green urban areas is used. According to the EUA the class green urban areas contains public green areas for predominantly recreational use such as gardens and parks. Not included in the green urban areas are private gardens within housing areas, sports facilities, and cemeteries. This green space data source is of a higher accuracy and resolution than the CORINE data and includes more urban green spaces in the Dublin area. The 22 identified parks in the MLDT were selected from the Urban Atlas green spaces, and, where unavailable, polygons representing the parks were created using GIS software and satellite imagery.

A combination of the CORINE, Urban Atlas, Open Street map, and PRIME 2 spatial datasets were used to identify and outline the urban green spaces used in the analysis.

3.6.1 CORINE

Co-ORdinated INformation on the Environment (CORINE) has the lowest level of resolution for all the land use GIS data used in this study, but also has the broadest range of coverage expanding nationwide.

CORINE Land Cover (CLC) programme, is administered by the European Environment Agency (EEA). Based on satellite images, CLC examines the shape, size, colour, texture and pattern of landscape area and classifies each area of land by type of cover.

The CORINE nomenclature distinguishes between 44 classes of land cover over three aggregation levels. The primary purpose of CORINE is to classify land by land cover types rather than by land use. Land cover refers to the physical characteristics of land, while land use refers to the purpose of land for humans. However, the CLC classification also provides some insights into the use of land. For example, the distinction between artificial and agricultural land indicates whether land is predominantly used for residences and for commercial and industrial activities, or whether the primary purpose is the production of agricultural goods.

3.6.2 Urban Atlas

UA is a large set of high-resolution digital land use/cover maps, covering more than 300 European Union Larger Urban Zones (LUZs) with more than 100,000 inhabitants. The LUZs were defined by Eurostat in an attempt to standardise the definition of a city boundary. LUZs approximate the functional area of a city, including the main core of the city as well as the surrounding hinterland, which was delimited by the analysis of commuting patterns.

The UA maps contain land use/cover information derived mainly from earth observations with support of other ancillary data, namely, base and topographic maps, city maps, the soil sealing layer, and off-the-shelf transport network and points of interest. Google Earth was used as well to assist interpretation. The mapping procedure was quite innovative, as it consisted of a semi-automated procedure with a logical sequence of decision rules to distinguish between different land use/covers. For example, linear transport features were automatically integrated into the land use maps from the off-the-shelf transport network to form the main spatial backbone of the database. Classification of the urban residential areas from high to low density was done automatically by overlaying the soil sealing degree, which served as a proxy for the built-up density.

3.6.3 Open Street Map

Open street map is an example of "volunteered geographic information" and is "open source" meaning it is free and compiled by amateur geographers and non-specialists. It has varying levels of quality depending on the area of study and in this research it is generally used as supplementary to official GIS datasets.

3.6.4 PRIME 2

PRIME 2 from the OSi is the highest resolution of spatial vector data available in Ireland with data capture resolution between 0.1m in urban areas and 0.5m in rural areas. In this analysis it was helpful to identify green space features and building and property outlines to additionally control for size of dwelling. PRIME 2 data includes building outlines and property outlines. This was used to estimate the size of a property in square meters where it was not available in the BER certificates. PRIME 2 data was acquired for the urban centres of Dublin, Limerick, Cork, Waterford and Galway under the national mapping agreement (see Blue Space Appendix Figure A 5: Extent of PRIME 2 data).

4 Methodology

4.1 Empirical hedonic specification

As discussed in detail in Section 2.3 the hedonic price function takes the following form:

$$Price=f\ S,L,E+\varepsilon$$

Where the price (or logged price) of the house is a function of the house's structural characteristics (number of bedrooms, bathrooms, garden, etc.), location characteristics (proximity to CBD, access to transport networks, Socio-economic factors, etc.) and environmental characteristics (such as proximity to green spaces, to the coast, etc). ε is the error term reflecting the gap between the conditional expectation and the actual (listed) value. The house price is thus a function of all of the attributes relating to the house and the resulting coefficients are the marginal implicit prices of the attributes. This analysis uses ordinary least squares and a semi-log or log-log specification (depending on the variables). The basic model looks as follows:

$$\log(\mathrm{price_i}) = \beta_0 + \mathrm{X}'_{1i}\beta_1 + \mathrm{X}'_{2i}\beta_2 + \mathrm{X}'_{3i}\beta_3 + \mathrm{X}'_{4i}\beta_4 + \mathrm{X}'_{5i}\beta_5 + \varepsilon_i$$

Where: $price_i$ can be replaced with $rent_i$ depending on whether the sales market or the lettings market is being analysed, X'_{1i} refers to a vector of property-specific attributes (type, bedrooms, bathrooms, etc), X'_{2i} refers to the time period (quarterly fixed effects), X'_{3i} refers to SFE, X'_{4i} captures a vector of location specific control amenities (distance to schools, transport networks, golf courses, etc), and finally X'_{5i} represents a vector of amenities which are the focus of this study.

Varying levels of SFE, clustered error terms within the level of spatial fixed effect, and robust standard errors are used to minimise bias, from omitted variables, and, standard errors (as discussed in Section 2.3.1.2).

4.2 GIS methodology

4.2.1 Viewshed generation

In order to create a novel measure for sea views the initial assumption that is required is that the area of sea that can be seen acts as a normal good, more is preferred to less. In reality the composition of the sea view, and not just the visible amount, might be what drives willingness to pay. Sea areas in combination with mountainous areas might be preferred to distant horizon sea views out from straight coastlines. Nonetheless the goal of the measurement was to find out what area of sea could be seen from each observation in the housing dataset.

Viewshed analysis is a 3D simulation methodology used in GIS software. If topographical surface data for a landscape is available, then, given a co-ordinate, a viewshed output can by generated by the software, representing, for that coordinate, the areas which can be seen and the areas that cannot (see Blue Space Appendix, Figure A 1). Due to the computational challenge of generating viewsheds for every observation in the dataset, the process was reversed; the sea area's viewshed (what areas of the land could be seen from the sea) was mapped onto the landscape. This was done by filling the sea area with evenly distributed points, as viewsheds can only be computed for points and lines, not areas/polygons (see Figure 4.1).

Four levels of sea buffers were generated to fill with sea points. These buffers extended around the entire coastline of the Republic of Ireland. The buffers were drawn without the small islands that didn't include dwelling observations to avoid inner points being far out to sea, the reasoning for this will be made clearer in the following section. The first buffer stretched out 500 metres from the shoreline and contained evenly distributed points (inner points) spaced 250m apart. The second buffer stretched from 500m-5000m (middle points) with points spacings at 500m, the third buffer 5000-1000m (outer points) at 500m spacings and the fourth buffer extended out from 10km to 30km out to sea with 3km spacings (outer 30k points).

4.2.1.1 Parameter selection

The visibility tool was used in ArcPRO to generate viewsheds. A maximum of 1000 points could be used in any process and the output would be a raster representing for each pixel the aggregate number of sea points that could be seen (see Figure 4.1). Observer height was set to 1.8m, representing the average height of a person standing up, seapoint height was set to 0m as the sea points were on the surface of the water. A default refractive coefficient was also incorporated to represent the bending of light over long flat surfaces due to air temperature differentials.

A maximum visible distance parameter required a decision on how far away a sea point could effectively be seen. Setting this parameter to very large distances increased computational time exponentially after a certain point due to the greater number of raster pixels that needed to be taken into consideration in calculations. The decision was made that 5klm inland would be a reasonable cut-off distance for having a 'meaningful' sea view. Therefore, for each buffer the maximum visible distance was the distance from the land to the furthest edge of the buffer, + 5km, so the inner buffer sea points had a maximum visible distance of 5500m, the middle points, 10,000m (5000+5000) etc. The DEM raster for Ireland was clipped relative to the sea points that were being processed and the maximum visible distance that was set, as processing time also increased exponentially the larger the geographical extent of the DEM raster. Separate viewsheds were run for transitional water bodies as well as coastal water bodies as a robustness check. This was due to the fact that it is difficult to distinguish some transitional water bodies as being either sea or river.

Once each collection of viewsheds (inner coastal, inner transitional, middle coastal, middle transitional, outer coastal, and outer 30k coastal[15])were complete they were

[15] No transitional water bodies extended out beyond 5km

merged together using the mosaic tool for the entire coastline of the Rep. Of Ireland and the values were extracted to the set of housing coordinates. The same approach was applied to the LiDAR sub-sample and values extracted.

4.2.1.2 Limitations and solutions

The final viewshed rasters represented, for each 10m pixel of land in the country, how many sea points (from each category, inner, middle, etc) could be seen. The limitation to this however is that the underlying DEM did not take into account buildings and trees and other potential view obstructions. As a result, it is probably over-estimating the number of points which can be seen in reality. To make these scores more robust, only listings which mention the term 'views' in the text of the ad are given a sea point score, if 'views' is not mentioned, the sea point score will be zero (see type 1 and type 2 errors in Blue Space Appendix, Table A 1). The assumption here is that any house with a sea view is going to mention it in the text of the ad as it is a unique selling point. However due to the limitations of the phrase finding, one cannot be certain that the ad was indicating views of something other than the sea, such as mountain views or woodland views etc. There may also be cases where the view is partially blocked by buildings or trees and therefore the sea point score would not be a true to reality. Furthermore, there could be listings in which the sea view is so obvious from the location and pictures that it is not mentioned in the text of the advertisement. Nonetheless these cases are considered by the researcher to be rare enough to warrant concern. Therefore it can be reasoned that this is a measurement of view potential and not actual view.

In the LiDAR sample, which is of a much higher resolution and therefor can represent sea views more realistically[16], the "views" robustness interaction was not required. However, there are some issues with LiDAR viewsheds in that the point coordinate of the property is situated at the front door, which may not be the side of

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[16] See Blue Space Appendix Figure A 3: Example of LiDAR detail in inner point viewshed projection on Galway city coastline

the property that faces the sea, or the sea might only be seen from the first or second floor. To overcome this separate viewsheds from different observer heights were generated as a robustness check.

4.2.2 Viewshare control

A more compact measurement of sea view was generated to allow for a simpler sea view control in the floods and green space chapters. This is used to estimate the share of view from each dwelling. Similar to the previous sea view measures, the view share measurement is interacted with the 'views' dummy for robustness. The proxy for sea view share, for observation i, is:

$$seaview\_share_i = \frac{simulated\ visible\ sea\ area_i}{total\ area\ within\ local\ horizon_i} * 'views'_i$$

To allow for locations with views extending beyond 30km from the coast (places at higher elevation and near the coast), an additional extrapolation factor is included. The area of sea more than 30km from the coast that might be visible from each residence given its local horizon is mapped. It is assumed that the fraction of this sea area that is actually visible is equal to the share of the 10-30km zone also within the local horizon that was predicted to be visible in earlier analysis. In essence, the area of visible sea in the 10-30km zone is grossed up to the extent that the local horizon extends beyond 30km. This methodology for generating sea view share was created for a paper I co-authored which looked at the effect of blue space on depression outcomes (Dempsey et. al. 2018).

4.3 Blue space

4.3.1 “Playground" variables

Euclidean distances to each amenity were generated for each listing. Where access points to the "playground" variables were available they were used for distance measures, otherwise distance to the nearest edge of the feature was used.

4.3.2 "Picture" variables

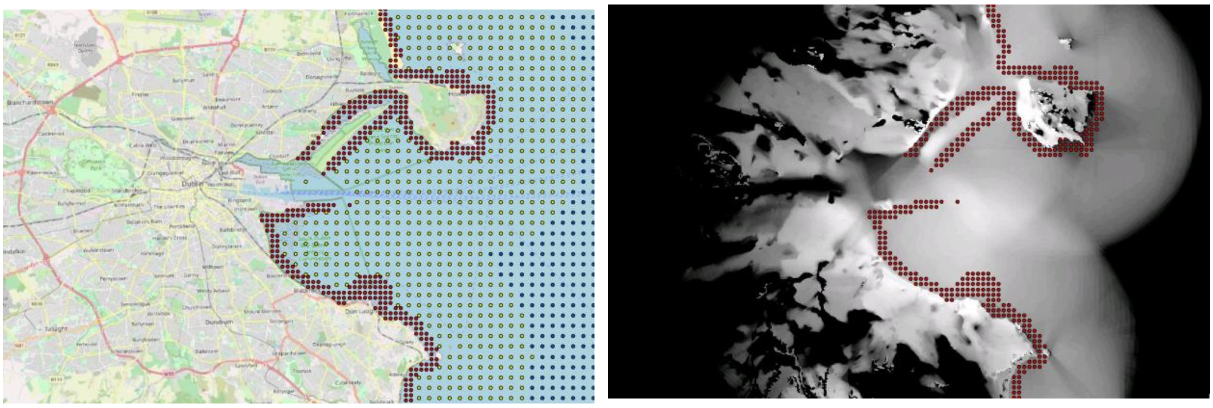
Developing a measure of sea view

A number of previous studies developed non-categorical measures of sea view, including Benson et al. (1998), Samarasinghe and Sharp (2008), Hamilton and Morgan (2010), Barazini and Schaerer (2011), Yasumoto et al. (2011), Wallner (2013) and Yamagata et al. (2016), see Section 2.4.2.1 for more detail. To measure the area of water visible from a property, the viewshed for that property was generated and the scope and extent of the sea-view measured. This was done for each individual property and was possible given the small datasets used in these studies. Both the absolute size of the dataset used here and its large geographical scope preclude the use of these techniques.

As discussed in Section 4.3.2 the number of sea points visible from separate buffers were generated for each 10m parcel of land. The buffers are shown in the left-hand panel of Figure 4.1, while the right-hand panel shows the resulting view ‘scores’ for land.

As this novel methodology generates a score for every parcel of land, it can be used on a dataset of any size, for a fixed computational cost. With the rise of administrative datasets, this will be useful in other settings. This process also minimises the steps needed to determine the area of sea that can be seen from a property using GIS software. Conversely, if individual viewsheds are computed for each property, there would be four additional steps need to achieve the same result: simulation of the viewshed, conversion of the viewshed raster to polygon, the intersection of the viewshed polygon with an ocean polygon, and the calculation of the area of sea-view ocean polygon.

Figure 4.1: Calculating view breadth



Note: The left-hand panel shows core (red) and two outer sets of points in Dublin bay. The right-hand panel shows the core points and the resulting viewshed output: the whiter the pixel, the greater the number of sea points that can be seen from its location.

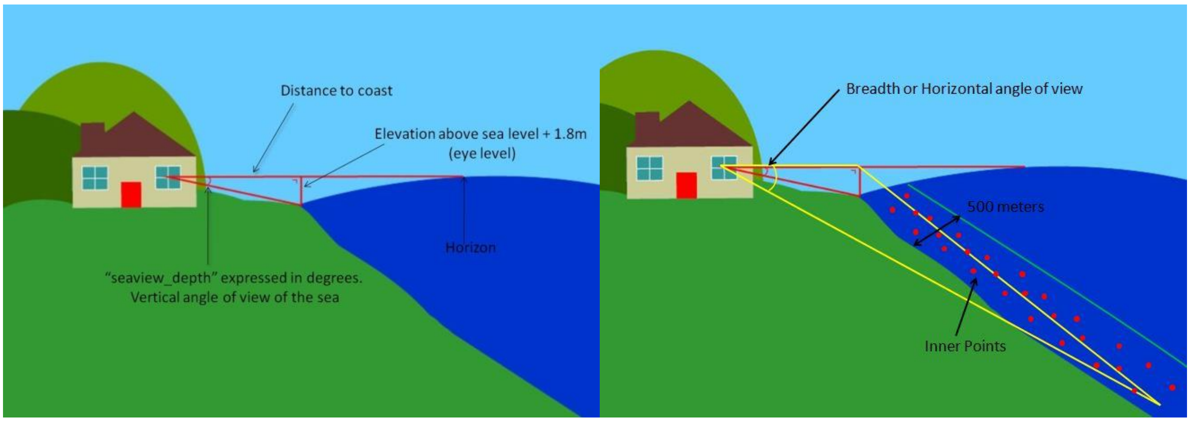
The above methodology captures in particular the (horizontal) breadth of the sea view but may not capture as accurately the (vertical) depth of the view. This is due to the fact that a large sea surface area from a bird's eye perspective will not always have the same visual impact when perspectives are varied by elevation, and therefore the scoring system will not always gauge the vertical visual impact of the sea. In order to capture view depth, the vertical angle from the closest visible coast out to the horizon was used. This will be highest for perspectives that are at a high elevation and also close to the coast. Figure 4.2 gives an illustration of the horizon angle measured in degrees.[17]

As described above, the limitations of countrywide DSM mean that it is likely to overstate the true number of sea points that can be seen for many dwellings.[18]

[17] A noteworthy limitation of the view depth measure is that it is calculated based on the nearest inner point by Euclidean distance, and not necessarily the nearest *visible* inner point. This may be a cause for concern for houses close to cliffs or on the crest of mountains.
[18] See Blue Space Appendix, Table A 1for Type 1 and Type 2 errors comparing the views term and the GIS view measure.

Therefore, in the baseline, only listings which mention the term *views* in the text of the advertisement are classed as having a view breadth (either close or distant). If there is no mention of *views* in the text of the listing, its score will be zero. As mentioned in Section 3.4.2.2, robustness checks include an alternative score calculated using LiDAR data that captures the built environment and other factors that may affect the view.

Figure 4.2: Calculating view depth



Note: This figure gives a stylized example of the calculation of view depth (the vertical angle of the view of the sea) and how it compares to view breadth (horizontal angle).

The two measures of sea view included for each dwelling, *view_breadth* (the log of the inner views score) and *view_depth* (the horizon angle) are calculated for each listing, *i*, as follows:

- $view\_breadth_i = \ln(innerscore_i) * 'views'_i$

$$Where: view\_breadth_i = 0 \; if \; innerscore_i = 0$$

- $view\_depth_i = \left(\tan^{-1}\left(\frac{eye\ level_i}{distance\ to\ coast_i + 250}\right)\right) * 57.2958$

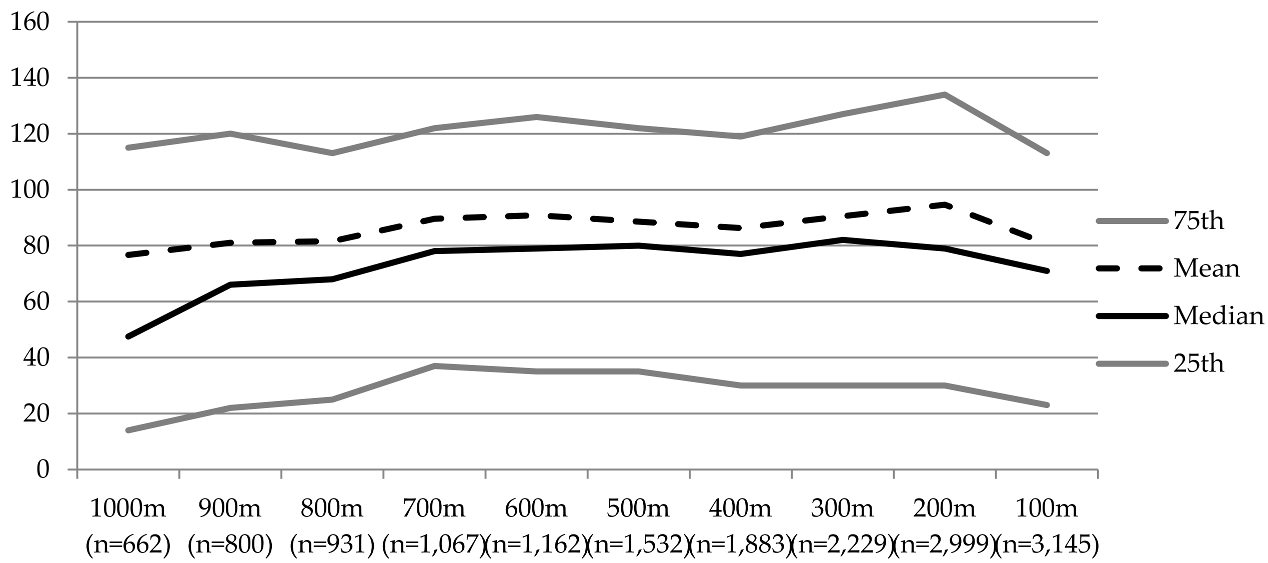
$$Where: eye\ level_i = (elevation_i + 1.8),$$

$$view\_depth_i = 0 \; if \; 'views'_i = 0 \mid innerscore_i = 0$$

4.3.2.1 Causal identification

For view breadth and depth amenities, there is one additional support to interpreting the coefficients presented as causal estimates of willingness to pay by households. This stems from the varied topography of Ireland, which means that there is variation of the view measures even at similar distances from the coast. This is shown in Figure 4.3, which show summary statistics for 24,166 properties with at least one (inner) point visible and less than 1km from the coast. Specifically, it shows the mean, median and interquartile range for view breadth, by distance from the coast, using the measure of (inner) points as the vertical axis. For properties within 100 metres of the coastline and with a view, the typical number of visible points is 71. For properties between 700m and 800m, the median is 68. These summary statistics give comfort that sufficient variation exists to separately measure view-based and distance-based coastal amenities.

Figure 4.3: Distribution of visible points as a function of distance to coastline



Note: The above figure shows summary statistics of the number of (inner) points visible for properties with at least one inner point visible in their viewshed, by distance to the coastline, with sample sizes for each distance bin reported in the horizontal axis.

4.3.3 Empirical Specifications

As outlined in Section 4.3.1 and 4.3.2 above, the baseline regressions include five regressors relating to blue-space amenities: sea view breadth and depth, and distance to three OSi classifications of coastline (sand/shingle, beach, and cliff), captured by vectors of distance-based categorical variables. And, building on Section 4.3.1 and as discussed in Section 2.3.1.2 for each of the three datasets – sale listings, rental listings, and sale transactions – four possible SFEs are considered. Lastly, for each amenity-related variable, in each of the three datasets, and for all four sets of SFE, both robust standard errors and those resulting from clustering at the level of the SFE on top of the robust standard errors are reported. In other words, for each variable in each dataset, there are eight results reported: two methods of calculating statistical significance for each of four SFE.

In addition to the analysis of sale and rental listings datasets in their entirety, we also analyse the sale transactions dataset, and examine the source of any differences between those results and results from sale/rentals listings. The large size of the listings datasets is exploited and it is examined how amenity prices vary over time, across geographies and over the housing price distribution, and also perform robustness checks, including the use of a proximity matched sample, a sample from areas with straight coastline and a sample using higher-resolution LiDAR data.

Ultimately, the preferred specifications in the larger listings datasets are with Small Area SFEs. Effectively, for two properties within the same Small Area (in urban areas, 200m-300m typically) and with the same observable characteristics, and similar access to other location-based amenities, coefficients show the effect of, for example, being within 100m of a particular coastline type (or not) and the effect of additional view breadth/depth.

4.4 Floods

4.4.1 Treatment of location

Location was calculated by *daft.ie* using a quasi-official mapping of addresses to coordinates known as Geodirectory. This process is necessarily imprecise, as addresses are often non-unique or entered with error. The script used to map addresses to exact location returns a confidence level, to which the location is mapped (e.g. 'street-level' or 'building-level'). Given the subject of the analysis, only listings with the highest level of location accuracy (building-level) are used. In the transactions dataset, all dwellings are mapped using the newly established official Eircode dwelling-level identifiers, providing precise location information for each dwelling. Given the manual reviews of the matching process, the exact locations in the transactions dataset come with a high degree of confidence. Having exact coordinates allows the calculation of not only distance to relevant measures of flood risk, as described above, but also a variety of other location-specific amenities. These include nearest city centre, transport facilities, schools, and natural amenities; a full list is given in Section 3.3.1, Floods Appendix, Table A 3 and Floods Appendix, Table A 4.

Nonetheless, despite these inclusions, there are always likely to be some spatial processes or area attributes that remain unobserved in the data. For this reason (and as discussed in Section 2.3.1.2), SFE are included, to capture the impact on housing prices of factors that are not included in a given specification, including location-specific and population-specific attributes. Four options are considered: local markets, 'micro-markets', Electoral Divisions, and Small Areas. The first two are based on *daft.ie*'s breakdown of real estate markets nationwide. Local markets refer to cities, postal districts (within Dublin city), and counties elsewhere in the country; there are a total of 54 markets in Ireland and 25 within Dublin. Micro-markets refer to collections of named areas on the *daft.ie* system. They are aggregated up from approximately 2,500 areas around the country into micro-markets, based on the volume of market activity, and geographical and socio-economic coherence. There are 375 micro-markets included in the dataset, of which 118 are in Dublin.

The latter two options for SFE are based on Census divisions of the country, and use the coordinates of the property, rather than the named area in the listing. There are just over 3,440 Electoral Divisions (EDs) in the country. Reflecting the focus of the analysis on AFAs, the nationwide listings sample cover 1,028 EDs, while the Dublin transactions sample covers 322. Lastly, Census ‘Small Areas’ (SAs) are a new spatial categorisation of Ireland, introduced in the 2011 Census and with an average of 180 dwellings per SA. Of 18,641 SAs in the country, 10,815 are covered in the sale listings dataset and 4,557 in the transactions dataset. The rentals listings dataset includes 1,002 ED's and 10,702 SA's. Table 4.1 below outlines the number of spatial units in the samples and the mean and median number of observations per unit.

Table 4.1: Spatial fixed effects by number of units/observations within units

Sales listings sample, 2006-2018 (national)

Fixed Effect	Number of spatial units in sample	Mean Number of Observations	Median Number of Observations
Local Market	54	7,847	6,874
Micro-Market	377	1,891	1,427
Electoral Division	1,027	768.9	519
Small Area	10,875	40	34

Sales transactions sample, 2010-2018 (Dublin)

Fixed Effect	Number of spatial units in sample	Mean Number of Observations	Median Number of Observations
Local Market	26	2,241	1,990
Micro-Market	118	576	435
Electoral Division	322	242	145
Small Area	4,558	11.8	11

Rental listings sample, 2006-2018 (national)

Fixed Effect	Number of spatial units in sample	Mean Number of Observations	Median Number of Observation
Local Market	54	15,302	13,454
Micro-Market	382	4,584	3,177

Electoral Division	1,002	1488	1215
Small Area	10,702	177.3	87

Note: The above table displays the number of units of SFE as well as the mean and median number of observations per unit of fixed effect. All of the above samples are within AFAs, as discussed in the text.

4.4.2 **The identification challenge**

The key identification challenge for estimating the value of flood risk, or willingness to pay to avoid flood risk in a hedonic housing price regression framework, is the possibility that proximity to a given (dis)amenity may be correlated with other relevant dwelling attributes or with other spatial processes related to the location of the dwelling that affect its market value. The richness of the data and some unique features allows for the exploitation of spatial precision and timing to identify the causal effect of flood risk on housing prices. The set-up is similar to difference-in-differences, as a comparison is made between, for example, dwellings at risk to otherwise similar dwellings not at risk, before and after the release of information on risk.

One basic concern for a hedonic model of flood risk and housing prices relates to controlling for the attributes of the dwellings themselves. If dwellings "exposed" to flood risk are somehow different from those not exposed, then the *ceteris paribus* condition in the regressions does not hold; one could be comparing flood-exposed 'apples' with non-exposed 'oranges'. The study exploits the richness of information in the datasets on dwelling attributes, to minimise the concern that omitted variables related to the dwelling itself may be driving results. For example, the two listings datasets include 30 variables based on the text of the ad, including indicators for wide range of dwelling attributes, such as "jacuzzi" and "garage". The transactions dataset includes attributes from the dwelling's official energy efficiency assessment. In addition, the large size of the dataset enables the restriction of the sample by dwelling type, to focus on dwellings that are more likely to be homogenous effect on unobserved variables.

Nonetheless, there remains the concern that factors other than the individual dwelling's attributes that affect its value could still be correlated with flood risk – in particular spatial processes, related for example to other amenities and neighbourhood characteristics. As a first step in addressing these concerns, in all the specifications the study controls for a range of location-specific attributes, including distance to nearest city centre, transport facilities, schools, and natural amenities (see full list in Floods Appendix, Table A 3 and Floods Appendix, Table A 4). The study also includes Census-based measures of neighbourhood quality, in particular educational attainment and unemployment rates at the SA level.[19]

However, without further strategies, identification would depend on the strong assumption that flood risk is exogenous, conditional on the included observable housing price determinants (dwelling-level attributes and location-specific amenities). Omitted variable bias is a pervasive issue in hedonic models of housing prices (as outlined in Section2.3.1.2), and there are many unobservable spatial processes that can influence the price function of housing (see Von Graevenitz and Panduro, 2015, for a discussion of alternative approaches used to address this problem). To capture unobservable spatial processes, highly localised SFE in all the main specifications are included, and to test the sensitivity of the findings on the main variables of interest to controlling for different levels of SFE (see Von Graevenitz and Panduro, 2015; Bosker et al. 2018).

The nature of the datasets allows for the exploitation of timing, leading to cleaner identification. In particular, the timing of the release of new information on flood

[19] Such controls could be considered as "bad controls". Bad controls are variables that are themselves outcome variables in the notional experiment at hand. That is, bad controls might just as well be dependent variables too. Good controls are variables that we can think of as having been fixed at the time the regressor of interest was determined (Angrist and Pitschke, 2008). The existence of flood risk might therefore affect the socio-demographic make-up of an area through sorting. Section 6.3.4 shows how inclusion of these controls affects the main results. Excluding these neighbourhood quality controls leads to a *larger* estimated flood discount, which suggests that flood risk is correlated with lower neighbourhood quality in the data. Results are also presented using SA fixed effects, such that these neighbourhood attributes get absorbed by the spatial fixed effect.

risk, which occurred during the middle of the listings datasets, allows the researcher to estimate the before-and-after effect of flood risk on housing prices. The contrasting findings for the effect of flood risk on sales listings prices before and after the release of the information provides reassurance that the causal effect of flood risk on housing prices (conditional on the availability of quality information on flood risk) is robust, and not some other unrelated spatial process that happens to be spatially correlated with flood risk.

The identifying assumption is therefore that flood risk is exogenous to housing prices, conditional on the timing of the release of new information on flood risk. The concern might remain, though, that there are confounding factors that could be both spatially correlated with flood risk and temporally correlated with the release of the new information on flood risk, and that affect sales but not rental markets.[20] One candidate could be local trends in the housing market, if these happened to correlate with areas at risk of flooding, and also differ by sales and rental segments of the market. Given that Ireland has experienced a pronounced housing market cycle during the sample period, this might add further to this concern. However, the standard specifications always include time period (year-quarter) fixed effects, to control for the national housing market cycle. Furthermore, as a robustness check, spatio-temporal fixed effects to control for regional/local market trends are included and results suggest that the estimation of the flood discount is essentially unaffected.

There may be other factors that affect the *salience* of flood risk during the sample period, and the study may be confounding these with the information shock, if they happen to correlate with the timing of new information. Flood events, in particular, might be a relevant source of changes in flood *salience* or flood risk perceptions. In all the main specifications, the study controls for past flood events (timing and location, as discussed previously in the floods data section, and further below). The study also

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[20] A significant flood discount for sales is found, after the release of information about flood risk, but no equivalent discount for rentals.

shows that the result that the flood discount exists after information is released, but not before, is unaffected by the inclusion or exclusion of events in the same regression. The study also checks the robustness of the main findings to exclusion of dwellings that were affected by a particularly large flood event that occurred in the same year as the information release.

One final concern, in relation to identification, is that selection effects may exist, both with AFAs and with flood defences. The selection of AFAs involved prioritising scientific assessment in flood risk areas considered most likely to be impacted by future flooding, which in general meant areas with a relatively large amount of development, rather than all areas at risk of flooding.[21] The selection of AFAs is thus clearly not random. In the main analysis I restrict the sample to only include dwellings in AFAs, rather than all dwellings, so that dwellings designated at risk are being compared to other dwellings in AFAs not at risk (with both sets of dwellings having received the same information shock). I also check the robustness of the main findings using the PFRA maps of flood risk, which covered the entire country, rather than restricting the sample to dwellings in AFAs, and find a similar pattern of results. Selection issues might be a more serious concern with the allocation of flood defences, given the relatively small number of schemes, the potential for political considerations to affect their prioritisation, and the relatively small share of the housing stock affected.[22] For this reason, I am cautious in interpreting the magnitude of the estimated effect of installing new defences on the value of protected dwelling, given that the estimated effects are unlikely to be representative of the value of reducing flood risk for *the average at-risk dwelling* in Ireland.

[21] The AFAs include all large urban areas in Ireland, as well as many smaller agglomerations. Of the 300 AFAs, approximately one quarter had populations of less than 500 people and half had less than 2,000 people.

[22] As per Table 3.2: Frequency of flood risk and defence variables in Section 3.5, just 1,375 dwellings out of ~190,000 (or less than 1%) in the *listings data* (listed in 2011 or later) are protected by the 68 flood relief schemes for which there is detailed information available to the researcher.

4.4.3 **Variations to the specification**

The main specification, as outlined in Section 4.1, is the basis of the estimate of the flood discount and provides three main findings – the sale flood discount, the impact of new information on it, and how it differs from the rental flood discount. In the main specification, the effects of distance from flood risk zones, of flood defences and of past flood events are also estimated. Flood risk and flood defence variables are as described in Section 3.5, with ten categories of flood risk/defence, in addition to the not-at-risk control.

To estimate the effect of the information shock, two variations on the main specification are implemented: first the sample is split into pre information shock (2006-2010, inclusive) and post-information shock (2011-2018, inclusive) sub-periods, and run the analysis separately on the two subsamples; and, separately, the flood risk indicator (within medium-to-high risk zones) is interacted with the year of the dwelling's listing to show how the flood discount has varied over time. The results of the latter exercise, shown in Figure 6.2 in Section 6.3.2, illustrate the dramatic change in the price effect of flood risk after the release of the flood risk maps in 2011.

Section 6.3.4 below presents three main sets of robustness checks of the main findings. The first of these is to show how estimates of the flood discount are affected by inclusion of various sets of controls. It begins with the most parsimonious model possible, with only the flood risk indicators included as explanatory variables, gradually adding in groups of controls in a step-wise fashion until it arrives at the fully specified model as per the headline results. This process allows the effect and importance of various groups of controls to be isolated, including for example spatial controls and those that capture "blue space" amenities.

A second set of robustness tests involves variation to the level of the SFE that are included. As outlined in Section 2.3.1.2, four different levels of spatial fixed effect are considered. The trade-off between different scales of fixed effect is that larger spatial units allow more variation within the spatial unit for the regressors of interest, while smaller units minimise the potential for unobserved spatial processes correlated with the error term leading to omitted variable bias and unreliable estimates. The preferred specification includes ED fixed effects, balancing the trade-off of capturing unobserved spatial factors and reliable estimation of location effects, as outlined in Table 4.1.

As recommended by Von Graevenitz and Panduro (2015), variations on the main specification using each of the four available levels of SFE are reported. Observing the sensitivity of the estimated coefficient on the variable of interest to changes in the level of spatial fixed effect can give an indication as to whether there is some omitted spatial process influencing the variables of interest. This set of robustness tests also includes versions of the main specifications with spatio-temporal fixed effects added to control for regional/local market trends, and clustering errors within SFE units to capture any remaining spatial correlation in the error term. The results of these checks both support the choice of ED fixed effects and demonstrate the robustness of the findings to variation in the level of SFE, to clustering, and to the inclusion of spatio-temporal fixed effects on top of location fixed effects.[23]

A third set of robustness tests involves comparison of results using the main listings dataset with the alternative transactions price dataset, described previously in Section 3.5. Results are presented using a matched sample that allows for direct comparison of transaction and list prices. Aside from comparing transactions and list prices as the dependent variable, there are a number of other distinctions between the two datasets. Results are presented in a step-wise fashion, allowing the effects of the additional dwelling-level attributes available in the transactions data, the different measures of dwelling location across the two datasets, and the obvious

[23] As an additional robustness test, border-discontinuity-design (BDD) style analysis is also implemented, where comparison group is restricted to dwellings within a set distance from the boundary of the flood risk area. The data allow me to mimic the three-step estimation strategy in Bosker et al. (2018): controlling for highly localized fixed effects, restricting the sample by dwelling type, and implementing a border-discontinuity-design type restriction on the comparison group. Results of these specifications are included in the Floods Appendix, Table B 3: Border Discontinuity style analysis.

difference in sample and geographic coverage to be observed in turn. These results indicate that the headline finding likely represents a lower bound on the true value of the flood discount.

A final variation on the main specification involves estimation of the flood discount across the value distribution of housing prices. Flood risk may be borne unequally in the housing market for several reasons. Estimations are based on unconditional quantile regressions (UQR) (Peeters et al., 2017). The advantages of the UQR, relative to (conditional) quantile regressions, are that its coefficients are directly interpretable as marginal effects (Firpo et al., 2009) and are consistent under alternative sets of covariates or specifications of the hedonic function (Maclean et al., 2014). Results are then interpretable in a policy or population context (Borah and Basu, 2013).

4.5 Green space

4.5.1 Green space buffers

In order to generate measures of green space and park space density for each observation, buffers were created at radii of 200m and 2000m around each dwelling. These buffers were then intersected separately with green space and park space to find the area of green/park space within a certain distance of each dwelling. This density metric is commonly used in the green space hedonic literature as a measure of green space exposure. Summary statistics of the key regressors relating to green space, as well as the transacted price, are shown in Table 4.2.

Table 4.2: Summary statistics of key green space variables

Variables	Obs	Mean	Std. Dev.	Min	Max
Price (€)	39,643	357,212	216,197	30,000	2,000,000
% GS within 200m	39,643	6.81	8.52	0.00	63.38
% GS between 200m and 2km	39,643	6.60	2.74	0.00	14.44
% park within 200m	39,643	0.87	5.11	0.00	87.02
% park between 200m and 2km	39,643	3.43	7.09	0.00	54.85
% of park space within 2km	39,643	3.41	7.04	0.00	54.61
% of park/GS within 200m	39,643	7.68	9.55	0.00	87.02
% of park/GS within 2km	39,643	10.00	7.10	0.00	57.43

Table 4.3 outlines the number of spatial units in the sample and the mean and median number of observations per unit.

Table 4.3: Spatial fixed effects by number of units/observations within units

Fixed Effect	**Number of spatial units in sample**	**Mean Number of Observations Within Spatial Unit**	**Median Number of Observations Within Spatial Unit**
Micro-Market	118	576	435
Electoral District	322	242	145
Small Area	4,557	11.75	11

4.5.2 Identification strategy

In this analysis the strategy for identifying the implicit price for urban green space would be based on the exogenous variation of proximity to green space at the property level. The treated properties would be those within a certain distance of an urban green space (either 200m or 2km). These would then be compared with a control group of properties beyond those distances, in which access to a green space amenity is lacking, conditional on dwelling characteristics and local amenities, in the context of a hedonic house price framework. Challenges related to OVB will be dealt with through the use of spatial fixed effects and a rich amount of variation in green space locations dispersed throughout Dublin city.

5 Picture and Playground: Valuing Coastal Amenities

5.1 Introduction & context

Living within or in close proximity to desirable natural areas and environmental resources such as coastlines and beaches is thought to provide a large number of positive welfare benefits to the public (Millennium Ecosystem Assessment (MA), 2005; TEEB Foundations, 2011, MacKeron and Mourato, 2013). As the demand for outdoor recreation has grown in recent years, more and more people have chosen coastal areas for permanent and temporary residences. Coastlines provide aesthetic pleasure as well as recreational uses such as walking, swimming, fishing, surfing, kayaking and sailing to residents and tourists. The key hypothesis investigated in this study is that prices in both sales and lettings segments reflect a willingness to pay for amenities not directly available in the marketplace, such as proximity to coastal features and amenities. Numerous studies have shown that proximity to coastlines has a positive effect on house prices *ceteris paribus* (Brown and Pollakowski (1977), Milon, Gressel, and Mulkey (1984), Parsons and Wu (1991)).

Few studies however have directly compared coastal aesthetic values ("picture") to recreational values ("playground") based on the marginal willingness to pay revealed from house price data. Can it be determined whether there is higher willingness to pay for access to coastal recreation than a view of the coast or vice versa? This has implications for development and planning policy; if views are valued higher than access, development should taper up away from the coast to allow for more properties with views rather than the other way around. This is especially relevant in urban settings.

The coastline itself can be broken into several different geomorphologic categories: sand, shingle, cliff, rocky, etc. This study attempts to disentangle the value added to the Irish housing stock from proximity to these various coastal categories (a unique approach in the literature) as well as the aesthetic value, through the use of the hedonic house price model. The study uses a dataset of sales and rental listings in Ireland from 2006-2018 which amounts to over 2 million observations from the online accommodation portal, *daft.ie*. This is combined with the best available spatial data for the coastline of Ireland sourced from various government agencies (OSi, EPA, NPWS, OPW, Census 2011)[24].

This study has four goals: firstly, to develop a unique continuous measure of sea views based on 3D GIS simulation; secondly to elicit aesthetic, as well as recreational values for the coastline based on the hedonic house price model and compare the magnitudes of these effects directly; thirdly, to compare the price and rental effects of coastal amenities; and finally, to analyse how the price effects of "picture" and "playground" amenities changes over the housing market cycle and varies over the price distribution. Discussion on the data and methodologies used is in sections 3.4 and 4.3, respectively.

5.2 Empirical Specification Recap

Conceptually, the value of a dwelling takes the following form:

$$Price = f(S, L, E) + \varepsilon,$$

where the (logged sale or monthly rental) price of the house is a function of the house's structural characteristics (S; such as number of bedrooms, bathrooms, or the presence of a garden), its location characteristics (L; such as proximity to CBD, access to transport networks, socio-economic factors) and its environmental characteristics (E; such as proximity to the coast or sea views). The error term, ε, reflects the gap between the predicted and actual (listed) prices. The dwelling price is thus a function of all attributes relating to the dwelling and the resulting coefficients are the implicit marginal prices of the attributes.

[24] OSi: Ordinance Survey Ireland; EPA: Environmental Protection Agency; NPWS: National Parks and Wildlife Service; OPW: Office of Public Works

More specifically, this analysis uses ordinary least squares and a semi-log or log-log specification (depending on the variable), as is typical in this type of study. Allowing for the long duration of the sample, and the focus on coastal amenities, the baseline specification is, therefore, as follows:

$$\log(price_i) = \beta_0 + X'_{1i}\beta_1 + X'_{2i}\beta_2 + X'_{3i}\beta_3 + X'_{4i}\beta_4 + X'_{5i}\beta_5 + \varepsilon_i \quad (2)$$

Where: $price_i$refers to sale or (annualised) rental price, depending on the segment; X'_{1i} to a vector of property-specific attributes; X'_{2i} to the time period (quarterly fixed effects); X'_{3i} to SFE; $X'_{4i}$to a vector of location-specific control amenities (including distance to schools, transport networks, golf courses, etc); and X'_{5i} represents the regressors of interest, a vector of variables capturing coast-specific amenities. To account for possible heteroscedasticity, standard errors that either robust or clustered at the level of the SFE unit are included are used when calculating statistical significance (see section 2.3.1.2 for further discussion).

The regressors of interest include seven variables capturing blue space coastal amenities. There are three 'picture' variables, reflecting aesthetic benefits: view breadth and depth, all as defined in Section 4.3.2. In addition, there are four 'playground' measures included to capture recreational amenities: coastal shingle, beach, Blue Flag sites, and cliffs. In each case, relative to a base category of being more than 500 metres away, a vector of categorical variables is included for three distance ranges: 0.5km-0.25km, 0.25km-100m, and <100m (see also Section 4.3.1).

5.3 Results

5.3.1 Baseline Results

and present the results of interest for the sales and rental listing samples, for each of the five coastal amenities of interest. Due to the log-log nature of the specification for view depth and breadth, the coefficients can be interpreted as elasticities. The categorical nature of the 'playground' variables means that the coefficient on any of the four distance bins can, with the relevant transformation, be interpreted as the average percent price difference between that bin and the base category (any listing more than 500m from the coastal feature).

As outlined in Section 2.3.1.2, the preferred level of SFE for listings datasets is the Census Small Area (SA), with the Electoral Division (ED) the next-best alternative, due to their smaller geographic size and thus ability to control for otherwise omitted variables. The principal results for each of the five blue-space amenities are summarised below:

1. **Sand/shingle**: A dwelling within 100m of sand/shingle coast, compared to one more than 500m away, has on average a listed sale price that is 16.6% higher[25], an effect that tapers off for dwellings in 100-200m and 200-500m distance bins (6.5% and 3%, respectively). For rental listings, the effect on housing prices is much smaller: an estimated premium of just 1.7% for dwellings within 100m is statistically significant (with robust standard errors; the *t*-statistic falls from 2.6 to 1.5 if clustered by small area).
2. **Beach**: Dwellings that are close to designated beaches attract a significant price premium. In the sales listings dataset, being less than 100m from a beach is

[25] Throughout, and for the sake of accuracy, the chapter reports suitably transformed results from the regression results given the dependent variable is in natural logs, i.e. one subtracted from the exponent of the coefficient.

associated with a 22% price premium and, as with shingle coast, this diminishes with distance (9% and 3% for bins of greater distance). For rentals, the effect is smaller but still large and statistically significant: 10.4% for within 100m and just under 5% for those between 100m and 500m.

3. **Cliffs**: There is little evidence that proximity to cliff coastline is associated with higher listed sale prices of housing: the effect of being less than 100m from cliffs is 3.9%; however this is not statistically significant with either robust or clustered standard errors. While coefficients in the rental sample are also positive (and again smaller than those for listed sale prices), they are also not statistically significant.
4. **Seaview breadth**: In all eight listed sale and rental samples, the effect on prices of breadth of a sea-view is positive and statistically significant. An increase of one on the log scale, for example going from 55 to 150 inner-points, is estimated to increase prices by 1.3% in the sale listings sample and by 1.0% in the rent listings sample. These results are strongly statistically significant across both methods of calculating standard errors.
5. **Seaview depth**: The depth of a sea-view also has an impact on housing prices. For sale listings, a one-degree increase in the angle of sea-view depth is associated with a 1.7% higher price, while the effect for rental listings is 0.2%, but just marginally statistically significant. Clustering at the level of census small areas still corresponds to a tightly specified coefficient for sea-view breadth in sales and rental listings, and sea-view depth in sales listings, but not in rental listings

Table 5.1: Regression results from hedonic model of listed sales prices, 2006-2018

Treatment of SE	Robust T-statistics				Clustered at level of spatial fixed effect			
Level of spatial FE	Local Market	Micro market	Electoral District	Small Area	Local Market	Micro market	Electoral District	Small Area
Dependent Variable: natural log of the listed sale price								
Playground Variables								
Sand/Shingle								
500 - 200m	0.060	0.046	0.024	0.030	0.060	0.046	0.024	0.030
	18.0	13.7	6.8	5.3	4.7	4.0	2.0	2.8
200 - 100m	0.093	0.069	0.045	0.063	0.093	0.069	0.045	0.063
	15.6	11.5	7.3	7.2	4.7	4.6	2.9	4.2
<100m	0.178	0.151	0.143	0.154	0.178	0.151	0.143	0.154
	21.3	18.5	17.0	13.5	9.9	8.1	8.6	9.1
Beaches								
500 - 200m	-0.046	-0.050	-0.020	0.025	-0.046	-0.050	-0.020	0.025
	-5.5	-5.8	-2.2	1.8	-1.2	-1.5	-0.6	1.2
200 - 100m	0.053	0.041	0.075	0.089	0.053	0.041	0.075	0.089
	2.6	2.0	3.7	3.5	1.7	1.2	2.1	2.6
<100m	0.182	0.157	0.172	0.197	0.182	0.157	0.172	0.197
	5.8	5.1	5.7	5.7	4.0	3.2	3.9	3.6
Cliffs								
500 - 200m	-0.032	0.005	-0.009	0.011	-0.032	0.005	-0.009	0.011
	-4.9	0.8	-1.4	1.1	-0.9	0.3	-0.4	0.4
200 - 100m	-0.014	0.037	0.020	0.021	-0.014	0.037	0.020	0.021
	-0.9	2.5	1.4	1.1	-0.3	1.2	0.8	0.7
<100m	0.032	0.056	0.030	0.038	0.032	0.056	0.030	0.038
	1.2	2.2	1.2	1.4	0.7	1.4	0.8	1.0
Picture Variables								
Seaview breadth	0.014	0.014	0.014	0.013	0.014	0.014	0.014	0.013
	16.2	17.6	17.6	14.9	3.8	6.7	8.6	10.8
Seaview depth	0.021	0.020	0.018	0.017	0.021	0.020	0.018	0.017
	13.6	13.4	11.7	10.1	2.5	4.1	4.8	6.9
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	271,866	271,866	271,866	271,866	271,866	271,866	271,866	271,866
R-squared	0.773	0.796	0.809	0.84	0.773	0.796	0.809	0.84
rmse	0.292	0.277	0.268	0.25	0.292	0.277	0.268	0.25
Number of absorbed SFE	54	335	1,617	11,558	54	335	1,617	11,558

Notes: Robust t-statistics reported below coefficients. Columns show different levels of SFE denoted at header, while controls include location, dwelling and time listed on the market, as discussed in the text. Robust t-statistics are reported in all columns, while clustered t-statistics combined with robust t-statistics are reported in columns 5-8.

Table 5.2: Regression results from hedonic model of listed rental prices

Treatment of SE	Robust T-statistics				Clustered at level of spatial fixed effect			
Level of spatial FE	Local Market	Micro market	Electoral District	Small Area	Local Market	Micro market	Electoral District	Small Area
Dependent Variable: natural log of the listed rental price								
Playground Variables								
Sand/Shingle								
500 - 200m	-0.003	0.006	-0.012	0.002	-0.003	0.006	-0.012	0.002
	-1.8	3.5	-6.2	0.6	-0.3	1.1	-1.2	0.3
200 - 100m	0.018	0.019	-0.002	0.002	0.018	0.019	-0.002	0.002
	6.1	6.5	-0.5	0.3	0.9	2.4	-0.1	0.2
<100m	0.055	0.041	0.028	0.017	0.055	0.041	0.028	0.017
	14.1	10.9	6.7	2.6	2.1	3.8	2.0	1.5
Beaches								
500 - 200m	-0.036	-0.010	0.012	0.042	-0.036	-0.010	0.012	0.042
	-7.2	-2.1	2.3	4.1	-1.7	-0.7	0.7	2.1
200 - 100m	-0.001	0.000	0.018	0.044	-0.001	0.000	0.018	0.044
	-0.1	0.0	2.0	2.9	-0.1	0.0	1.0	1.7
<100m	0.042	0.061	0.086	0.099	0.042	0.061	0.086	0.099
	2.4	3.6	5.3	4.8	2.0	2.3	3.2	2.9
Cliffs								
500 - 200m	-0.018	-0.009	-0.003	0.009	-0.018	-0.009	-0.003	0.009
	-3.8	-1.9	-0.7	1.1	-0.6	-0.6	-0.3	0.7
200 - 100m	-0.002	0.000	0.012	0.029	-0.002	0.000	0.012	0.029
	-0.1	0.0	0.8	1.7	-0.1	0.0	0.5	1.0
<100m	-0.023	-0.027	-0.014	0.013	-0.023	-0.027	-0.014	0.013
	-1.2	-1.5	-0.8	0.6	-0.6	-0.9	-0.4	0.3
Picture Variables								
Seaview breadth	0.010	0.010	0.010	0.010	0.010	0.010	0.010	0.010
	21.1	21.8	23.3	21.1	4.7	5.6	6.4	9.5
Seaview depth	0.004	0.004	0.002	0.002	0.004	0.004	0.002	0.002
	3.2	3.8	1.5	1.6	0.4	0.8	0.4	0.8
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	474,901	474,901	474,901	474,901	474,901	474,901	474,901	474,901
R-squared	0.838	0.853	0.855	0.87	0.838	0.853	0.855	0.87
rmse	0.183	0.175	0.174	0.166	0.183	0.175	0.174	0.166
Number of absorbed SFE	54	353	1,524	11,163	54	353	1,528	11,171

Notes: Robust t-statistics reported below coefficients. Columns show different levels of SFE denoted at header, while controls include location, dwelling and time listed on the market, as discussed in the text. Robust t-statistics are reported in all columns, while clustered t-statistics combined with robust t-statistics are reported in columns 5-8.

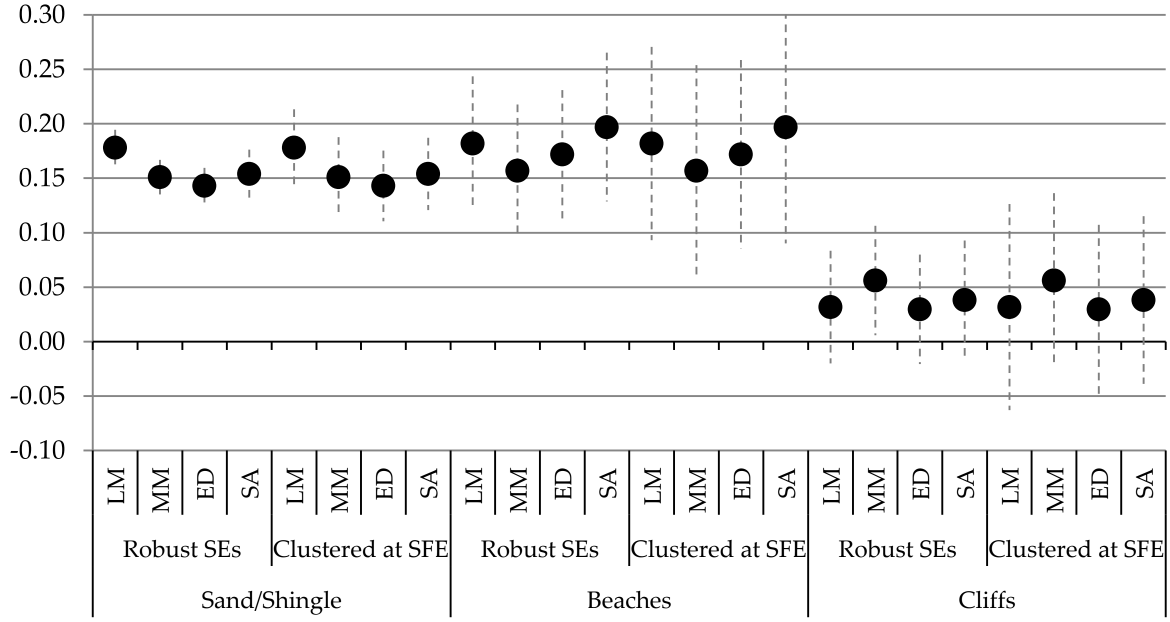
Table 5.3 summarises the estimated price effects for each of the five amenities across both sale and rental segments. A one-SD increase in sea-view breadth is associated with an increase in listed sale price of just over €4,900 and in the monthly listed rental price of €13. The effects for sea-view depth are somewhat smaller: just over €4,031 for listed sale prices and just €1 for rents. For distance-based variables, the table shows the price effect, at average sale and rental prices, of being within the closest-distance bin (less than 100m) compared to the control category (more than 500m). In the sale segment, the effect is largest for beaches (just over €51,000) and smallest for cliffs (€8,820), although this is only marginally statistically different from zero. Rental effects are small for shingle €32– for beaches, the estimated rental effect is €98. Figures across sale and rental segments can be compared through the implied annual rental yield on amenities. This varies from 3% for sea-view depth to just 0.3% for sea-view depth.

Table 5.3: Standardised price effects, by amenity and segment

	Sale price			Monthly rental price		
Variable	**Effect**	**Mean**	**S.D.**	**Effect**	**Mean**	**S.D.**
Sea-view breadth	€4,965	83	72	€13	126	85
Sea-view depth	€4,031	2.05°	1.68°	€1	1.42°	1.42°
	Coeff * Av. Price		**N**	**Coeff * Av. Rent**		**N**
Shingle <100m		€42,468	3,123		€32	5,423
Beach <100m		€51,080	201		€98	224
Cliffs <100m		€8,820	316		-€15	261

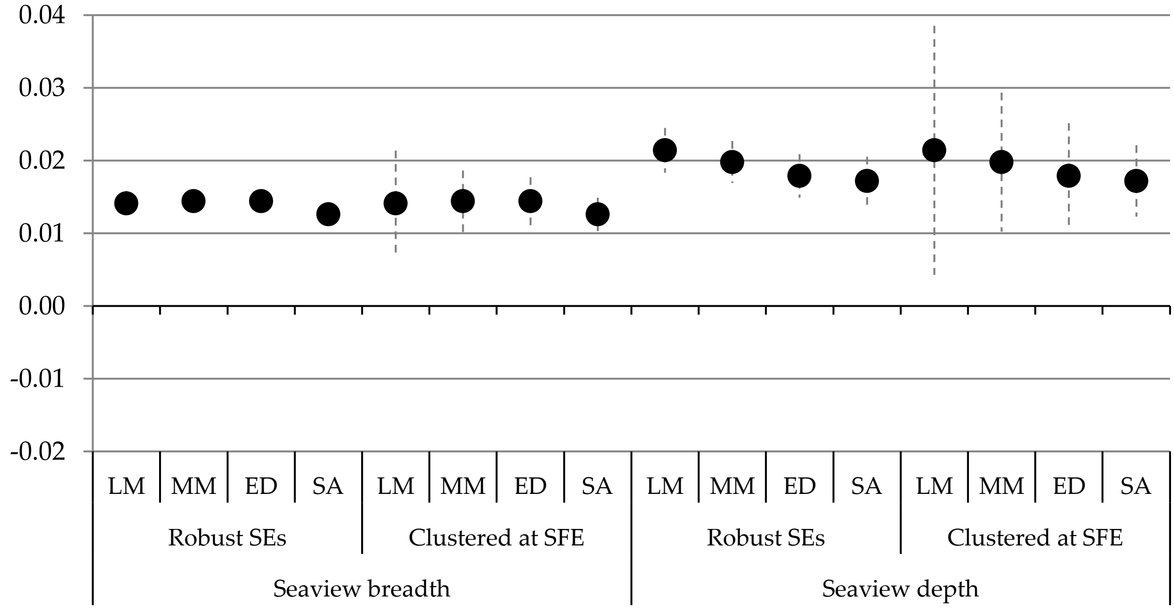
Notes: The above table shows summaries of the estimated price effects of each of the five coastal amenities of interest. For the two view-based regressors, the effects are based on one-standard-deviation effects. For the three distance-based regressors, the effects are the transformed coefficient for the closest distance category (<100m) multiplied by the average price. In all cases, results from the nationwide samples, shown in and , and using SA fixed effects. Number of observations, N, for the closest distance category are also displayed.

Figure 5.1: Estimated coefficients and confidence intervals for distance-based amenities (within 100m), by SFE and standard error: sale listings dataset



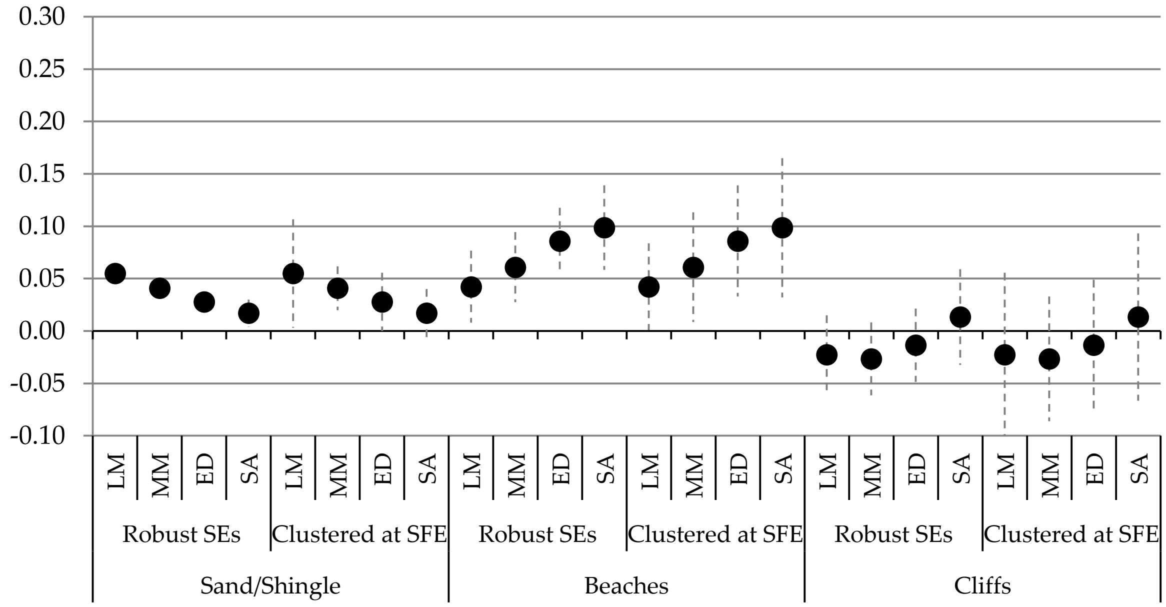
Note: This figure shows, for the sale listings sample, the estimated coefficients and associated 95% confidence intervals, for the three distance-based blue-space amenities, across each of eight specifications: four levels of SFE and two types of SE. Axes are standardised across listings datasets.

Figure 5.2: Estimated coefficients and confidence intervals for view-based amenities, by SFE and standard error: sale listings dataset



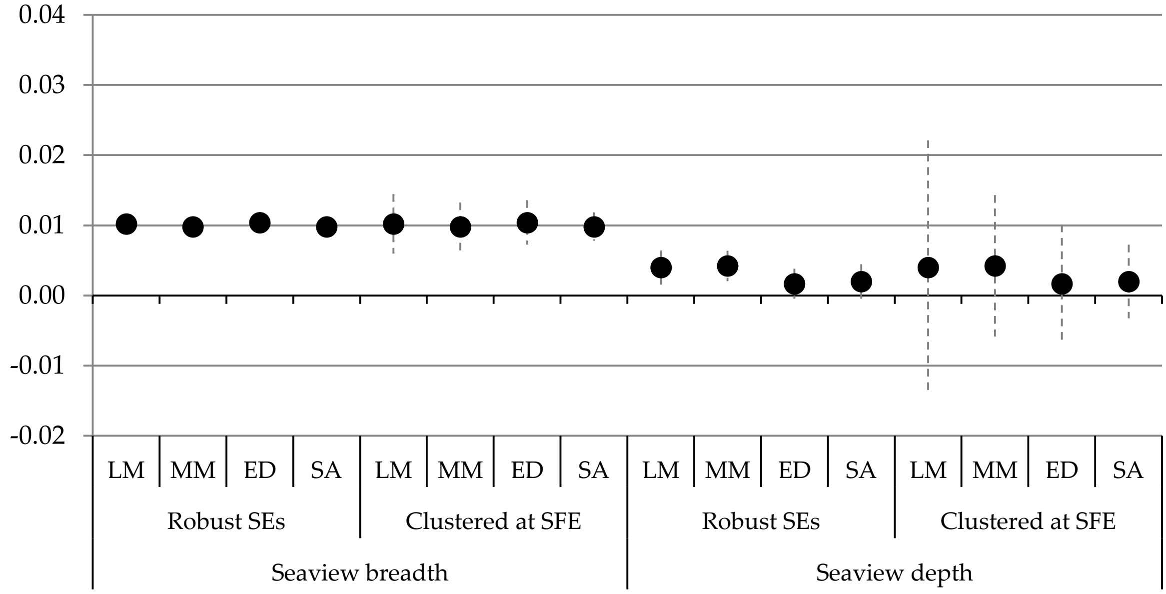
Note: This figure shows, for the sale listings sample, the estimated coefficients and associated 95% confidence intervals, for the two view-based blue-space amenities, across each of eight specifications: four levels of SFE and two types of SE. Axes are standardised across listings datasets.

Figure 5.3: Estimated coefficients and confidence intervals for distance-based amenities (within 100m), by SFE and standard error: rental listings dataset



Note: This figure shows, for the sale listings sample, the estimated coefficients and associated 95% confidence intervals, for the three distance-based blue-space amenities, across each of eight specifications: four levels of SFE and two types of SE. Axes are standardised across listings datasets.

Figure 5.4: Estimated coefficients and confidence intervals for view-based amenities, by SFE and standard error: rental listings dataset



Note: This figure shows, for the sale listings sample, the estimated coefficients and associated 95% confidence intervals, for the two view-based blue-space amenities, across each of eight specifications: four levels of SFE and two types of SE. Axes are standardised across listings datasets.

As outlined in Section 1.1.1.1, advantage is taken of the large size of the dataset to test the sensitivity of the estimated coefficients to different levels of SFEs. Especially given that much of the existing literature, by necessity, uses larger spatial units, these results may inform future research on the potential for unobserved spatial processes correlated with the variables of interest. Figure 5.1-Figure 5.4 present, for each of the sale and rental segments, and for both 'picture' and 'playground' amenities, the estimated coefficients and associated 95% confidence intervals for each of the five amenities of interest, as per the results given in and .

It is noted firstly that results are, in large part, similar across SFEs. For example, coefficients from the sale listings dataset for shingle, beach and cliff distance bins largely match in sign, statistical significance and usually size. This is particularly true of the two view-based amenities where coefficients are typically more precisely estimated and, especially in the case of view breadth, vary minimally across SFEs.

Nonetheless, there are some differences worth noting, in particular relating to trends the magnitude of coefficients. In the rental sample, for example, there is a downward trend in the magnitude of the coefficients on shingle as the SFE gets smaller – from 5.6% with local market SFEs to 1.7% in small area SFEs – while the opposite is true for beaches. Given the small geographic scale of Census Small Areas, the scope for omitted variable bias is greatly reduced – but the trend highlights the potential for inappropriately large SFE to give coefficients with misleading magnitudes.

This particularly true of the Local Market (LM) fixed effects. Especially for the rental listings dataset, the coefficients from a regression with LM fixed effects are the least correlated with those from a regression with SA fixed effects. Their large size – with an average of almost 10,000 sale listings and a population average of almost 100,000 people – also means that estimated coefficients are, in certain cases, less precisely estimated. By contrast, there is some support for using fixed effects at the level of the micro-market, geographical units with an average of 2,000 sale listings and a population average of less than 15,000. As markets may be geographically stratified, it is worth noting that these are estimates of a national average.

5.3.2 Sale transactions

The results presented in Section 5.3.1, while including the preferred sets of results, are based on listed sale and rental prices. There is strong support in the literature for the use of listed prices, where transacted prices are unavailable (see section 2.3.1.3). Nonetheless, as discussed in Section 3.4, a directly comparable dataset of sale transactions for Dublin is employed, the largest city in Ireland for the period 2010-2018. This dataset includes not only transaction prices (and dates) but also additional dwelling characteristics from the BER energy performance certificate. Each transaction is matched not only to BER certificates but also to its online listing, giving a 'triple match' dataset of 38,523 transactions that allows an examination of whether any differences in results are due to the changed outcome variable, additional regressors, or changes in sample.

Table 5.4 presents results for this transactions dataset (in Column 1) and connects them to the results presented for the sale listings dataset (in Column 6), step-by-step. All specifications use ED fixed effects and robust standard errors, taking into account both the smaller size of the transactions dataset and the results described above in Section 5.3.1. In Column (2), the outcome variable is listed price, rather than transacted price, while the sample and list of regressors are identical. Column (3) drops additional regressors, available through the energy performance certificates, and thus regressors match those used in Section 5.3.1, but the sample remains the transactions sample. This sample restriction is then relaxed in Columns (4) and (5), which include all listings over the same period (2010-2018) in Dublin and nationwide, respectively. Column (6) increases the sample to include all years 2006-2018, thus reproducing results from Table 6.4.

In general, the pattern of results across the specifications is similar to the results presented for the sale listings dataset: sand/shingle, beaches, view breadth and view depth are all associated with higher listed sale prices in a statistically significant way. There are, however, some important differences between Columns (1) and (6).

At first glance, the most pronounced difference is much reduced precision of the estimate on beaches (with the t-statistic closer to an absolute value of 2, not 6). However, this likely stems from the nature of the sample: Dublin has a limited number of beaches and thus a much-reduced number of observations in, for example, the 0m-100m distance bin. Overall, the coefficients in Column (1) are not statistically significantly different from the coefficients in Column (6). In particular, there is little difference when the outcome variable is changed from transacted to listed sale prices, a finding of relevance for economies without readily available transactions datasets. Formal statistical tests of equality between parameters based on three model comparisons [(1) & (2), (4) & (5), (1) & (7)] are given in Blue Space Appendix, Table C 6.

Table 5.4: Regression results from hedonic model of transacted sale prices, 2010-2018

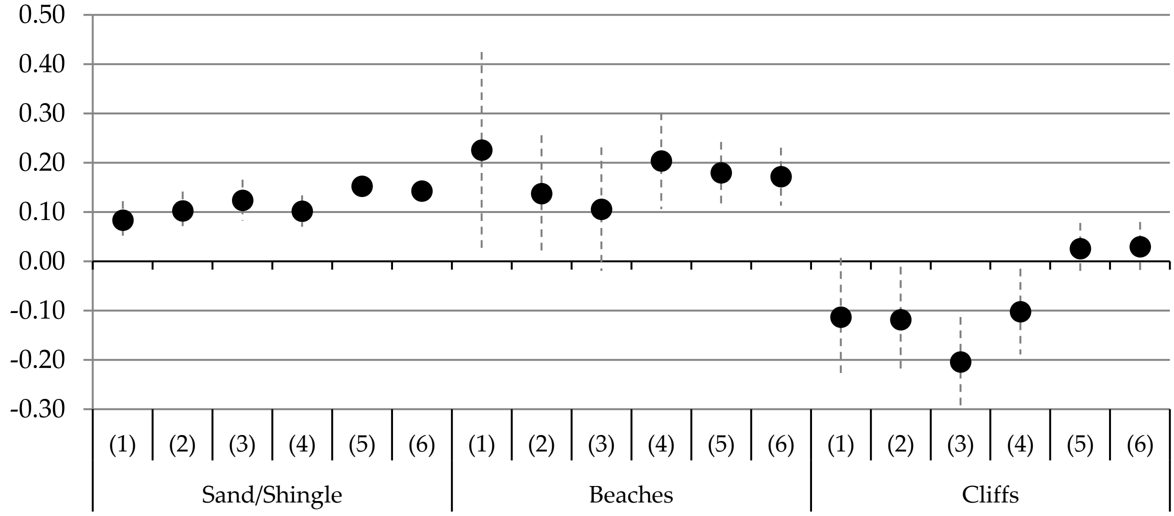
Outcome Variable (price)	Transacted	Listed	Transacted	Listed	Listed	Listed
Sample and regressors	PPR & BER	PPR & BER	PPR	Dublin	National	National
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable: natural log of the transacted or listed sale price (as discussed in the text)						
Playground Variables						
Sand/Shingle						
500 - 200m	0.008	0.000	-0.004	-0.012	0.027	0.024
	0.9	0.0	-0.4	-1.7	6.7	6.8
200 - 100m	0.017	0.019	0.013	0.005	0.052	0.045
	1.3	1.5	0.9	0.5	7.7	7.3
<100m	0.084	0.103	0.124	0.102	0.153	0.143
	4.4	5.3	5.9	6.3	17.0	17.0
Beaches						
500 - 200m	0.025	0.041	0.045	0.066	-0.011	-0.020
	1.1	2.0	2.1	3.9	-1.1	-2.2
200 - 100m	0.119	0.102	0.100	0.134	0.095	0.075
	3.3	2.8	2.9	3.6	4.2	3.7
<100m	0.226	0.138	0.106	0.204	0.180	0.172
	2.2	2.3	1.7	4.1	5.6	5.7
Cliffs						
500 - 200m	-0.044	-0.034	-0.022	-0.055	-0.004	-0.009
	-2.9	-2.0	-1.3	-4.6	-0.5	-1.4
200 - 100m	-0.083	-0.065	-0.041	-0.088	0.016	0.020
	-2.3	-1.6	-0.9	-3.0	1.0	1.4
<100m	-0.113	-0.118	-0.204	-0.102	0.026	0.030
	-1.8	-2.2	-4.4	-2.3	1.0	1.2
Picture Variables						
Seaview breadth	0.008	0.007	0.011	0.015	0.014	0.014
	5.2	4.9	6.8	14.1	16.2	17.6
Seaview depth	0.004	0.007	0.006	0.006	0.019	0.018
	0.7	1.5	1.1	1.8	11.7	11.7
Controls	YES	YES	YES	YES	YES	YES
Spatial FEs	ED	ED	ED	ED	ED	ED
Standard Errors	Robust	Robust	Robust	Robust	Robust	Robust
Observations	38,523	38,523	38,523	83,386	205,586	271,866
R-squared	0.889	0.903	0.881	0.856	0.81	0.809
rmse	0.179	0.163	0.181	0.209	0.277	0.268
Number of absorbed SFE	318	318	318	319	1,617	1,617

Notes: Robust t-statistics reported below coefficients. Columns show results for different outcome variables, regressors and samples, as discussed in the text.

Nonetheless, there are differences in the estimated size of the price effects, as shown for distance-based amenities in Figure 5.5 and view-based amenities in Figure 5.6. For example, the premium associated with being less than 100m from sand/shingle coastline in Column (1) is roughly half the size in Column (6): 8.8% versus 15.4%. The bulk of the difference is not the change in outcome variable but rather extending the sample from Dublin only to the entire country – i.e. going from Column (4) to Column (5). As discussed further in Section 5.3.3, this reflects urban-rural differences in the valuation of blue-space amenities. The same is true for sea-view depth, where the coefficient falls from 1.9% to 0.6%, and also cliffs, where the coefficient is negative albeit not statistically significant, when the sample is restricted to Dublin.

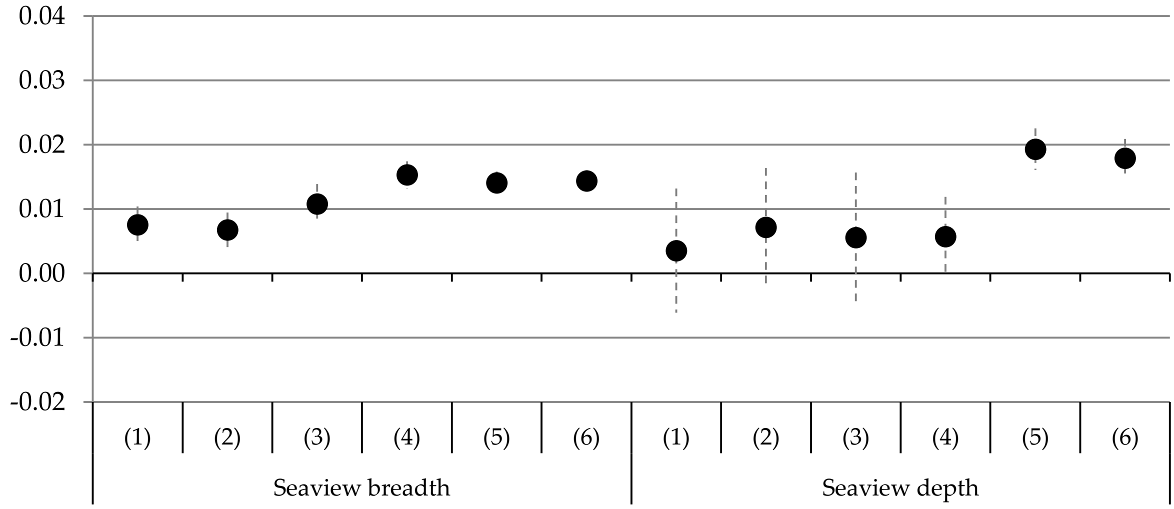
For properties closest to designated beaches, and for sea-view breadth, there appears to be little difference in the effects of these amenities in a Dublin-only or nationwide sample. However, there are still differences between the preferred specification in and Column (1) in Table 5.4: the effect of being very close to beaches is larger in the transactions sample than in the listings sample, while the coefficient on sea-view breadth is roughly half the magnitude (0.8% vs. 1.4%). In the case of proximity to beaches, the effect is not estimated with precision, due to the relatively small number of properties that meet the various criteria: within 100m of a designated beach in Dublin that sold 2010-2018 and was successfully matched to both BER and online listings. For sea-view breadth, however, the differences appear to be both systematic and not connected with the spatial or temporal scope of the different datasets. In particular, the omission of certain regressions (available through the BER) and the extension of the Dublin dataset to include properties listed that were not matched to a transaction increased the estimated coefficient. This implies a correlation between second-order building attributes (i.e. beyond size, type and location) and view breadth and an analysis, iteratively testing the effect of omitting these extra controls one-by-one, reveals floor area to be most important. This highlights a correlation between floor area and sea-view breadth, which is important for future researchers to be aware of.

Figure 5.5: Estimated coefficients and confidence intervals for distance-based amenities (within 100m), for sale transaction and listing datasets



Note: This figure shows, for the specifications discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the three distance-based blue-space amenities.

Figure 5.6: Estimated coefficients and confidence intervals for view-based amenities, for sale transaction and listing datasets



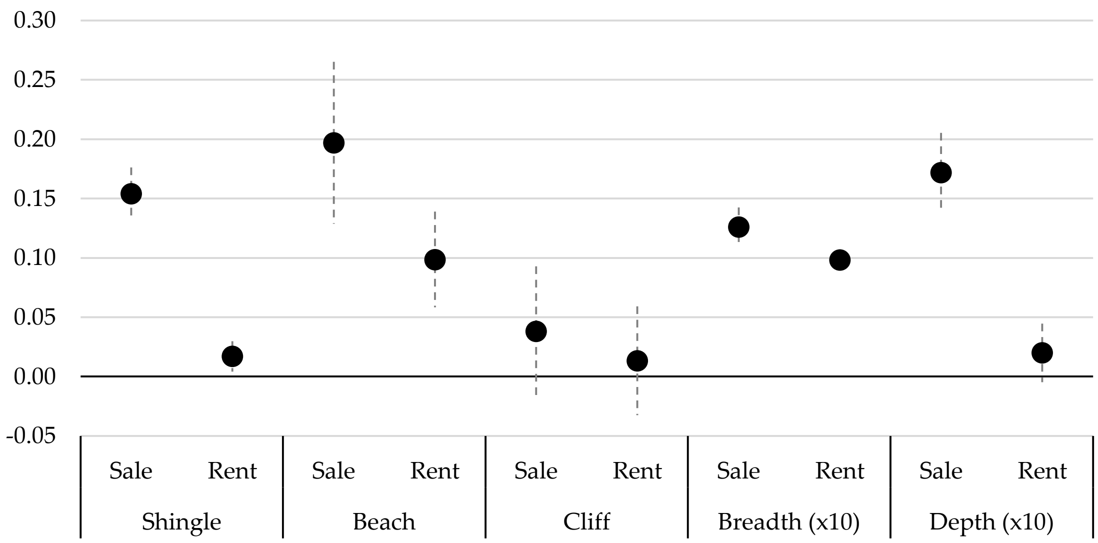
Note: This figure shows, for the specifications discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the two view-based blue-space amenities. Axes are standardised to those presented for listings datasets.

5.3.3 Results by tenure, market cycle, geography and quantile

While results from the regressions in Section 5.3.2 by and large confirm the pattern presented in Section 5.3.1, some of the differences suggest addition research questions about the nature of demand for the amenities of interest. In particular, differences by tenure and geography and over time period and market conditions may be useful in gaining a deeper understanding of the demand for various blue-space amenities. This section examines systematic differences in amenity prices along these dimensions, starting with how the price of amenities varies across tenure.

The results in Section 5.3.1 suggested differences in amenity prices across listed sale and rental segments. Figure 5.7 presents a direct comparison of the results for each of the five blue-space amenities across both segments, using the full listings samples for both, robust standard errors and small-area SFE. The point estimates in each case are larger in the sale segment than in rentals. However, in only two instances – being within 100 metres of sand/shingle coastline and sea view depth – is the difference in coefficients clearly outside the respective 95% confidence intervals.

Figure 5.7: Coefficients and 95% confidence intervals for amenities by tenure

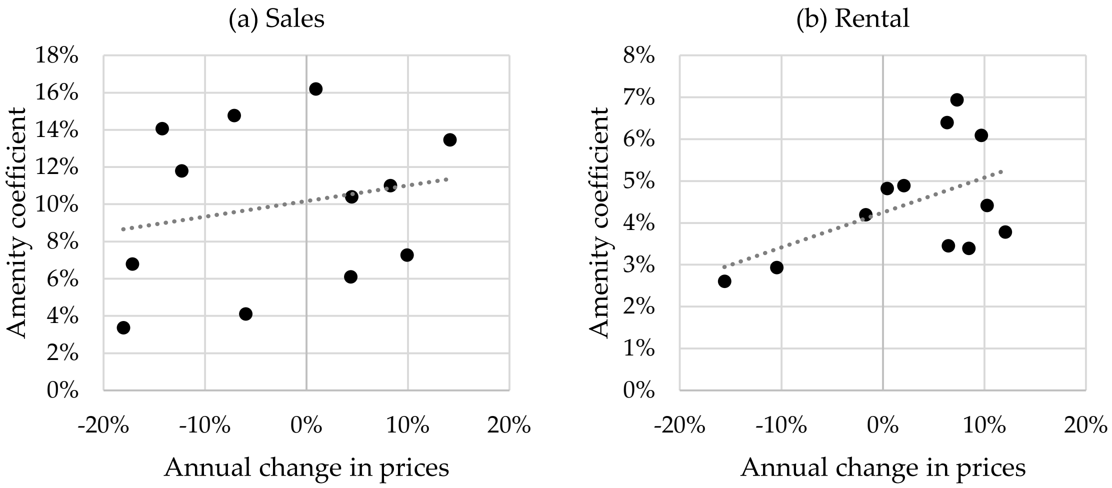


Note: This figure shows the estimated coefficients and associated 95% confidence intervals for blue space amenities by tenure. For sea-view breadth and depth, the coefficients have been scaled up by one order of magnitude, for ease of exposition.

Lyons (2013) outlines two potential hypotheses that may explain why sale prices may be greater in magnitude than rental prices. Firstly, there may be factors, such as indivisibilities related to search costs, that restrict renters' willingness to pay for amenities, in particular factors that are of secondary importance. In this scenario, renters are restricted from revealing their true willingness to pay, i.e. renters 'underpay'. Alternatively, factors may that encourage buyers to 'overpay': for example, buyers may worry about the cost of accessing amenities in the future, leading to a greater immediate valuation by buyers than renters. Such buyer lock-in concerns would be most prevalent at the height of a bubble and thus would be associated with pro-cyclical amenity pricing.

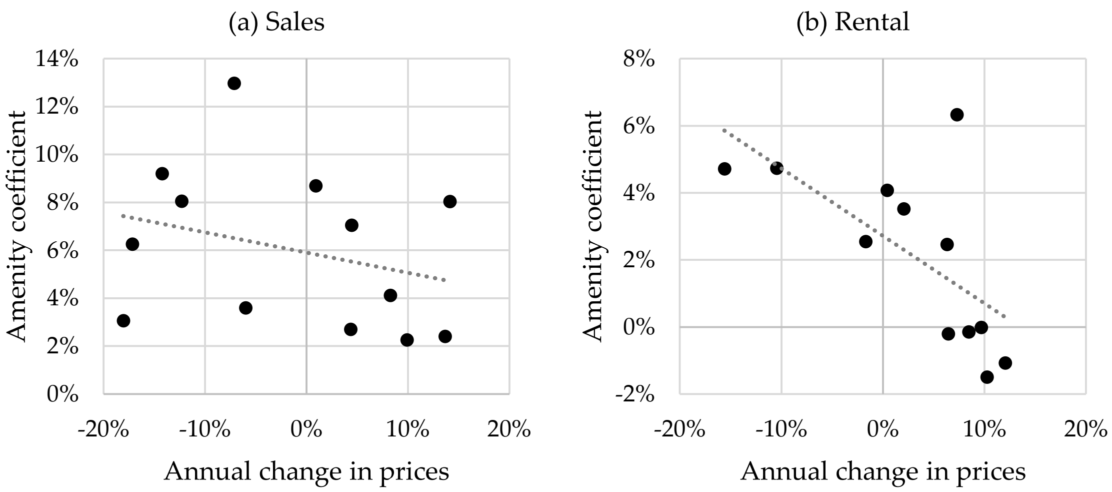
Figure 5.8 and Figure 5.9 present scatterplots of the estimated amenity prices for two core amenities – views and access to beaches – together with the estimated annual changes in listed prices. To aid identification, given the effective split of the sample into thirteen subsamples, a summary categorical variable for view is presented in Figure 5.8, while Figure 5.9 presents results for any property within 250m of the coast. In both figures, the left-hand panel shows results for the sales segment, while the right-hand panel shows results for the rental segment. For the categorical view amenity, there is some evidence of pro-cyclical amenity pricing: when prices rose by more, the coefficient on views was greater in size. For proximity to the coast, however, any correlation is negative – when market conditions are weaker, the coefficient on proximity to amenity coastline tends to be larger.

Figure 5.8: Scatterplot of coefficients by year and annual change in listed prices: categorical view amenity, sale and rental datasets



Note: This figure shows, for the coefficients on the relevant amenity, by year, together with the change in housing prices in that year, by segment.

Figure 5.9: Scatterplot of coefficients by year and annual change in listed prices: >250m to the coast, sale and rental datasets



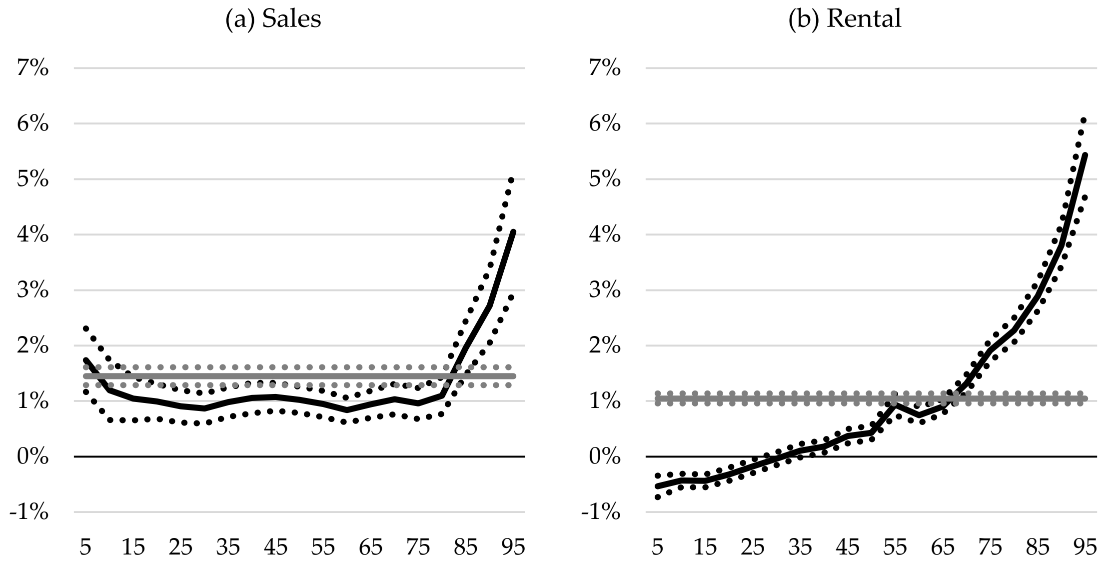
Note: This figure shows, for the coefficients on the relevant amenity, by year, together with the change in housing prices in that year, by segment.

The presence of pro-cyclical amenity pricing, in the case of views, may support the idea of 'lock in' effects but a positive relationship between amenity pricing and market conditions is also consistent with alternative hypotheses, including that blue-space amenities are a luxury good, where demand rises more-than-proportionately with income. This hypothesis is supported in Figure 5.10 and Figure 5.11, which present results from quantile regressions (more methodological detail on unconditional quantile regressions in Section 6.3.2.2) and show how view breadth and proximity to beaches vary over the housing price distribution. The grey line (and its associated 95% confidence interval, shown in dashed lines) shows the OLS estimate in each case, while the black line (and its associated 95% confidence interval) shows the estimate for each ventile.

There is clear evidence from Figure 5.10 and Figure 5.11 that the price of blue-space amenities is greatest, in percentage terms, for the top end of the housing price distribution.[26] Figure 5.10 shows the coefficient for view breadth, by ventile, for sale and rental segments. In both segments, the overall average OLS effect is being driven by the top 15%-25% of the housing price distribution, with the top ventile in particular exhibiting an amenity price that is multiples of the OLS effect (roughly 3 times and 5 times, for sale and rental segments respectively). While the OLS estimates suggest that the sale price effect is larger than the rental price effect, this is not the case for the top third of the respective distributions, with the estimated rental coefficient at least as large as the sale coefficient from the 65th percentile up.

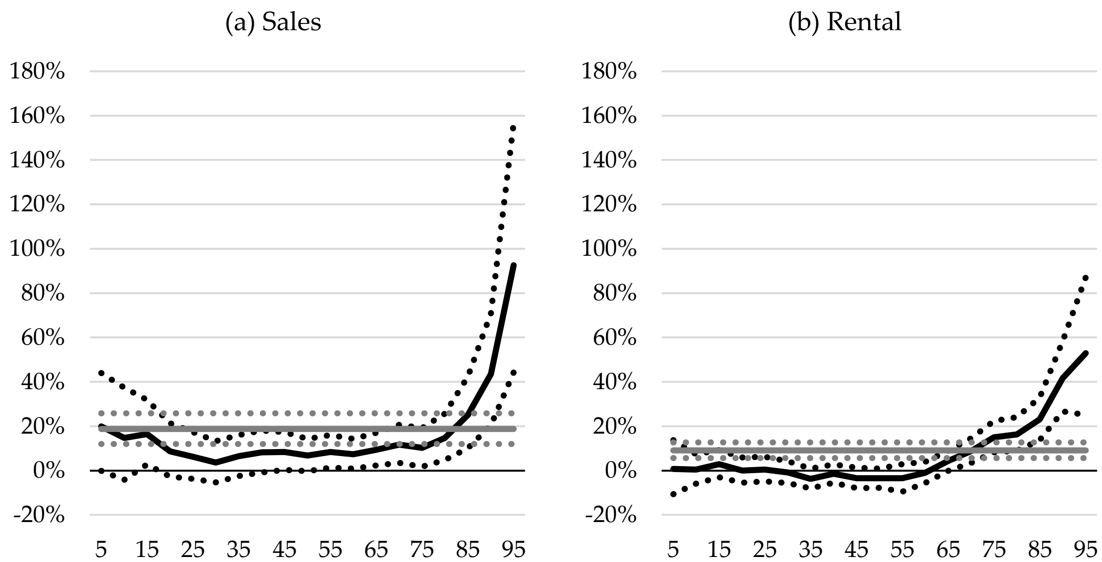
[26] See Blue Space Appendix B for similar graphs for the other three principal blue-space amenities. In general, the amenities display the same features over the housing price distribution: higher amenity prices for higher housing values and for sale, compared to rentals.

Figure 5.10: Coefficients and 95% confidence intervals for quantile regressions: view-breadth amenity, sale and rental datasets



Note: This figure shows the estimated coefficients and associated 95% confidence intervals for quantile regressions on the same amenity across sale and rental segments, with standardised axes.

Figure 5.11: Coefficients and 95% confidence intervals for quantile regressions: >100m to beach amenity, sale and rental datasets



Note: This figure shows the estimated coefficients and associated 95% confidence intervals for quantile regressions on the same amenity across sale and rental segments, with standardised axes.

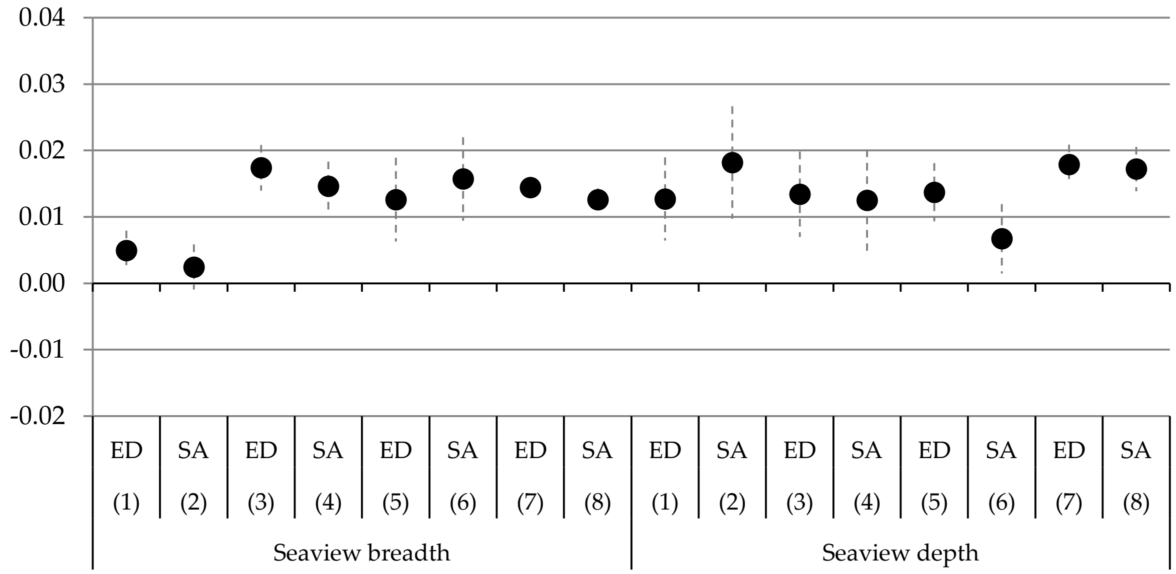
For closest proximity to beaches, the feature that the estimate price effects are largest for the top end of the housing price distribution is also present. For housing in the top ventile, being within 100m of a beach is associated with a 92% price premium (applying the appropriate transformation to the coefficient of 0.65), roughly four times the average OLS premium of 17%. For rental prices, the equivalent figures are a 53% premium at the top end of the distribution, compared to an OLS premium of 3%. These figures – and similar results for view depth and proximity to sand/shingle coast, shown in Blue Space Appendix, Figure B 4 – are strongly supportive of blue-space amenities being luxury services.

In further analysis, summarised in Blue Space Appendix, Table C 4, the differences in results by bedroom number and property type, for sale and rental segments, as well as across geography, including Dublin/non-Dublin and all urban/rural markets, are explored. Results by bedroom are supportive of the hypothesis that blue-space amenities are luxury goods: coefficients in the sales sample for sand/shingle and beaches are largest for 4-5 bedroom properties. Different results across Dublin and nationwide samples, presented in Section 5.3.2, suggest the possibility of geographical differences in the willingness to pay for blue-space amenities, as well as differences by level of income or wealth. For distance to sand/shingle, there is a clear difference between Dublin/urban and non-Dublin/rural samples: across all urban markets, the sales coefficient for sand/shingle is half that of elsewhere (0.106 vs. 0.2). Similarly, the sales coefficient for sea-view breadth is far greater in rural markets (0.0198) than in urban ones (0.0124).

5.3.4 Robustness and extensions

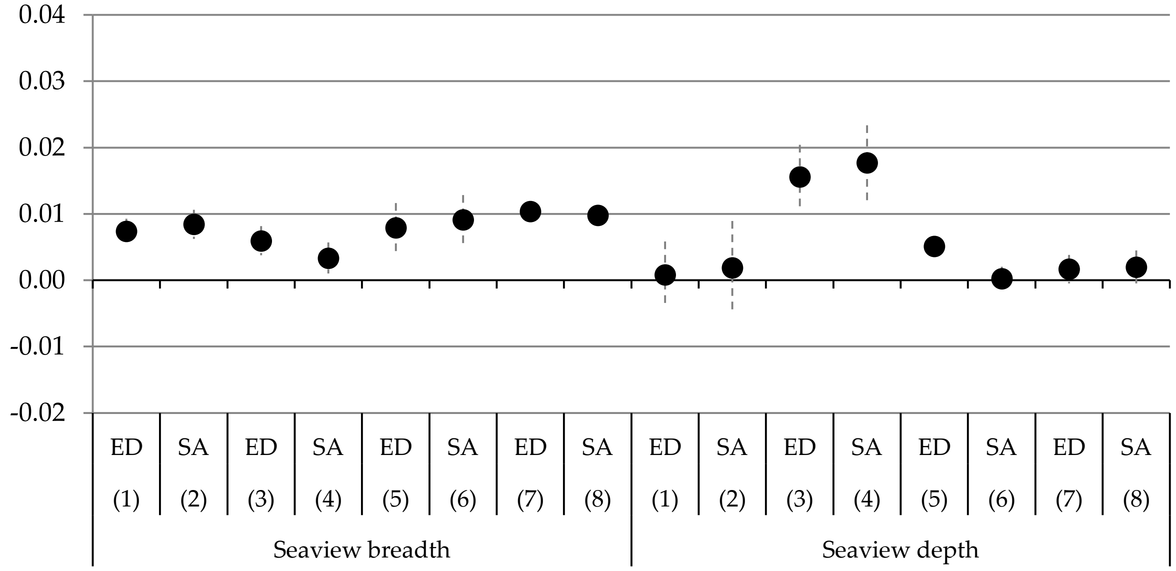
Section 1.1 so far has presented results on the relationship between coastal amenities and housing prices across three principal datasets, four levels of spatial fixed effect and two types of clustering, as well as examining variation over time and the housing price distribution. The results point to a clear link between the amenities of interest and housing prices. To further strengthen the interpretation of these results as causal effects, in particular for view-based amenities, this subsection undertakes three additional sets of robustness checks – using a matched sample of dwellings, using LiDAR data, and using 'straight coast' samples – before presenting results from some extensions.

Figure 5.12: Estimated coefficients and confidence intervals for view-based amenities, sale listing dataset, across robustness checks



Note: This figure shows, for the robustness checks discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the two view-based blue-space amenities. Axes are standardised to those presented for listings datasets.

Figure 5.13: Estimated coefficients and confidence intervals for view-based amenities, rental listing dataset, across robustness checks



Note: This figure shows, for the robustness checks discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the two view-based blue-space amenities. Axes are standardised to those presented for listings datasets.

Figure 5.12 and Figure 5.13 show, for the sale and rental listings datasets respectively, the results of these further robustness checks in relation to view-based amenities.[27] In addition to baseline results for ED and SA spatial fixed effects, there are three sets of robustness check, with results for both ED and SA spatial fixed effects for all three, giving eights sets of coefficients in both figures:

1. The first robustness check, results (1) and (2) in both figures, involves using a sample of dwellings with a view that have a match (in terms of type) within 100m without a view. Using such a sample reduces to the risk of omitted variables driving the results but does limit the variation – it focuses on otherwise-similar dwellings that vary in view but, by

[27] Regressions results relating to this Figure are given in Blue Space Appendix, Table C 1 and Blue Space Appendix, Table C 2, whileBlue Space Appendix, Figure C 4 and Blue Space Appendix, Figure C 5 present results for distance-based amenities, for the sake of completeness.

design, ignores otherwise-similar neighbourhoods or areas that vary in view.

2. Results (3)-(4) involve restricting the sample to sections of the coast that are, roughly, straight segments of the coast. The intention is to maximise the accuracy of view breadth, by eliminating bays, where additional inner points may be counted even if they are not close to the property in question.
3. The third robustness check, results (5)-(6), involves the use of higher-resolution LiDAR data, to test whether the results are affected by any lack of accuracy in the OSi 10-meter DEM, which does not include buildings.

For view breadth, the results from the baseline largely hold for all robustness checks across sale and rental listings. For sales, an exception is the matched sample, where the coefficients are substantively smaller (e.g. 0.5% vs. 1.4% with ED SFEs). For rentals, the exception is the straight coast sample (0.6% vs. 1.0% with ED SFEs). For view depth, again the broad pattern from the baseline holds, although results from the LiDAR sample suggest a smaller sales premium, while the 'straight coast' sample suggests a larger rental premium (which is otherwise close to zero).

A wide range of further analyses are employed, whose results are reported in Blue Space Appendix, Table C 5, to test the reliability of the results. Omitting the requirement for 'views' to be mentioned in the text of the ad (specification (2)) does affect the results, with no longer a statistically significant positive coefficient on the log of sea view breadth[28], for sale listings. The additional of local market trends (interacting year or quarter with the local market) in specification (1) does not affect the results. Similarly, the inclusion of more distant sea points (between 0.5km and 5km) in specification (4) has no effect on existing results – although these points are

[28] However if sea view depth is omitted from this regression, sea view depth remains positive and statistically significant (specification (3)).

themselves statistically significant and positive. Omitting sea angle, as a measure of view depth, in specification (6) means that the coefficients for proximity to cliffs become positive and statistically significant. This is an instructive result, highlighting that any amenity value from proximity to cliffs – at least in the sample analysed – appears to derive from the aesthetic amenities, rather than from recreational ones (such as cliff walks). 'Blue flag' beaches – i.e. those recognised as meeting international criteria for quality and safety – do not appear in specification (4) to enjoy any additional premium over other beaches. Lastly, the omission of flood risk in specification (5), potentially highly correlated with blue space amenities, especially proximity-based ones, does not affect the results. Given the apparent concentration of flood risk around rivers, rather than seas, this result is less surprising than might otherwise be expected.

5.4 Concluding remarks

The extensive examination in this study of five core blue-space amenities indicates households are clearly willing to pay for access to sea views and to beaches and sand/shingle coast. The large datasets used to generate these results can also be used to examine a number of related issues. The study finds systematic and instructive differences in the premium across market segments. In particular, clear evidence is found firstly that the sale price of amenities is systematically higher than the rental price and secondly that in both segments the willingness to pay for blue space amenities is greatest at the top end of the housing price distribution. The differences are also documented across urban and rural markets, for view breadth as well as access to sand/shingle, and differences over time, with the price of the view amenity pro-cyclical and that of access to desirable coast counter-cyclical.

While a number of robustness checks are undertaken, the results have their limitations. The findings are robust to the use of transaction prices (and the inclusion of additional controls), but it is clear that sample composition matters. Restricting the sample to start in 2010, rather than 2006, has an effect on some results – as does restricting the sample within Dublin to those listings that can be matched to a transaction. Taken together with the significant variation in amenity pricing over time, the results do not imply a stable price for these amenities, but one that is context-specific. The measure of views relies on the accuracy of digital surface models and, even though the results are largely confirmed in a specification using LiDAR data for a subset of the coastline, these are still just proxies for the true view at each location.

For policymakers, understanding that blue space amenities are valued has implications in a range of areas, not least the taxation of real estate and policies relating to land use and development. As blue space amenities are reflected in property values, and appear to be luxury goods, their omission from the systems used for appraisal is likely to be regressive, with wealthier households enjoying an effective tax rebate as well as their amenities. In relation to land use policies, the challenge is for urban planners to enable supply in amenity-rich areas, which are often already developed and plans for new homes are most likely to meet opposition from existing residents.

Finally, the researcher believes that the study makes four principal contributions to the broader literature examining 'blue space' amenity pricing. Firstly, the novel method for calculating view breadth and view depth is one with a fixed computational cost, and thus is more appropriate for the age of 'big data' than hugely computationally intensive existing methods. Secondly, the results suggest a rule of thumb in the choice of SFE: spatial units with too large an average population (0.1m in this setting) are likely to deliver biased results, with important variation at the sub-unit level correlated with the amenities. However, there is little difference in the pattern of results where SFE are based on units with average populations of roughly 2,000 and roughly 200. This implies the need for a relatively large dataset to measure these amenities. It is also shown, thirdly, that the consistency of results across transacted sale prices and listed sale prices, which implies that listed prices are a reliable proxy for transaction prices, where these are unavailable. Finally, the results are the first to compare in a like-for-like setting the price of blue space amenities across sale and rental segments. The finding that listed sale prices are larger in magnitude opens up future research avenues about the nature of household searches and their relationship to the market cycle.

6 Information Matters: Evidence from flood risk in the Irish housing market

6.1 Introduction & context

Flood risk is the most pervasive and costly natural hazard, with an estimated one billion people in 155 countries exposed worldwide (JRC, 2017). With the prospect of rising sea levels and more intense rainfall events due to climate change, flood risk is expected to increase in many locations over coming decades. Projections of the future costs of flooding depend not only on the risk of flood events but also on societies' exposure to those events. Changing exposure to flood risk alone is projected to result in a near ten-fold increase in the global costs of flooding between 2005 and 2050, from US$6 billion per year to US$52 billion, while adding in the increased risk due to climate change could see those costs rise to as much as US$1 trillion per year, in the absence of further measures to manage flood risk (Hallegatte et al., 2013). This underlines the importance of the extent to which flood risk is taken into account in private decisions, especially where the costs are borne, at least in part, by taxpayers in the form of various subsidies to flood risk such as subsidised insurance, flood relief schemes and disaster assistance.

Due to the immobile nature of real estate and its prevalence in the typical household's balance sheet, the housing market represents a unique and important window into how private actions reflect flood risk. Theory would suggest a price discount for dwellings at risk of flooding, given the associated costs. The standard methodology in this literature builds on Rosen's (1974) theoretical framework of hedonic prices. However, individual households may lack good information on flood risk, and there is also the issue of moral hazard. In their Nobel Prize-winning contribution, Kydland & Prescott (1978) highlighted the problem of over-exposure to flood risk, in settings where taxpayers bear some of the costs of flooding. Husby et al. (2014) show that flood defences built after major flooding in the Netherlands in

1953 had a positive effect on long-run population growth in protected areas. In short, where market signals are weak, there may be a tendency towards over-exposure to flood risk.

These issues have meant that the true welfare costs of flooding are not always reflected in private individuals' willingness to pay to avoid flood risk. There are also numerous empirical challenges to estimating flood discounts, for example there may be highly correlated positive amenities, such as sea-views or access to the coast or river walks, which make it challenging to convincingly identify the value of households' willingness to pay to avoid flood risk. A recent review of the literature on flood risk and housing prices finds widely varying results, with estimates of the price effect ranging from -75% to +61% (Beltran et al. 2018a). While a meta-analysis in the same study suggests a much tighter range of -7% to +1%, the review also highlights the limitations of the existing literature. One notable limitation from Beltran et al. (2018a) is the absence of blue space control variables, specifically sea views. This has hindered studies that try to estimate the effect of coastal flood risk capitalisation.

In general, the existing literature estimating the effect of flood risk on housing prices, hereafter the 'flood discount', can be divided into two broad strands. The first strand estimates flood discounts by comparing the value of dwellings within hazard risk zones to those elsewhere, controlling for a range of dwelling attributes (e.g. MacDonald et al., 1990 and Bin et al., 2008a,b). However, interpreting the results of such studies as causal depends on the strong assumption that hazard risk is exogenous, conditional on other observable determinants of housing prices. The second strand of the literature tests the effects of specific flood events on housing prices. A common finding in these studies is that there are significant discounts after flood events, which fade over time; see, for example, Bin & Polasky (2004), Bin & Landry (2013), Atreya et al. (2013) and Beltran et al. (2019). A similar finding in Gallagher (2014) shows a spike in demand for flood insurance following flood events, at county level in the US, an effect that declines with time since the flood. Identification in these studies relies on the timing of events, which is more plausibly exogenous. Nonetheless, as noted by Bosker et al. (2018), this strand of the literature identifies changes in households' risk perceptions following a recent flood event, rather than directly identifying their level of risk perceptions.

This study examines the relationship between flood risk and both sale and rental prices for housing in Ireland. The empirical approach combines elements from the two strands of literature noted above. It exploits spatially and temporally precise official data for Ireland, on flood risk, historical flood events and flood defences, to identify the level of flood discounts – i.e. households' willingness to pay to avoid flood risk – as well as *changes* in flood discounts in response to the publication of flood risk information, flood events and flood mitigation measures. Specifically, this study tests the effect on housing prices of the release of highly detailed scientific assessments of flood risk in the form of new risk maps. This information has been made widely and easily available online and the findings indicate that it has led to the emergence, for the first time, of an observable price signal on flood risk in the Irish housing market. In the preferred specification, the estimated flood discount is 3.1%. A simple illustrative exercise shows that the estimate of the flood discount corresponds closely to the appropriate flood discount based on expected damages, for reasonable parameter values, albeit the estimated market discount is slightly lower.[29]

[29] A recent British government report on flooding during the winter of 2015/16 found the average claim per residential property flooded was GBP50,000 (report available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/672087/Estimating_the_economic_costs_of_the_winter_floods_2015_to_2016.pdf , last accessed July 2020). Taking average damages per flood of €60,000 for an individual dwelling, a 3% discount rate, and a 30-year time horizon, the capitalized value of flood risk with a 1% probability of occurrence per year is €12,360 in present value terms, equivalent to a flood discount of 4.1% for a dwelling valued at €300,000.

This study also reports on a survey of actors in the housing market's attitudes to flood risk, which finds that the general public in Ireland is concerned about flooding, that those concerns have increased for many over the last 10 years, and that a large majority of people expect the problem to get worse in the coming decades. Recent flooding in Ireland has been costly, with roughly €1bn, or close to €800 per household, in insured losses over the period 2000-2014. Moreover, the Irish government has committed to spending large sums on flood relief schemes: the 68 schemes in the analysis cost €226.6 million in total, with an additional €1 billion of planned public expenditure, or roughly 0.5% of national income, on flood relief schemes over the next 10 years (OPW, 2018).[30]

In spite of these costs and the apparent concerns about flood risk, the survey results also reveal a continuing information deficit in relation to flood risk. A quarter of those surveyed said they didn't know if flood risk was relevant for the areas in which they were looking. Of those who said they thought it was relevant, more than a third said they weren't aware of the risk in the specific areas in which they were looking to buy or rent. This finding indicates that the availability of scientifically assessed information on flood risk, while creating an important price signal, on its own may not be sufficient to ensure a well-informed public (see also McDermott and Surminski, 2018).

The survey also asked about the appropriate price discount for dwellings at risk of flooding. The results indicate a stated preference flood discount that is an order of magnitude larger than revealed preferences, at around 31% compared to 3.1% in the hedonic price models. The larger stated preference discount might partly reflect the nature of the methodology, for example in relation to salience of flood risk. But it

[30] The stated intention is that these schemes will provide protection to 80% of the 34,500 dwellings in Ireland assessed as having a 1% chance of experiencing a significant flood event in any year. In scaling by national income, the measured used in Ireland is modified Gross National Income (GNI*), which was valued at €197.5 billion in 2018, according to data from the Central Statistics Office (CSO), available here https://www.cso.ie/en/releasesandpublications/ep/p-nie/nie2018/ (last accessed in May 2020).

could also be that the full welfare costs of flooding are still not reflected in Irish housing prices. In particular, there is suggestive evidence in the data that perceptions of the probability of flooding are much higher than the scientifically assessed risk presented in official flood risk maps, particularly for relatively low risk areas.[31] Indeed, the larger stated preference flood discount corresponds closely to the value that emerges from an expected damages calculation, if survey respondents are implicitly applying the highest risk category (a 10% probability of flooding per year) to dwellings at risk of flooding, regardless of the information about risk provided in the question. This interpretation is supported by the similarity of the average discount across respondents who were asked about dwellings with a 10%, 1% or 0.1% probability of flooding per year, and by the stated expectation of a large majority of respondents that flood risk will get worse in the coming decades.

The flooding data include official nationwide maps of scientifically assessed coastal and fluvial flood risk, released in the middle of the study period, an official dataset of 2,031 historical flood events, and information on the spatial extent of 68 public flood defence schemes implemented during the period (as discussed in Section 3.5). By exploiting the timing and spatial extent of these different 'treatments' relating to flooding – events, assessed risk and flood defences – the set-up is similar to difference-in-differences, as comparison is made, for example, dwellings at risk to otherwise similar dwellings not at risk, before and after the release of information on risk. The housing data come from three extremely rich datasets, comprising a total of over one million observations of sales and rental listings from the real estate website *daft.ie*, with national coverage over the period 2006-2018, supplemented by a directly

[31] For example, a relatively large flood discount of 1.1% is observed for dwellings located inside low risk flood zones – i.e. those with a 0.1% probability of flooding per year – and also for dwellings located outside of, but within 100m of, these low risk zones, where the assessed risk must be less than 0.1% per year. The magnitude of the estimated discount in these locations implies very large damages per flood, if the low probability of flooding literally is taken. A more plausible interpretation of this finding might be that the market is overestimating the probability of flooding, for these relatively low risk locations.

comparable dataset of nearly 46,000 sales transactions in Dublin over the period 2010-2018.

There are three principal findings from the hedonics. The headline finding, as already noted, is that exposure to flood risk brings a substantial discount – by an average of 3.1% in the preferred specification. This discount emerges only after the release of information on flood risk, providing reassurance that the effects of exposure to flood risk, and not the effects of unobservable correlated factors are being identified. This result also provides the second major finding – that information matters. Third, it finds no equivalent flood discount on rental prices, suggesting that flood risk is somehow less relevant or less salient in rental markets. This is also reflected in the findings from the survey. Respondents who were looking to rent a home were about half as likely to rate avoiding flood risk as important in deciding where to live, compared with those looking to buy, and renters were about five times more likely than buyers to rate avoiding flood risk as not at all important in their decision.

There are three additional findings, in relation to flood defences, market memory of flood events, and the distribution of the flood discount. First, flood defences work: the discount for flood risk disappears after the construction of defences. In fact, a short-lived premium for dwellings defended by new flood relief schemes in the period immediately after their installation is documented. Secondly, the market's memory of flood events is short: on average, a 4.3% price discount for being within 100 metres of a flood event but also that this largely disappears after two years is observed. And thirdly, flood risk is borne unequally: dwellings in the lowest two quintiles of value suffer a 6-7% discount, compared to no statistically significant discount across most of the upper half of the value distribution.

A causal interpretation of the results relies on the various treatments, such as being in a flood risk zone or the timing of new information on flood risk, being uncorrelated with other factors not included in the analysis that may affect housing prices and rents. Identification rests ultimately jointly on the timing and spatial extent of three flood-related phenomena – flood events, defences, and information release. At a basic level, the study is able to estimate flood discounts while simultaneously controlling for historical flood events and the (time-varying) installation of flood defences. The richness and spatial precision of the data further allows me to show robustness to the inclusion of very localised SFE and clustering within spatial units to account for unobserved spatial heterogeneity, as well as trends in housing prices specific to the local market. It also allows for the inclusion of a large suite of additional control variables in the analysis, including potentially important factors plausibly correlated with flood risk, such as a continuous measure of sea views. Collectively, these controls should maximise the comparability of treated and untreated groups.

The results build on a number of recent contributions to the literature. The most closely related research to this study is Pilla et al. (2019), who compare directly the effects of assessed risk and a large flood event for the case of Dublin, Ireland, after severe flooding in 2011. They find evidence that flood events had a bigger impact on housing prices than assessed flood risk. This reinforces the idea that actors in housing markets are not always well informed about flood risk. Similarly, Gibson and Mullins (2020) and Timar et al. (2018) find that flood risk perceptions update following flood events, suggesting incomplete information on existing flood risk. Ortega and Taspinar (2018) show a large discount on dwellings damaged by Hurricane Sandy that declines over time, but also evidence of updating of risk perceptions, with a growing discount for dwellings located in the flood zone that were not damaged.

Two recent studies have assessed the flood discount using national datasets, for the Netherlands (Bosker et al. 2018) and the U.S. (Hino and Burke 2020). Bosker et al. (2018) use a border discontinuity design to identify the effect of flood risk on housing values in the Netherlands, where flood risk and defences are both prominent. They find that housing prices are on average 1% lower in places at risk of flooding but with flood protections in place, suggesting that perceived flood risk is higher than official protection levels. Hino and Burke (2020) use a panel set-up, exploiting the updating of flood risk maps in the U.S., to identify the flood discount. Their findings suggest that housing markets in the U.S. do not fully price flood risk in the aggregate. The results are complementary to these recent contributions; given that the flood discount for undefended properties are estimated (as well as the effect of installing new defences). Market responses to information updating are also analysed, and present evidence suggesting that markets continue to under-price flood risk, even following the release and widespread availability of highly detailed scientific risk assessment.

The principal contribution to the literature is to estimate the effect on the flood discount of new information about risk. Whereas most of the existing literature focuses on updating of risk perceptions following flood events, the analysis differs in that it assesses the effects of the release of new information[32], in the form of detailed scientific assessment of flood risk, while simultaneously controlling for historic flood events, and flood defences. Indeed, it is also the first study that the researcher knows of to examine housing prices before and after each of three relevant dimensions of flood risk: flood events, scientifically-assessed flood risk, and the construction of flood defences. The study also exploits timing (of new flood risk information in particular) to obtain clean identification of the willingness to pay to avoid flood risk in the Irish housing market. Other contributions include a direct comparison of both stated and revealed preferences of the flood discount and of sale and rental price effects on a like-for-like basis. The study also shows that, on a like-for-like basis, list prices can act as a good proxy for transaction prices, where those are unavailable, which is often the case in lower-income countries. Lastly, the study documents the

[32] With the exception of a recent contribution by Gibson and Mullins (2020), who look at the effect of FEMA map updates in New York flood plains. However, they do not control for flood risk information, flood events, *and* flood defences.

effects on estimated flood discounts of important choices in empirical specifications, including the appropriate choice of spatial fixed effect, and the inclusion of specific controls, in particular blue space amenities.

The findings have rich implications for policymakers, including relating to flood risk management, insurance and flood defences, as well as for projections of future flood losses. The results present compelling evidence on the effectiveness of public investments in flood mitigation – both in terms of information provision and flood defences. But these two types of investments might be expected to have very different effects on future costs of flooding. Better information results in more awareness and a clear price signal, which should translate into less exposure to flooding in future, albeit the survey findings suggest there is still work to be done to translate scientific assessment of risk into public awareness. Moreover, the provision (and dissemination) of risk information is important to protect the integrity of public investments in flood relief schemes (to create a price signal on risk and protect taxpayers from escalating future costs). In contrast, flood defences – and the expectation of future investments in defences – might encourage development of flood-prone areas, with important implications for the future costs of flooding in a world with increasing flood risk.

6.2 Empirical Specification recap

Conceptually, the value of a dwelling takes the following form:

$$\mathrm{Price} = \mathrm{f}(\mathrm{S}, \mathrm{L}, \mathrm{F}) + \varepsilon, (1)$$

where the logged sale/rental price of the dwelling is a function of its structural characteristics (S; such as number of bedrooms, bathrooms, or the presence of a garden), its location and environmental characteristics (L; including the spatial unit fixed effect, proximity to CBD, to the coast and to green spaces, access to transport networks, and socio-economic factors), and flood-related variables (F; flood risk, past flood events, flood defences). The error term, ε, reflects the gap between the conditional expectation and the actual value. The dwelling price is thus a function of all of the attributes relating to the dwelling and the resulting coefficients are the implicit marginal prices of the attributes.

More specifically, this analysis uses ordinary least squares and a semi-log or log-log specification (depending on the variable), as is typical in this type of study. Allowing for the long duration of the sample, and the focus on flooding, the baseline specification is, therefore, as follows:

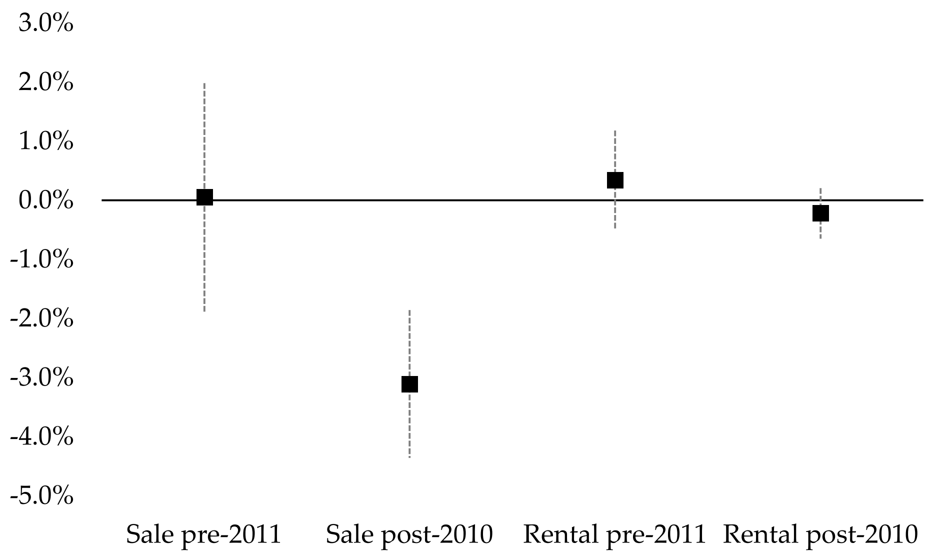
$$\log(\mathrm{price_i}) = \beta_0 + X'_{1i}\beta_1 + X'_{2i}\beta_2 + X'_{3i}\beta_3 + X'_{4i}\beta_4 + X'_{5i}\beta_5 + \varepsilon_i \ (2)$$

Where: $\mathrm{price_i}$ refers to the transacted or listed sale/rental price (depending on the sample); X'_{1i} to a vector of dwelling-specific attributes; X'_{2i} to the time period (quarterly fixed effects); X'_{3i} to SFE; $X'_{4i}$to a vector of location-specific amenities and controls; and X'_{5i} represents the regressors of interest, a vector of variables capturing flood-related effects. The vectors of dwelling- and location-specific controls, and SFE, are as discussed in Sections 2.3.1.2 and 4.4, with the exact set of dwelling attributes varying across the three datasets. Detailed discussion on the data and methodologies used for this chapter is in sections 3.5 and 4.4, respectively.

6.3 Results

This section presents findings from a range of empirical analyses, as described in the previous sections. It opens with the estimated impact on housing prices of the release of information regarding flood risk in 2011, and related results on the relationship between distance to flood risk and housing prices. The headline results are shown in Figure 6.1. Until the publication of information about which locations are scientifically assessed to be at risk of flooding, there is no statistically significant impact of flood risk on housing prices, either sale or rental. When that information is made publicly available, dwellings with at least a medium risk of flooding have listed sale prices that are on average 3.1% lower than those with no assessed risk of flooding. For rental prices, there is no effect of the publication of flood risk information on dwellings within the medium and high risk zone.

Figure 6.1: Estimated flood discount, by segment and sample



Note: the figure shows the estimated coefficients and confidence intervals for being inside the medium flood risk zone published in 2011, based on the *preferred specification for sale and rental listings before and after this information is released; see Table 6.1.*

It also presents additional results related to flood defences, flood events, and the flood discount across the housing value distribution, as well as a range of robustness checks. The results show that the headline finding is robust to the use of different samples (nationwide, or restricting to Dublin only), transaction prices as the outcome, and to different model specifications (including varying the level of spatial FE, inclusion of spatio-temporal FE, and a border-discontinuity-style analysis). It also shows how the estimate of the flood discount varies with the inclusion of different groups of controls. If anything, the additional specifications presented suggest that the headline finding likely represents a lower bound on the flood discount.

6.3.1 Information and the flood discount

Table 6.1 shows coefficients for various measures of flood risk, for both sale and rental listings, for two periods: prior to 2011, and from 2011 on, reflecting the release of information about flood risk.[33] The regressor of particular interest is for dwellings inside zones assessed by the CFRAM exercise to be at medium or high risk of flooding, as revealed in 2011. Prior to the release of this information on flood risk, there is no housing price discount for either sale or rental dwellings located within what were later revealed to be areas at risk of flooding (the coefficient on 'Inside medium/high' in the first and third columns of Table 6.1).

After the release of the information in 2011, the emergence of a significant flood discount of 3.1% for dwellings for sale with at least a medium risk of flooding is observed (the second column of Table 6.1). However, there is no equivalent discount for rental dwellings in flood risk zones (the final column of Table 6.1). The specifications reported in Table 6.1 include controls for various dwelling and neighbourhood attributes, past flood events, as well as time (year-quarter) and location (ED) fixed effects. The empirical specification that gives the 3.1% result above is referred to hereafter as the preferred specification.

.[33] The reported coefficients are for dwellings not protected by flood defences at the time of their listing.

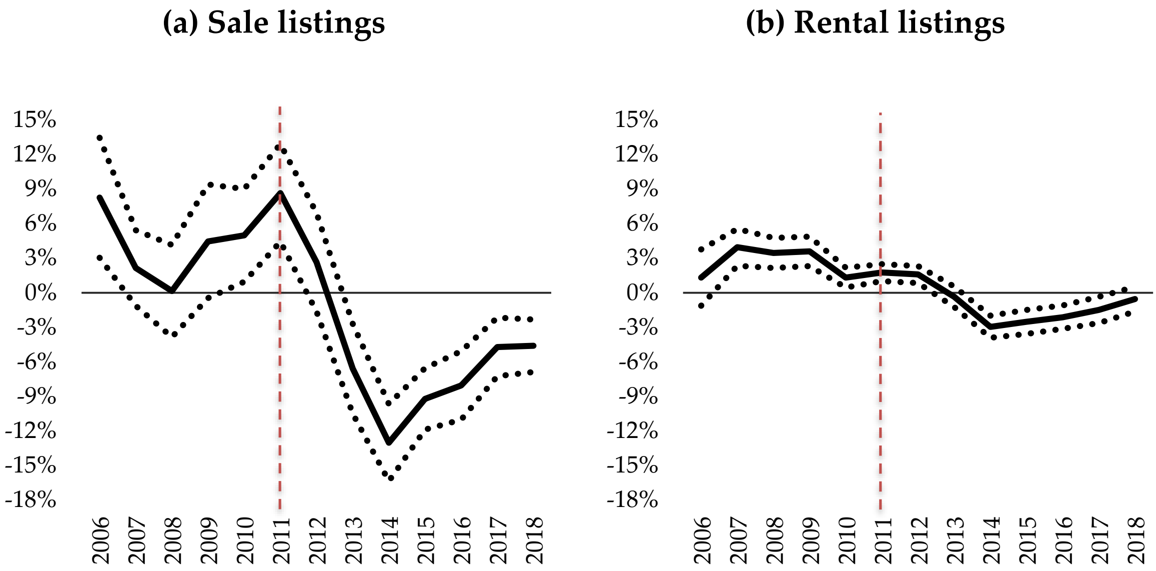
Table 6.1: The flood discount before and after information

Sample	Sale listings		Rental listings	
	2006-2010	**2011-2018**	**2006-2010**	**2011-2018**
500m-200m away	-0.006	-0.001	0.001	0.003
	-2.5	-0.3	0.5	3.2
200m-100m away	-0.001	-0.007	0.000	0.005
	-0.2	-2.9	-0.1	4.3
<100m from low risk	-0.014	-0.011	0.005	0.008
	-4.1	-4.2	2.0	6.2
Inside low risk	-0.007	-0.011	-0.013	0.009
	-1.0	-2.1	-3.3	4.5
Inside medium/high	0.001	-0.031	0.003	-0.002
	0.1	-4.9	0.8	-1.0
Observations	94,172	190,635	124,408	390,301
R-squared	0.788	0.842	0.841	0.878
RMSE	0.222	0.263	0.154	0.169
Spatial units	955	1,020	931	1003

Notes: Regression results show coefficients on various measures of flood risk, as discussed in the text, where the dependent variable is the natural log of the dwelling's listed price. Robust t-statistics are shown underneath each coefficient. Different columns show results across sale and rental listing datasets, before and after the release of flood-risk information. Controls include Census ED fixed effects, dwelling attributes, location amenities, and market conditions, as discussed in the text.

The timing of the emergence of the flood discount is further illustrated in Figure 6.2. This shows coefficients, and associated confidence intervals, from regressions similar to those reported in Table 6.1 (for sale and rental listings) but using the full time period available (2006-2018) and with the indicator for dwellings inside a medium to high risk zone (and not protected by flood defences) interacted with year dummies. It shows a clear change in the relationship between listed sale prices and flood risk, after the release of the new flood risk information in 2011. This pattern is far less evident in the rental segment, where the estimated coefficient is smaller in magnitude. In addition to the baseline specification, which includes year-quarter fixed effects, the headline finding is robust to the inclusion of local market trends, as described in Section 6.3.4.

Figure 6.2: Estimated flood discount, by year and segment



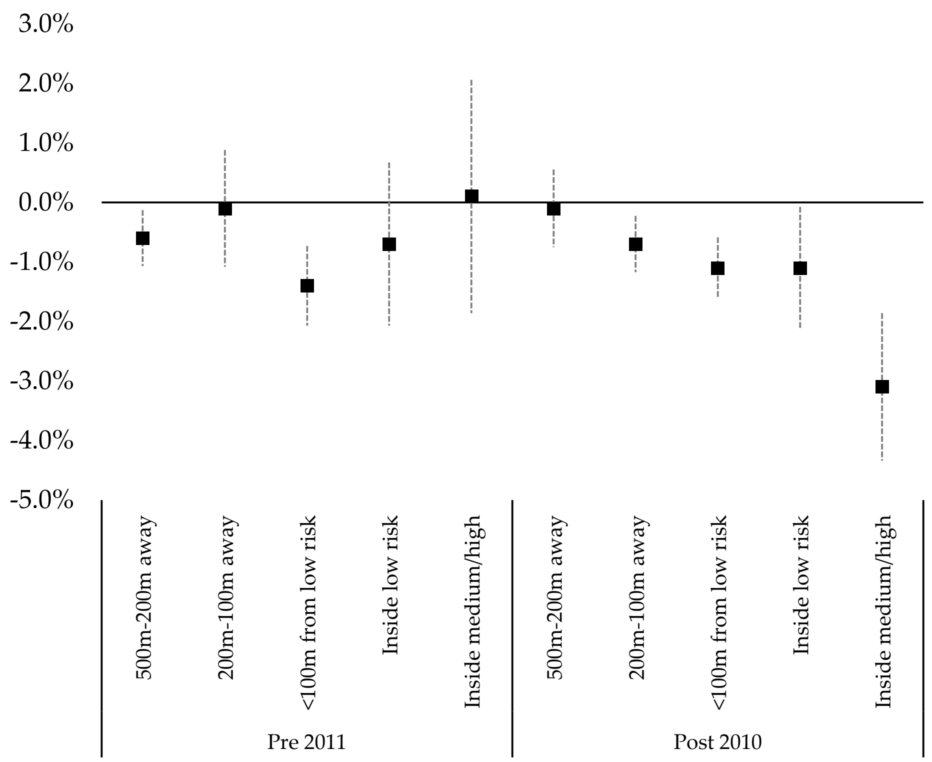
Note: The figures show the time-varying estimated flood discount (with 95% confidence interval) for dwellings within a medium to high flood risk zone, based on specifications similar to those reported in Table 6.1, but with the 2006-2010 and 2011-2019 samples combined and the flood risk indicator interacted with year. The red dashed vertical line in each panel indicates the release of the new information on flood risk (in 2011).

6.3.2 Variation in the flood discount

6.3.2.1 By distance to risk

The second main result from Table 6.1 is the relationship between distance and the flood discount for sale dwellings, once flood risk is published. Figure 6.3 shows the point estimates for each of the five flood risk categories by distance, for the pre-2011 and post-2010 samples of sale listings data, as reported in Columns (1) and (2) of Table 6.1. For sale listings after the release of flood risk information (solid black line; second column of Table 6.1), there is a clear negative relationship between proximity to flood risk and housing prices. The emergence of a statistically significant discount on flood risk after the release of information applies to all dwellings within 200 metres of the flood risk zone, and grows from 0.7% for dwellings 100m-200m away from the low flood risk zone to 1.1% for dwellings either within the low flood risk zone or within 100m of it and to 3.1% for dwellings inside the medium and high flood risk zone. Beyond 200 metres from a low risk zone there is no statistically significant flood discount for sale dwellings in the post-2010 sample.

Figure 6.3: Estimated effect of flood risk on housing prices, by distance categories and segment

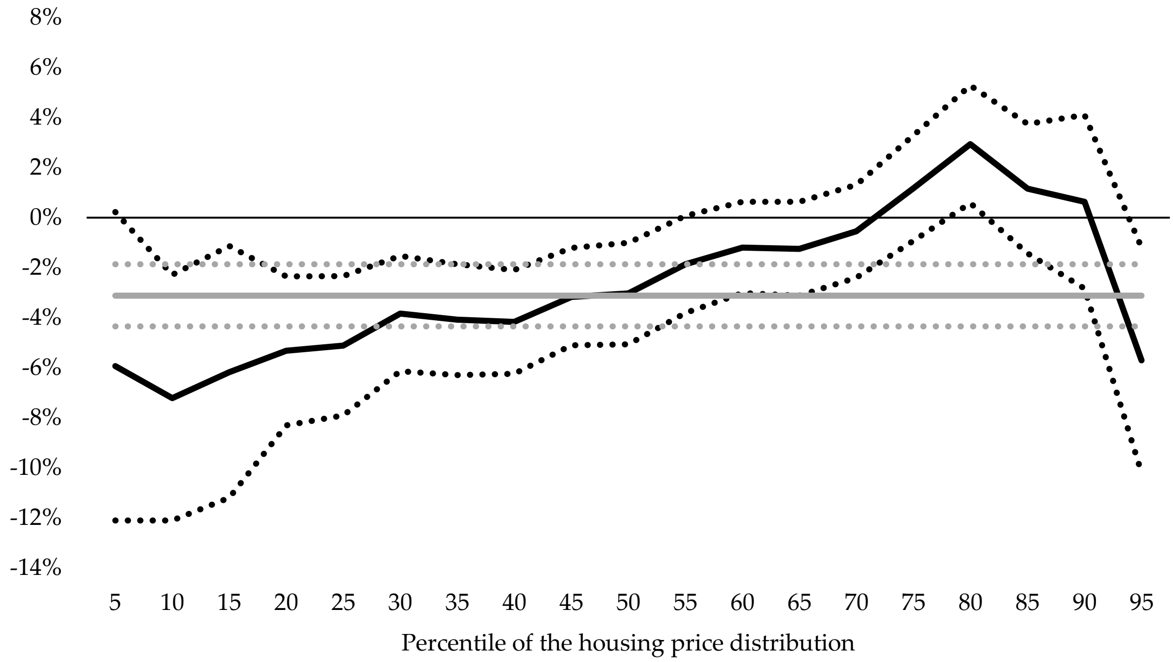


Note: The figure illustrates the magnitude of the estimated flood discount for each distance category (without flood defences) for the pre-2011 and post-2010 samples of sale listings data, as presented in Table 6.1.

6.3.2.2 Variation across the price distribution

Figure 6.4 graphs the marginal effects of flood risk on housing prices across the price distribution. These are estimated using unconditional quantile regressions and the post-2010 sale listings dataset. The figure shows a larger flood discount at the lower end of the price distribution: the bottom decile experiences a 7.2% discount for flood risk, compared to an estimated discount for the upper half of the distribution that is for the most part not statistically different from zero.

Figure 6.4: Estimated flood discounts over the price distribution, sale listings dataset



Note: This figure shows the flood discount for dwellings located within the medium/high flood risk zone on the y-axis and the price ventiles on the x-axis, based on the 2011-2018 sale listings sample. The solid black line indicates the point estimates from unconditional quantile regressions, with the corresponding 95% confidence intervals shown in dashed black lines. The solid grey line indicates the OLS estimate of the flood discount (from Table 6.1), with corresponding confidence intervals given by grey dashed lines. In all cases, the same controls as Table 6.1 are included, with ED locational fixed effects.

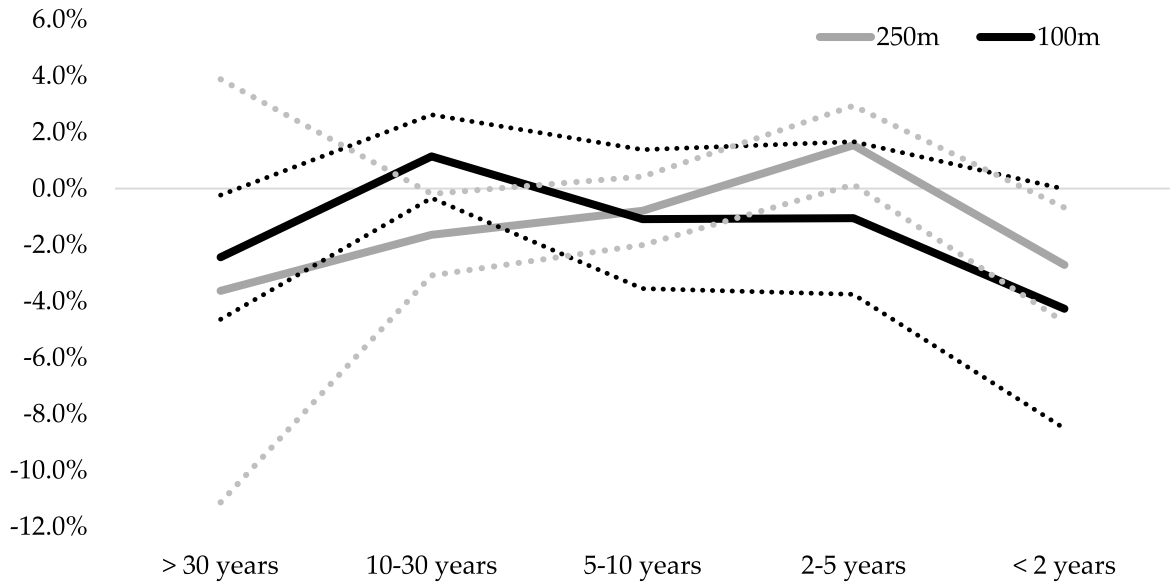
6.3.3 Events, defences and the flood discount

6.3.3.1 Past flood events

This subsection examines how both flood events and flood defences are reflected in housing prices. Pilla et al. (2019) show the relative impact on housing prices of a major 2011 flood event in the Dublin housing market. A database of over 2,000 flood events is used to examine whether this finding extends to other events and is persistent. To do this, flood events are included by date and location in all the main specifications. For each dwelling, the two treatments of interest are the time since the most recent flood event within 100 metres and the most recent event between 100 and 250 metres from that dwelling. These are categorised into five time intervals, as shown in Figure 6.5.

Full regression output for the relevant variables, across all three datasets, is given in Floods Appendix, Table B 1 For sale listings, dwellings within 100 metres of a flood event that took place less than two years ago are subject to a discount of 4.3%. This discount disappears after two years. There is a smaller effect for recent flood events slightly further from the dwelling (100-250 metres away): 2.7% for an event within the last two years. As shown in Figure 6.5, there is some evidence of an effect of major past floods. Relative to properties with no history of flood events nearby, dwellings where the most recent flood event was more than thirty years ago are subject to a discount of 2.4%.

Figure 6.5: Estimated effect of recent flood events on housing prices, by time distance, sale listings dataset

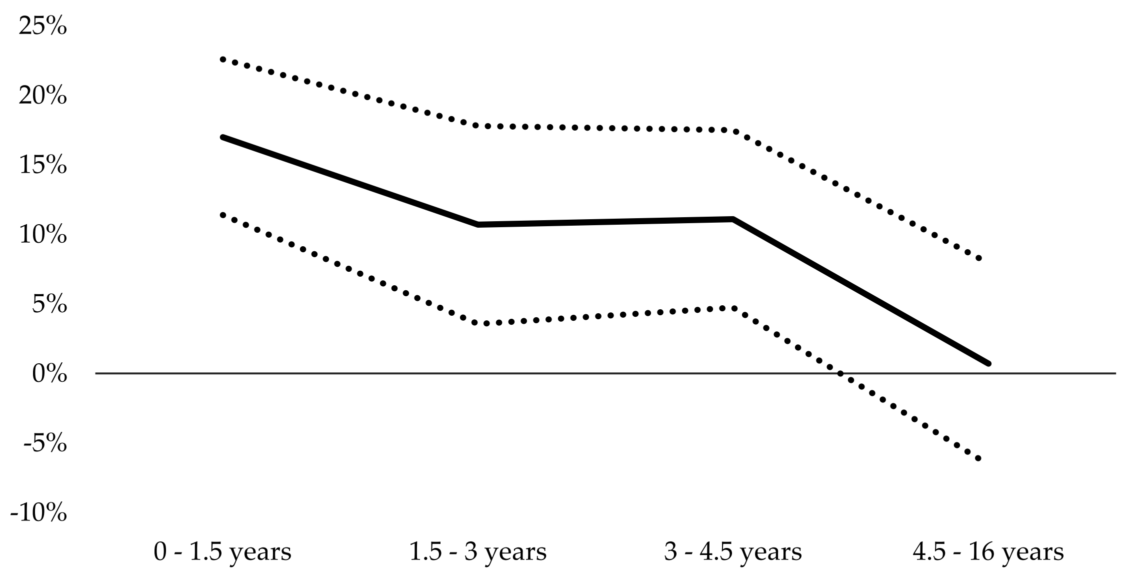


Note: *The figure illustrates the magnitude of the estimated effect of past flood events that occurred within 100m of a dwelling (black line) or 100m-250m from a dwelling (grey line), along with 95% confidence intervals, by intervals of time elapsed since the most recent flood event in each category. The specifications are as per those reported in Table 6.1. See Floods Appendix, Table B 1, for full regression results.*

6.3.3.2 Flood defences

Flood defences have a big effect on the listed sale price of housing (in line with the findings in Beltran et al. 2018b). Full results are shown in extended regression output for Floods Appendix, Table B 1. Compared to dwellings with a similar exposure to flood risk before the construction of flood defences, being within the area protected by flood defences once they are constructed is associated with a significant price premium. This price premium is estimated to be close to 10% – but only for dwellings within the medium/high risk zone. For dwellings at lesser risk, there is no positive effect on prices after the construction of flood defences. Similarly, there is only modest evidence of any effect on rental dwellings in the medium/high risk zone (2.3%, with a t-statistic of 2.1) and no other statistically significant effect for other risk categories. This pattern of results holds in a specification with even more granular fixed effects, as reported in Table 6.3.

Figure 6.6: Estimated flood defence premium, by time since scheme construction



Note: The figure reports coefficients (and confidence intervals) for the time-varying effect of flood defences on housing values, for dwellings within a medium to high risk zone. The specification is similar to that reported in Column 2 of Table 6.1.

The finding of a price premium in defended areas is consistent either with an otherwise omitted variable making dwellings in these locations particularly attractive once the flood risk has been mitigated or with the market over-reacting to the installation of flood defences, perhaps due to pent up demand for those locations. Exploiting information on the timing of flood defence installation, the study further investigates the reported premium, by looking at how the effect of flood defences on housing prices varies with time since installation. The results are illustrated in Figure 6.6 and show that the premium is in fact short-lived, consistent with the 'pent up demand' hypothesis, rather than an OV bias story. Within five years, the premium has disappeared and housing prices for dwellings located in areas assessed as at risk of flooding, but protected by flood defences, are not statistically different from housing prices in areas not at risk of flooding.

As noted earlier, it is likely that there are strong selection effects in the location of flood defence schemes, and so it is possible that these are locations of particular (idiosyncratic) value. For that reason, the estimated premium reported in Table 6.1 should not be interpreted as representing the value of installing flood defences for the *average dwelling* at risk of flooding, even over the short-run.

6.3.4 Robustness of the flood discount

Here, the various robustness checks to the results presented in Sections 6.3.1-6.3.3 are discussed. Below provides details on three sets of robustness checks: (i) a presentation of the estimated flood discount for various subsets of controls, (ii) varying the level of SFE, and (iii) using a dataset of transaction prices, rather than listed prices, for the sale segment.

In additional robustness checks, results suggest that the headline finding is essentially unaffected by: the inclusion or exclusion of past flood events as additional controls; the exclusion of dwellings affected by a particularly large flood event that occurred in the same year as the information release; the use of the nationwide PFRA maps (and nationwide housing sample), rather than the CFRAM maps (and the sample restricted to AFAs only); restricting the sample to similar property types only; and to the use of a border-discontinuity-design style approach where the control group is restricted to dwellings within a fixed distance of a flood risk zone.[34]

6.3.4.1 Step-wise inclusion of controls

As discussed in Section 5.1, a growing literature examines the relationship between flood risk and housing prices. Not all studies include the same controls, however, and Table 6.2 presents the results of eight empirical specifications, which vary by the sets of controls they include. Controls are added sequentially, building up the model from the most parsimonious to the most comprehensive, showing in turn how the addition of each set of controls affects the estimated flood discount. The first column presents a naïve regression, where housing prices are a function of flood risk only. The large negative coefficient on being within the medium/high flood risk zone implies that, all else equal, dwellings at risk of flooding have lower-value attributes than those not at any risk. Adding spatial FEs at the Census ED level in Column (2) leads to a substantial fall in the estimated flood discount, and a big increase in the R-squared. Adding time period fixed effects, to control for aggregate market conditions, in Column (3) has a relatively small effect on the estimated discount.

The addition of dwelling attributes in Column (4) leads to a further substantial decline in the estimated flood discount, suggesting that dwellings exposed to flood risk are on average of lower quality. The estimated flood discount of -1.4% in Column (4) is less than half the discount of -3.1%, in the preferred specification. This implies that even where empirical specifications include controls for market conditions, a detailed set of dwelling attributes, and local area controls for unobserved spatial attributes, the potential remains for significant OV bias.

The addition of a range of location-specific amenities, such as distance to CBD and transport facilities, in Column (5) does increase the estimated flood discount, from roughly 1.4% to 2%. It is the inclusion of 'blue space' controls in Column (6) –

[34] All of these additional robustness checks are detailed in Floods Appendix, Table B 2.

specifically distance to the coast and other water bodies and an estimate of sea views – that has a far larger impact on the flood discount, which increases to almost 4% (see Section 4.2.1 & 4.2.2 for more on calculation of sea views).

The addition of neighbourhood quality, through use of Census Small Area measures of educational attainment and unemployment in Column (7), reduces the estimated flood discount. This implies that flood risk and neighbourhood quality are negatively correlated in the dataset. As discussed in Section 4.4.2, it is possible that these are 'bad controls' and the true effect of flood risk is larger than in what is termed the preferred specification. Given the effect of including SA fixed effects (discussed below), the researcher errs on the side of these slightly smaller magnitudes.

Finally, Column (8) adds controls for historical flood events, reproducing the results from the preferred specification. This leads to a slight reduction in the estimated flood risk discount, which is not a surprise given the likely correlation between past flood events and assessed flood risk. But perhaps more surprisingly, this effect is not large. This last set of results underlines the idea that information about flood risk matters, and this effect is distinguishable in the data, and using the estimation strategy, from the effects of direct experience of flooding.

Table 6.2: Step-wise adding groups of controls

	No controls	+ ED fixed effects	+ Time controls	+ Dwelling attributes	+ Proximity to amenities	+ Blue space controls	+ Neighbourhood 'quality'	+ Flood Events
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	lnprice	lnprice	lnprice	lnprice	lnprice	lnprice	lnprice	lnprice
No flood defences								
500m-200m away	-0.220	-0.0208	-0.0205	0.00556	0.00348	-0.000137	-0.000576	-0.000666
	-60.5	-6.45	-6.68	2.83	1.77	-.0665	-.289	-.335
200m-100m away	-0.275	-0.0390	-0.0422	0.00391	0.000549	-0.00604	-0.00745	-0.00744
	-59.1	-9.67	-10.9	1.55	.217	-2.26	-2.87	-2.87
<100m from low risk	-0.323	-0.0816	-0.0853	0.00312	-0.00158	-0.0130	-0.0118	-0.0113
	-72.9	-19.8	-21.6	1.22	-.611	-4.67	-4.35	-4.16
Inside low risk	-0.238	-0.125	-0.129	0.00598	-0.000470	-0.0164	-0.0119	-0.0106
	-21.2	-16	-17.2	1.19	-.0933	-3.15	-2.31	-2.05
Inside medium/high risk	-0.399	-0.161	-0.164	-0.0137	-0.0197	-0.0389	-0.0320	-0.0311
	-35.9	-17.5	-18.6	-2.23	-3.2	-6.08	-5.08	-4.88
Spatial fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Dwelling attributes	No	No	No	Yes	Yes	Yes	Yes	Yes
Proximity to amenities	No	No	No	No	Yes	Yes	Yes	Yes
Blue space controls	No	No	No	No	No	Yes	Yes	Yes
Neighbourhood quality	No	No	No	No	No	No	Yes	Yes
Flood events	No	No	No	No	No	No	No	Yes
Observations	190,704	190,704	190,704	190,704	190,704	190,704	190,635	190,635
R-squared	0.043	0.575	0.613	0.834	0.834	0.835	0.842	0.842
RMSE	0.645	0.431	0.411	0.270	0.269	0.269	0.263	0.263

Note: The results in this table are based on the listings data (2011-2018) and are similar to those reported in Table 6.1. The dependent variable in each case is the natural log of the dwelling's listed sale price. The first column reports a specification with flood risk categories as the only explanatory variables (no other controls added). Each subsequent column adds a set of controls in sequence as per the column headings. Column 8 replicates Column 2 from Table 6.1 with the full set of controls included. In all but the first column, there are 1,020 spatial unit.

An important finding for the flood discount literature can be taken from this exercise, namely that due to the high correlation between 'blue space' amenities and flood risk dis-amenities, any estimate of the flood discount that does not explicitly control for 'blue space' amenities are likely to underestimate that discount.

6.3.4.2 Varying the level of spatial fixed effects

The results directly speak to the issues raised by Von Graevenitz and Panduro (2015) regarding the importance of the choice of spatial unit when attempting to control for omitted location-specific factors. Table 6.3 presents additional specifications showing how the results vary firstly with four different levels of SFE (in Columns 1-4) and secondly when spatio-temporal market-by-year fixed effects are added on top of location fixed effects, to allow for market-specific trends or shocks. In all specifications reported in Table 6.3, t-statistics are shown for standard errors that cluster at the level of the spatial unit used as the fixed effect.

The most obvious difference across the first four columns of Table 6.3 is between Local Market fixed effects (in Column 1) and the other three levels (Columns 2-4). The magnitude of the coefficient for dwellings located within a medium/high flood risk zone, when using market-level fixed effects (in Column 1), at -8.1%, is more than double that of the any of the other specifications. As discussed in Section 4.4.3, the trade-off in choosing the SFE is between capturing spatial processes that might happen to correlate with flood risk and allowing enough within-unit variation for identification. There are 54 'Local Markets' within the sample, with an average 37,000 households per market. The results suggest that, even with other area features included as controls, this level of aggregation is insufficient to capture location-specific features that may be correlated with flood risk. Again, this finding is important for the flood discount literature, where often SFE cover geographical units with tens of thousands of households.

Among the other three specifications, the estimated flood discount is similar in order of magnitude, ranging from 1.6% with micro-markets (in Column 2) to 3.1% for ED fixed effects (in Column 3). As discussed in Section 4.4.3, it is likely that the use of Small Area fixed effects may suffer from limitations in relation to statistical power, with an average of just 18 listings per Small Area in the listings sample (2011-2018), as well as potential correlation between the Small Area, which may be as granular as an apartment block, and the regressor of interest. Census EDs are the preferred specification, with an average of 185 listings per ED in the post-2010 sample.

The results in Columns 5 and 6 replicate those in Columns 3 and 4 but with the addition of local-market-by-year spatio-temporal fixed effects. The results are qualitatively and quantitatively similar in these more-demanding specifications. It is also worth noting, following the discussion in Section 6.3.2, that the premium on defended dwellings is reduced in magnitude and statistical significance in these last two specifications. Overall, one may conclude that these additional specifications reinforce the robustness of the estimate of the flood discount and highlight the importance of including highly localised SFE.

Table 6.3: The flood discount, for different spatial fixed effects

Level of Fixed Effect	Sale listings (2011-2018)					
	Local Market	**Micro-market**	**Census ED**	**Census Small Area**	**Census ED**	**Census Small Area**
					+ Spatio-temporal FE	
No flood defences						
500m-200m away	-0.020	-0.001	-0.001	-0.001	-0.003	-0.002
	-2.2	-0.2	-0.1	-0.2	-0.6	-0.4
200m-100m away	-0.037	-0.012	-0.007	-0.004	-0.011	-0.003
	-3.3	-1.5	-0.9	-0.6	-1.4	-0.5
<100m from low risk	-0.046	-0.013	-0.011	-0.002	-0.015	-0.003
	-3.8	-1.4	-1.2	-0.3	-1.7	-0.3
Inside low risk	-0.067	-0.012	-0.011	-0.012	-0.014	-0.011
	-3.2	-1.0	-0.8	-1.1	-1.2	-1.0
Inside medium/high	-0.081	-0.016	-0.031	-0.018	-0.032	-0.016
	-4.3	-0.9	-1.9	-1.5	-2.0	-1.3
After flood defences						
Inside medium/high	-0.030	0.072	0.097	0.118	0.06	0.056
	-0.9	1.9	2.7	3.2	1.9	1.5
Controls	YES	YES	YES	YES	YES	YES
Observations	190,635	190,635	190,635	190,635	190,644	190,644
R-squared	0.808	0.834	0.842	0.874	0.852	0.883
RMSE	0.289	0.269	0.263	0.241	0.254	0.233
Spatial units	54	375	1,020	10,809	1,020	10,809

Notes: Regression results show coefficients on various measures of flood risk, as discussed in the text, where the dependent variable is the natural log of the dwelling's listed price. t-statistics are shown underneath each coefficient, based on standard errors that are clustered within the spatial unit in each case. Different columns show results using different fixed effects. Controls include dwelling attributes, location amenities, and market conditions, as discussed in the text.

6.3.4.3 Using transaction prices rather than list prices

The next investigation is the extent to which the price effects found using a detailed dataset of list prices (as reported in Table 6.1) are reflected in a smaller database of transaction prices, which offers additional controls and more precise measures of location. Table 6.4 shows the results for a number of specifications, comparing results using transaction and list prices as the outcome.

Column 1 of Table 6.4 reports a specification similar to the preferred one (Column 2 of Table 6.1) but with four notable differences. Firstly, the outcome is the natural log of the dwelling's *transaction* price, as recorded in Ireland's Residential Property Price Register, rather than its listed price. Secondly, the geographic scope of sample differs, as the sample of 36,000 includes only dwellings sold in Dublin (as discussed in Section 3.2). Thirdly, the exact empirical specification includes some additional dwelling attributes, available through the linking of transactions with official energy performance certificates, including the overall energy efficiency assessment, exact size in square metres and building age, which were not available for the listings data. Finally, the transactions data use location information based on Eircodes, which may be more precise than the (building-level) location information generated algorithmically by *daft.ie* using the address entered by the advertiser.

The result, as reported in Column (1) of Table 6.4, is a substantially larger price discount of 6.2% for dwellings located within medium to high risk zones, as opposed to the 3.1% estimated discount from the preferred model with the sales listings data reported previously. In the remaining columns of Table 6.4, the source of this difference in estimated flood discount is investigated, by isolating in turn the effect of each of the four differences between Column (1) here and the main results from Table 6.1.

First, Columns (2) and (3) replicate the specification in Column (1), but this time on a matched sample of just under 30,000 dwellings for which there are both transaction and list prices. Column (2) reports the effect on transactions prices, for the matched sample, while Column (3) reports the effect on the list price, for the same sample. In both cases, the specification and controls included are identical to those used in Column (1). Use of the matched sample narrows the gap significantly, with a flood discount in transaction prices of 5.7% compared to one in list prices of 4.8%. Thus, the use of transaction prices, as compared to list prices, leads to a higher estimate of the flood discount (+0.9pp). Nonetheless, the difference is not statistically significant and lends support to the use of listed prices in settings where transactions data are not readily available, such as lower-income countries.

Table 6.4: Flood discount across transaction and list prices

	Transaction Prices (1)	Matched: Transaction Prices (2)	Matched: List Prices (3)	As per (3) No BER controls (4)	As per (4) Locations from listings (5)
No flood defences					
500m-200m away	0.003	-0.002	0.001	-0.000	0.001
	0.9	-0.5	0.4	-0.1	0.2
200m-100m away	-0.003	-0.004	-0.003	-0.009	-0.007
	-0.6	-0.8	-0.6	-1.7	-1.4
<100m from low risk	-0.012	-0.016	-0.008	-0.018	-0.012
	-2.4	-3.0	-1.6	-3.1	-2.2
Inside low risk	-0.027	-0.034	-0.025	-0.033	-0.021
	-2.7	-3.1	-2.6	-3.0	-2.0
Inside medium/high	-0.062	-0.057	-0.048	-0.069	-0.026
	-4.2	-3.7	-3.4	-4.4	-2.0
After flood defences					
Inside medium/high	0.027	0.040	0.049	0.049	0.077
	1.0	1.6	2.1	1.8	2.9
Controls	YES	YES	YES	YES	YES
Observations	35,922	29,253	29,253	29,253	29,253
R-squared	0.897	0.896	0.909	0.886	0.883
RMSE	0.172	0.173	0.159	0.178	0.180
Spatial units absorbed	322	316	316	316	318

Notes: Regression results presented in this table show coefficients on various measures of flood risk, as discussed in the text, where the dependent variable is the natural log of the dwelling's transaction price. The results in this table are based on the transactions price data. Robust t-statistics are shown underneath each coefficient. Column (1) uses the full transactions dataset. Columns (2) and (3) use a restricted version of the transactions data where each observation is matched to the listings data. Column (4) replicates Column (3) but omits additional BER controls. Finally, Column (4) replicates Column (3) but using location information from the listings data. Controls include Census ED fixed effects, dwelling attributes, location amenities, and market conditions, as discussed in the text.

Column (4) replicates Column (3), but excluding the additional dwelling-specific controls available through the BER database of energy performance certificates, such as dwelling age, exact size in square metres, and energy efficiency, which were included in Columns (1)-(3) here, but not available for the listings dataset used in Table 6.1. Compared to Column (3), the flood discount increases from 4.8% to 6.9%. Of the additional controls, it is exact floor area in square metres that has by far the largest impact on the estimated the flood discount. Without this, the flood risk discount may be overstated, at least in the case of Dublin.

Lastly, Column (5) examines the extent to which exact measures of location are important in determining the magnitude of the flood risk discount. As noted in Section 3.2, the exact coordinates of the dwelling are measured in two different ways across listing and transaction datasets. Of the two measures, the Eircode measure of location used in the transaction dataset is official and thus likely to be the more accurate. The specification in Column (5) is identical to Column (4), except now using the dwelling locations from the listings data, as opposed to the locations from the transactions data. The result shows that this makes a substantial difference to the estimated flood discount, which drops to 2.6% in Column (5) compared with 6.9% in Column (4). The lower degree of precision of dwelling location in the listings data is a form of measurement error, thus resulting in a bias attenuating the coefficient towards zero.

Column (5) of Table 6.4 is the most directly comparable to the results presented previously in Table 6.1, as both use an identical specification, with the only difference being the sample of dwellings included. Comparing the estimated flood discount of 2.6% from Column (5) of Table 6.4, with the headline finding of 3.1%, indicates that if anything the flood discount is lower for this smaller Dublin-only sample of dwellings, compared to the national sample used previously, when comparing like-for-like specifications. In all, the results of this table support the hypothesis that the headline result – of a flood discount estimated at 3.1% – represents a lower bound on the true figure. Both the use of transactions prices and of more precise location information result in a larger estimated flood discount.

6.4 Comparing market outcomes with stated preferences

The empirical analysis on preferences as revealed by market outcomes is supplemented by an online survey on actors in the housing market's perceptions and awareness of flood risk in Ireland. The survey was hosted on *daft.ie*, the most popular real estate website in Ireland, with a link to the survey in the strapline of the home page for approximately three weeks in June 2019. The survey attracted a total of 837 respondents, 36% of whom said they were interested in buying a home and 26% in renting a home.[35] There was no mention of floods in the title or description of the survey to avoid self-selection of respondents with a particular interest in the topic, with the aim of gaining insight on actors in the housing market's perception and knowledge of flood risk.

6.4.1 Perceptions of flood risk and flood defences

In addition to results discussed in the main study, the survey also probed the sources of flood risk salience. In particular, for those who indicated that their concern about flood risk had increased in the last 10 years, respondents were asked about the reasons for their increasing concern: 38% cited coverage of flooding in the

[35] Some respondents left questions blank, such that are not 837 responses for every question in the survey. There were also some questions on the survey that only appeared in logical sequence depending on the answer to the previous question. Further detail on the survey, including the full list of survey questions, are included in Floods Appendix C.

media, 27% cited increased awareness of climate change, while 12% chose “release of new information on flood risk” (n=351).

The survey also asked respondents about their attitudes towards flood defences. 18% of respondents said that flood defences had been constructed in or were planned for their area, while another 34% said they didn’t know (n=632). The majority (59%) agreed (or strongly agreed) with the statement that “Man-made flood defences provide an adequate protection against flood risk” (n=632). Half disagreed (or strongly disagreed) with the statement “Man-made flood defences reduce your enjoyment of an area, either visually or otherwise”, with 18% stating they didn’t know (n=626). And finally, a large majority (70%) agreed (or strongly agreed) with the statement “flood defences should be funded by general taxation” (n=632).

6.4.2 Attitudes to flood risk

When asked to rank various amenities and dis-amenities in terms of their importance in choosing where to live, on a Likert scale where 1 is ‘not important’ and 5 ‘very important’, 54% of respondents ranked “no risk of flooding” as “very important” (n=802). This was the joint highest (in terms of frequency of respondents choosing “very important”) along with neighbourhood quality (54%, n=816), and ahead of proximity to other amenities including transport networks, central business district, green spaces and schools.

A large share of respondents (45%) also said that flood risk had become more of a concern for them in the last 10 years, as against just 4% who said it had become less of a concern for them (n=758). Looking to the future, 81% of respondents expect flood risk in Ireland to increase by the year 2050 (n=633). In terms of direct experience of flooding, 12% of respondents said they had directly experienced flooding of a dwelling they were living in at some point in the past (n=633).

Concern about flood risk was notably different among those looking to buy compared with those looking to rent. Of those looking to buy a home, 58% rated avoiding flood risk as very important, while just 5% said it was not important (n=298). In contrast, of those looking to rent, similar fractions rated avoiding flood risk as very important (32%) and not important (25%) (n=202). Buyers were almost twice as likely to state that flood risk was relevant to their search, relative to renters (35% vs 19%; n=305 and n=216 respectively), and about half as likely to say they didn't know if flood risk was relevant (18% vs 35%). A similar proportion of respondents in each category (48% of buyers and 46% of renters) stated that flood risk wasn't relevant in the areas they were looking at.

6.4.3 Awareness of flood risk information

In spite of concern about flood risk, the responses to the survey also indicate a continuing information deficit among actors in the housing market. Of those who said that flood risk was relevant for their search, over a third (37%) said they weren't aware of the risk for those areas (n=217). Fewer than one in five respondents (17%) said they knew where to find flood risk information, while the majority (61%) said they didn't know, and 22% said they thought it would be difficult to find (n=643). When asked about official flood risk maps, only 22% said they were aware of the existence of these maps (n=758).

These findings have important implications for policy as well as for the results presented above. Firstly, the results of this survey imply that the availability of scientifically assessed risk information on its own appears insufficient to ensure a well-informed public, even when the stakes are relatively high and when respondents report high levels of concern. Greater efforts at information dissemination and communication to the public may be required; see McDermott and Surminski (2018) for a related discussion on translating scientific assessment of flood risk for local decision-making.

Secondly, if only one in five respondents say they are aware of the official risk maps, it also raises the question as to whether it is plausible that the release of these maps had the significant effect on the market that is observed in the data. Clearly, even a fraction of market participants being well informed could still be sufficient to move the marginal price. Moreover, it is likely that more sophisticated market participants – including various agents working on behalf of buyers and sellers – would be well informed and their assessments would affect both ask and bid prices.[36] As discussed by Stein (2009) in a different setting, where concerns around crowding or leverage are absent, the presence of well-informed traders would be expected to ensure that prices represent fundamental values, even when unsophisticated buyers still represent a significant fraction of the overall market.

6.4.4 Willingness to pay to avoid flood risk

A willingness-to-pay question was included in the survey, relating to people's perception of flood risk discounts on housing prices. Respondents were asked to imagine two identical houses, that differ only in that one is at risk of flooding and the other is not. Each respondent was randomly assigned one of six versions of the question: two versions for each of three levels of flood risk (0.1%, 1% and 10%), where one version for each level of risk included an illustration of the risk in terms of the probability of being flooded over the course of a 30-year mortgage. The exact wording of the questions is included in Section 3.5.4.1.

The mean flood discount across all responses was 31.4% (sd 21%, n=629). The mean shows little variation across the three different levels of risk specified in different versions of the question: 29% for a 0.1% risk of flooding (n=195), 31% for a 1% risk (n=210), and 34% for 10% risk (n=224).[37] This may indicate some issue with the interpretation or assessment of flood risk probabilities. On the other hand, within each risk category, the inclusion of the mortgage illustration creates no statistically

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[36] Indeed, the results from the hedonics show a significant flood discount for list prices (asking prices), and a slightly larger discount for transaction prices (the price actually paid). See Table 6.4 above.

[37] The difference between mean discounts for 0.1% and 1% risk is not statistically significant at conventional levels (one sided p-value=0.26); while the differences in mean between 1% and 10% risk, and between 0.1% and 10% risk are significant (one sided p-values for these differences are 0.03 and 0.009, respectively).

significant difference in means, which would suggest the opposite, i.e. statistical literacy.

These stated-preference results suggest a much larger flood discount – indeed, an order of magnitude larger – than the discount that emerges from the revealed preferences as quantified in the hedonic housing price analysis. The large gap between the two is consistent with a number of different narratives. One explanation could be salience: flood risk was listed in the survey and willingness to pay specifically elicited, unlike in the housing market. A second and potentially related explanation is that, in line with 'talk is cheap' criticisms of stated-preference methods, known as the hypothetical bias, respondents substantially over-state the true value to them of avoiding flood risk (Murphy et al., 2005). A third explanation is that the full costs of flood risk to housing market participants are still not fully captured in housing prices, perhaps in part as a result of a continuing information deficit amongst the public in relation to flood risk. There is also the related issue of implicit or explicit subsidies to flood risk, for example in the form of public investment in flood defences, paid from general taxation. As the results on defences demonstrate, these public investments eliminate the flood discount for protected dwellings. There is also substantial new investment in flood defence schemes planned in Ireland over the coming years, and the expectation of future protection may have an effect on market outcomes that would not necessarily show up in the survey findings.

The fact that no statistically significant flood discount is found for most of the upper half of the value distribution of housing in Ireland, would seem to support the idea that the welfare costs of flooding are still not fully reflected in Irish housing prices. It seems unlikely that the true welfare cost for higher-value dwellings is zero. If higher-value dwellings tend to be in areas that will attract future public investment in defences – for example, denser locations, where presumably proposed flood relief schemes are more likely to meet benefit-cost requirements for investment – this may partly explain the lack of a discount for higher-value dwellings. The allocation of flood defence investments and its distributional effects is an important outstanding question for future research.

The large majority of respondents to the survey expect flood risk to get worse in the coming decades. They also value flood risk of very different magnitudes (in terms of the probability of flooding per year) at roughly the same level of flood discount. This points to what is perhaps the most plausible way to reconcile these seemingly disparate estimates of the flood discount: that respondents to the survey are implicitly attaching substantially larger probabilities to flood risk than the scientifically assessed level of risk. Indeed, the larger stated preference flood discount corresponds closely to the value that emerges from an expected damages calculation, if survey respondents are implicitly applying the highest risk category (a 10% probability of flooding per year) to dwellings at risk of flooding, regardless of the information about risk provided in the question.[38] This interpretation is supported by the similarity of the average discount across respondents who were asked about dwellings with a 10%, 1% or 0.1% probability of flooding per year, as well as by the finding from the hedonics that dwellings in areas with relatively low risk (0.1% probability of flooding per year) and dwellings located just outside these areas (with presumably even lower risk) still attract relatively large flood discounts.

On the one hand, this over-weighting of the risk, particularly for lower risk areas, may reflect problems with risk information and its communication to the public – although as noted, this is not what is suggested by the results from the survey on the

[38] Based on average damages per flood of €60,000 for an individual dwelling, a 3% discount rate, and a 30-year time horizon, the capitalized value of flood risk with a 10% probability of occurrence per year is €123,600 in present value terms, equivalent to a flood discount of 41% for a dwelling valued at €300,000. In contrast, based on the same set of parameter values and a 1% probability of occurrence per year, average damages per flood of close to €500,000 for an individual dwelling would be required to justify a flood discount of over 30%. Similarly, for flood risk with a 0.1% probability of occurrence per year, damages per flood of close to €5M per individual dwelling, would be required to justify a flood discount of 30%.

mortgage illustration. Alternatively, this may reflect a conscious choice by respondents to treat the scientific assessments as underestimates of the true risk. These rival hypotheses constitute an important open question for future research in this area.

6.5 Concluding remarks

This chapter examines the relationship between flood risk and housing market outcomes, using the case of Ireland since 2006. In particular, it exploits rich housing data – including a dataset of almost 800,000 listings and 36,000 transactions in areas at risk of flooding – and detailed official data relating to flood risk, previous flood events, and completed flood defences. The study finds clear evidence of a flood discount in the housing market, with the emergence of a 3.1% price discount for dwellings in medium to high flood risk zones, after the publication of flood risk information in 2011. It also finds evidence that flood defences work in reversing this discount, that flood risk is borne disproportionately by dwellings in the lowest quartile of value, and that the market's memory of flood events is short.

Because advantage is taken of the fact that new information about flood risk was released in the middle of the sample period, the estimates are unlikely to be biased by some unobserved process that is correlated with flood risk *and* the severity of flood risk. In addition, a number of robustness checks – including varying the level of spatial fixed effect, clustering the error terms, and comparing estimates from different samples – largely confirm the reliability of the estimates for willingness to pay to avoid flood risk zones. Nonetheless, the results have limitations. While the volatility in the housing market during the years analysed may help internal validity and robustness of the results, they may also limit the external validity, as housing systems with less dramatic mismatches between supply and demand may exhibit different relationship between (dis)amenities and housing prices than a system like Ireland's. Also, the datasets used have significant strengths and are largely consistent with each other but ultimately findings for the full period from 2006 rely on listings, while transactions data are limited to one city.

Nonetheless, the researcher believes that the findings are identifying the causal effect of flood risk on housing prices. They have important policy implications for flood risk management, insurance and flood defences, as well as for projections of future flood losses in a world of increasing flood risk. The point estimates and frequencies presented here can be used in combination with other information to give a preliminary estimate of the aggregate effect of flood risk on Irish housing wealth. As of 2020, Ireland had roughly 1.75m occupied dwellings. According to the listings data, roughly two-thirds of Irish homes are located in areas potentially at risk of flooding. All dwellings within 200 metres of flood risk are, according to the preferred specification, subject to a statistically significant discount, implying a total of just over 420,000 affected dwellings. Applying these discounts and frequencies to a system with an average dwelling value of €300,000 gives a total effect of flood risk on housing of approximately €1.35bn, compared to an overall stock of wealth in residential real estate of approximately €520bn. As discussed in Section 6.3.4, this is likely a lower bound to the true flood discount and this figure also does not take into account other costs of flooding, such as damage to public infrastructure or commercial real estate. For that reason, this is perhaps best thought of as an attempt to reflect usually more hidden costs of flooding, such as the effect on households of disruption, including mental health costs.

Perhaps most importantly for policymakers, however, the results present compelling evidence on the effectiveness of public investments in flood mitigation – both in terms of information provision and flood defences. But these two types of investments might be expected to have very different effects on future costs of flooding. Better information results in more awareness and a clear price signal, which should translate into less exposure to flooding in future, albeit the survey findings suggest there is still work to be done to translate scientific assessment of risk into public awareness. In contrast, flood defences – and the expectation of future investments in defences – might encourage development of flood-prone areas, with important implications for the future costs of flooding in a world with increasing flood risk.

Lastly, the research has at least four important findings for the growing literature in this area, beyond those specific to the market analysed. Firstly, the study documents that the sale price effect is substantively larger than the rental price effect. Secondly, it documents the importance of appropriate choice of spatial fixed effect, when attempting to estimate the flood discount. Specifically, spatial units with tens of thousands of dwellings may give biased estimates of the flood discount, even when rich dwelling and other location controls are included. Thirdly, the study shows the importance of including specific controls, when estimating the flood discount. In particular, while the omission of exact floor area may exaggerate the flood discount, the omission of 'blue space' amenities – in particular sea views/distance to beaches – may create a downward bias in estimated flood discounts. These controls have often been omitted from previous empirical analysis of flood discounts, but the results suggest their inclusion in future studies should be standard. Finally, the results show that, on a like-for-like basis, list prices act as a good proxy for transaction prices, where those are unavailable. Given the prevalence of flood risk in lower-income settings, where formal housing statistics are typically weaker, this is a useful finding for both researchers and policymakers.

7 The Impact of Green Space on Irish Property Values

7.1 Introduction & context

As the world continues to urbanise, accommodating the growth of cities will involve planning, by public and private sectors, to match new housing supply to demand. Current U.N. projections estimate that two thirds of humans will live in cities by 2050, with an additional 2.5 billion urban residents in that year, compared to 2010 (UN 2014). To best match supply to demand, it is critical that consumer preferences for location-specific amenities are well understood. A principal example of such amenities is green space, which includes managed urban park, tree cover, and more natural settings, including woodlands. These amenities can offer not only direct utility benefits, which may be captured in housing market outcomes, but also indirect positive externalities including carbon capture, in the context of on-going climate change.

This study focuses on willingness to pay for the direct benefits of green space to households. It does this by examining the impact that urban green space amenities have on the sale value of housing, using a dataset of almost 40,000 real estate transactions in Dublin, 2010-2018. In this way, it can be viewed as a revision to the estimates provided by Mayor et al. (2009; hereafter MLDT), using not only more up-to-date transactions, but also higher-resolution information on urban green space and a richer set of controls, most notably unobserved spatial factors, a concern highlighted by von Graevenitz and Panduro (2015), among others.

The analysis finds no premium for non-park green space near a property but a statistically significant premium for park space in particular. It finds that park space within 2km is an amenity valued by housing market participants, with a 10% increase in park space within 2km of a dwelling causing a 5.5% increase in price. This difference between studies may stem from market conditions, which changed dramatically between 2001-2006 and the period since 2010, or from selection effects, with the MLDT database concentrated in higher value areas. Overall, the results imply that Dublin's parks have a value of roughly €3.4bn capitalised into the city's housing stock, as of 2019.

7.2 Empirical Specification recap

Conceptually, the value of a dwelling takes the following form:

$$Price = f(S, L, E) + \varepsilon,$$

where the logged listed sale price of the house is a function of the house's structural characteristics (S; such as number of bedrooms, bathrooms, or the presence of a garden), its location characteristics (L; such as proximity to CBD, access to transport networks, socio-economic factors) and its environmental characteristics (E; such as proximity to green spaces or the coast). The error term, ε, reflects the gap between the conditional expectation and the actual value. The house price is thus a function of all of the attributes relating to the house and the resulting coefficients are the implicit marginal prices of the attributes.

More specifically, this analysis uses ordinary least squares and a semi-log or log-log specification (depending on the variable), as is typical in this type of study. Allowing for the long duration of the sample, and the focus on coastal amenities, the baseline specification is, therefore, as follows:

$$\log(price_i) = \beta_0 + X'_{1i}\beta_1 + X'_{2i}\beta_2 + X'_{3i}\beta_3 + X'_{4i}\beta_4 + X'_{5i}\beta_5 + \varepsilon_i \text{ (2)}$$

Where: $price_i$refers to the transacted sale price; X'_{1i} to a vector of dwelling-specific attributes; X'_{2i} to the time period (quarterly fixed effects); X'_{3i} to SFE; $X'_{4i}$to a vector of location-specific control amenities and X'_{5i} represents the regressors of interest, a vector of variables capturing green/park space amenities. To account for possible heteroscedasticity, robust standard errors are used when calculating statistical significance.

The model specifications were designed to mimic those of MLDT to investigate the differences in estimations when a larger sample with a more detailed set of controls are used. One of the main concerns in the hedonic house price modelling literature is the issue of omitted variable bias. Von Graevenitz and Panduro (2015) strongly criticise the use of spatial (parametric) econometric models to overcome this issue. Such methods assume a structure of the unobserved effects by the use of either a spatial weights matrix or a spatially fixed effect.

The authors use a Generalised Additive Model (GAM) to create a "flexible" fixed effect to maximise variation and minimise unobserved processes. They concluded that a good alternative approach would be to test the sensitivity of the variables of interest by using different levels of SFE (see Section 2.3.1.2 for a more detailed discussion). Due to the large sample size in this study the use of a GAM model was computationally unfeasible, so the approach taken was to report each specification with three different levels of spatial fixed effect. The trade-off between different scales of fixed effect is that larger spatial units allow more variation whereas smaller units minimise the potential for unobserved processes which are correlated with the error term leading to omitted variable bias and unreliable estimates. The three levels of fixed effect used, from largest to smallest, were micro-markets, census electoral districts, and census small areas.

For detailed discussion on the data and methodologies used in this chapter, as well as the identification strategy, please refer to sections 3.6, 4.5, and 4.5.2, respectively.

7.3 Baseline Results

As described in Section 7.1, the MLDT specifications are run on the newly constructed dataset. There are three different levels of spatial controls that can be used: real estate 'micro-markets', based on collections of named areas of the city; and two levels of official spatial units, Electoral Divisions (EDs) and Small Areas (SAs). Micro-markets are likely to capture many spatially fixed factors that would otherwise not be controlled for and the 118 micro-markets in the sample are similar to the 105 in MLDT. However, given the small number across the city, it is likely they will be insufficient to address the concerns outlined in work such as von Graevenitz and Panduro (2015). On the other hand, while SAs have an average size of roughly 180 dwellings and are thus likely to capture local spatial factors, such a small size means that statistical power will be challenging, with many SAs having three or fewer transactions during the period analysed. It is for this reasons that EDs are the preferred specification. There are in total 322 EDs included in the dataset, compared to over 4,500 SAs.

Table 7.1: Regression results using MLDT green space density specification

	FE: Micro-market			FE: Electoral Division			FE: Small Area		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: natural log of the transacted sale price									
Regressors of interest									
Within 2km of Phoenix Park	-0.0338***	-0.0334***	-0.0323***	-0.00827	-0.00790	-0.00684	-0.00255	-0.00258	-0.00248
	(-4.64)	(-4.58)	(-4.44)	(-.889)	(-.85)	(-.737)	(-.122)	(-.123)	(-.119)
% GS within 200m	-0.0181	-0.00873		-0.0130	-0.00648		-0.0354*	-0.0326	
	(-1.58)	(-.769)		(-1.05)	(-.522)		(-1.67)	(-1.53)	
% GS between 200m and 2km	0.0765	0.0590		0.116	0.112		-0.805**	-0.811**	
	(1.04)	(.801)		(1.22)	(1.18)		(-2.09)	(-2.1)	
% park within 200m	-0.117***			-0.0936***			-0.0627		
	(-5.22)			(-3.91)			(-1.36)		
% park between 200m and 2km	0.372***			0.576***			0.339*		
	(10.5)			(10.3)			(1.68)		
% of park space within 2km		0.339***			0.548***			0.317	
		(9.55)			(9.53)			(1.55)	
% of park/GS within 200m			-0.0419***			-0.0339***			-0.0371*
			(-3.9)			(-2.94)			(-1.88)
% of park/GS within 2km			0.322***			0.492***			0.159
			(9.45)			(9.37)			(.819)
Controls									
Dwelling	YES	YES	YES	YES	YES	YES	YES	YES	YES
Transport	YES	YES	YES	YES	YES	YES	YES	YES	YES
Neighbourhood	YES	YES	YES	YES	YES	YES	YES	YES	YES
Blue space	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	39,203	39,203	39,203	39,203	39,203	39,203	39,203	39,203	39,203
R-squared	0.885	0.884	0.884	0.889	0.889	0.889	0.920	0.920	0.920
RMSE	0.182	0.182	0.182	0.178	0.179	0.179	0.161	0.161	0.161

Table 7.1 presents the regression output for the MLDT density specification, which distinguishes between green space (GS) and park space. The overall results are similar in nature: more green space, in particular parks, within a close distance of a dwelling is associated with a higher value of that dwelling. However, the magnitude of the coefficient on parks/green space is smaller. MLDT typically find price responses to a 10% increase in parks or green space of between 5% and 9%. The price responses from this larger and more recent dataset are roughly half the size and with more instances of coefficients that are insignificant or even negative.

An important difference between the two studies concerns green space other than parks. While MLDT find that a 10% increase in green space, other than parks, between 0.2km and 2km leads to a 7.6% increase in property values, the results in this study are statistically indistinguishable from zero in the preferred specification (with ED fixed effects). However, the headline finding for park space is similar across the two studies. In this study, a 10% increase in park space within 2km of a dwelling is associated with a 5.5% increase in price, compared to a 6.7% in MLDT.

The differences between the two studies may stem from market conditions or from selection effects. The MLDT study uses a database for the years 2001-2006, a time of loose credit conditions, elastic supply and rapidly rising prices in the Irish housing market. Conversely, the period in this study (2010-2018) covers periods of both falling and rising prices but tight credit conditions and inelastic housing supply. The relationship between amenity prices and housing market conditions is an active topic of research (see Section 2.4.4) and in this regard understanding the value of green space in different market conditions is a topic worthy of future research.

It may also be the case that some of the difference in results across the two studies stems from the composition of transactions included. The MLDT study used data provided by the Sherry Fitzgerald estate agency, an agency principally associated with the top end of the Dublin housing market. This is evident, for example, from Figure 2 of their study, which shows the transactions covered: the dwellings are clustered in higher-value areas of the city, in particular the south and east of Dublin. Conversely, the study here uses properties from all parts of the Dublin housing market. If green space is income elastic, i.e. if higher income households place greater value on green space, then this would be consistent with the results in the two studies. In addition, it may be the case that green spaces are more valuable to all households, regardless of income, in higher-income areas. As with the cyclicality of green space pricing, the relationship between green space and income is a useful strand of future research, which the researcher has already commenced by looking at the value associated with individual green spaces.

Figure 7.1: Graphical summary of results compared to MLDT

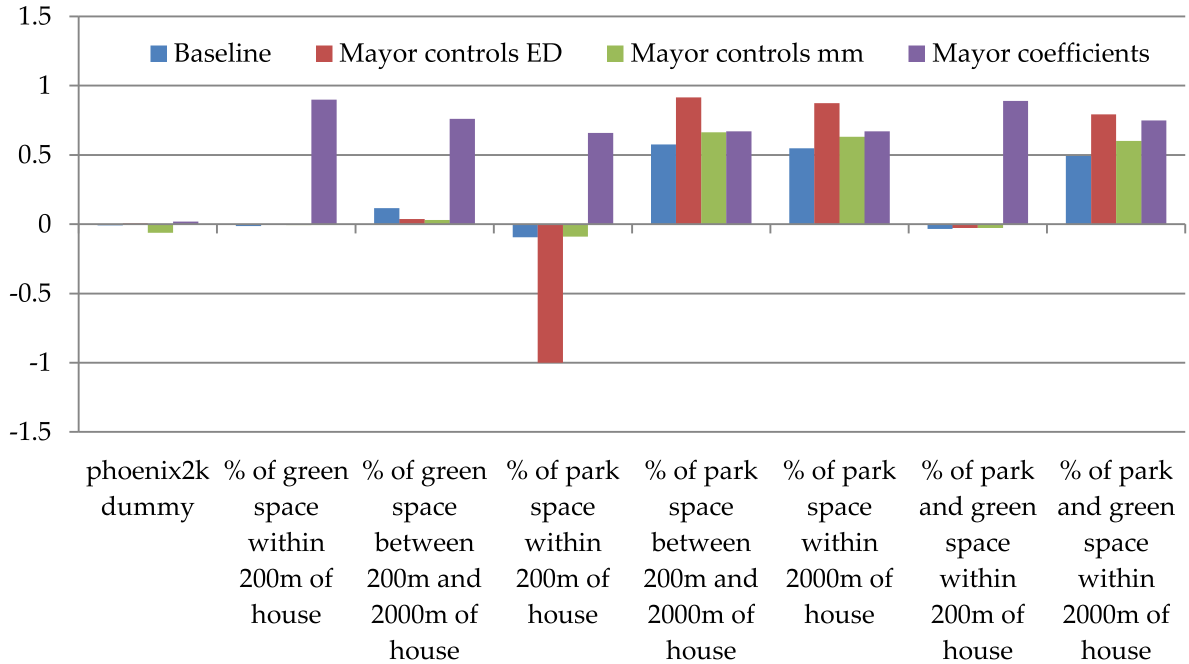

Figure 7.1 compares the coefficients from MLDT of the variables of interest to three separate specifications using the improved dataset. The first specification (blue) is the baseline results from Table 7.1 with ED fixed effects. The second (red) set of coefficients are an attempt to mimic the MLDT suite of control variables where possible, with ED fixed effects. The third (green) group are the same as the second but with micro-market fixed effects, and the fourth (purple) group are the MLDT coefficients, as reported in Table 3 of their paper. It is clear from Figure 7.1 that the

majority of the difference in results is not due to empirical specification, to the extent that this study is able to mimic MLDT's exact empirical specification. This is particularly evident for results relating to all green space (either within 200m or between 200m and 2km), park space within 200m and park/green space within 200m.

Important exceptions to this general finding are the results for park space, either between 200m and 2km or within 2km in total. There, the coefficient varies relatively substantially between the baseline and a specification with similar spatial controls but mimicking, to the greatest extent possible, the MLDT dwelling controls. This highlights the potential correlation between dwelling characteristics, such as age, and proximity to parks.

This study can use these results to estimate the minimum valuation placed on Dublin parks by residential property markets. The results indicate that 3.4% of the area within 2km of the average dwelling in Dublin is park space. Given the valuation results, a 1% increase in park space within this range would be associated with a 0.55% increase in a property's value. This means that, for the typical home in the city, almost two percent (1.9%) of its value comes from parks nearby. With the average property value in Dublin totalling approximately €375,000 in 2019, parks add just over €7,000 to the value of the average home. Since there are 480,000 dwellings in the capital, Dublin's parks have a value of €3,361m capitalised into the nearby housing stock. The attributed value also has fiscal significance. Local property tax is at a rate of 0.018%, implying Dublin's local authorities receive €6m in revenues each year due to the presence of park amenities.

7.4 Concluding remarks

The results show a statistically significant price premium for dwellings in the vicinity of parks: 10% more park space within 2km of a dwelling is associated with a

5.5% higher price. Overall, the results imply that Dublin's parks have a value of roughly €3.4bn capitalised into the city's housing stock, as of 2019.

There are some differences in the findings and past research by Mayor et al. (2009, MLDT), which was based on transactions from 2001-2006. While this study finds a similar premium on park space, MLDT also found a premium on non-park green space. The analysis finds no premium for non-park green space near a property. These differences may stem from market conditions, which changed dramatically between 2001-2006 and the period since 2010, or from selection effects, with the MLDT database concentrated in higher value areas. Stratification of the data based on time periods is something that could be incorporated in future work. In addition to incorporating more recent transactions, the dataset is sufficiently larger that a more appropriate level of spatial controls can be included, while linking the dataset with Building Energy Rating data allows the inclusion of important dwelling characteristics.

There are limitations to this study that may be addressed with additional data, and there is scope for further research to cast light on the relationships between urban green space and housing market outcomes. The future work agenda comprises three broad strands. The first is to explore outcomes other than the transaction price, including the length of time taken to sell a property, the level of interest in a property (matching the transactions here with listings from an archive of online listings), or the gap between the listed and transaction price.

Second, it should be possible to supplement the existing analysis using additional sources of information. This includes the use of the PRIME 2 database to add attributes of green space. Through the use of GIS software, each green space polygon in the urban atlas dataset can be categorised based on its size, its proximity to the coast, and whether the following features are present: water bodies (ponds, lakes, streams, rivers, canals), sports facilities, woodlands, walking paths, playgrounds, and whether there is a cemetery on the grounds. This wealth of information poses challenges in designing the appropriate empirical specification and this work is at an early stage currently. An additional dimension along which the current specification could be supplemented include time, with conditions in the Dublin housing market varying considerably over the time covered (2010-2018). It may also be possible to add listings data covering a longer time period (from 2006), allowing a closer examination of the relationship between market conditions and willingness to pay for green space.

Lastly, the available data might allow modelling using a novel two-stage empirical approach. Specifically, a first-stage regression would estimate the value associated with each green space for which there are sufficient transactions (or listings) nearby. This would provide an estimate of the valuation of each individual green space. A second-stage regression would use the estimated implicit prices for each individual green space as the outcome of interest. The implicit price for each individual green space would be a function of its measurable individual characteristics (from PRIME 2 data) such as park size, presence of water features, woodlands, playgrounds, etc. These characteristics would be modelled as explanatory variables, as well as measurable socio-demographic and other factors, such as education level and age structure, in the surrounding area. Most studies that go beyond estimating implicit prices use the same sample from the first stage analysis as the second-stage, by individual – or pooled – property level observation. In this case the first-stage analysis would be at the level of individual property but the second stage would be at the level of individual green space. This would be an important contribution to the study of the preferences for green space attributes in the methodological context of the hedonic house price model.

8 Conclusion

Section 8.1 of this chapter summarises the thesis and highlights key findings from each of the three empirical chapters. Section 8.2 outlines some suggested policy conclusions and recommendations that arise from the various empirical investigations in the thesis. Section 8.3 outlines the contributions this research offers to the related academic literature. In Section 8.4 the limitations of the research are discussed and possible future research avenues arising out of this work are explored in Section 8.5. A final word on the thesis is given in Section 8.6.

8.1 Summary of thesis and key findings

The aim of the thesis was to elicit reliable estimates of the value of various environmental amenities and dis-amenities through the use of the hedonic house price model.

Chapter 2 outlines the conceptual development of the theory of *value*, and how it is defined in the context of non-market valuation with respect to environmental economics. Alternative techniques for estimating WTP for non-market goods are outlined and a brief validation of the hedonic model as being the most appropriate for this study. An outline of the economic theory that underpins the hedonic model follows, as well as a literature review on the three empirical chapters of the thesis.

The data and methodology chapters illustrate in detail the spatial data used and how they were processed and converted into metrics representing the environment for each study. Data limitations and solutions are outlined as well as strategies to reduce measurement error in the variables of interest. In the design of variables of interest, the ease interpretation of results is a priority.

8.1.1 Blue space findings

In the first empirical chapter (chapter 5), "blue space" amenities were found to have a significant positive value in the Irish housing market. Proximity to both shingle/sand coastline and designated beaches enjoy premium prices. The "access" effects were large enough to be economically important. For example, in the preferred specification, being less than 100m from a beach is associated with a 22% price premium compared to otherwise similar properties more than 500m away. This corresponds to an average price effect of just over €51,000. Sea views also showed a positive valuation, using both breadth and depth indicators. An increase of one on the log scale, for example going from 55 to 150 inner-points, is estimated to increase prices by 1.3% in the sale listings sample and by 1.0% in the rent listings sample. Similarly, a one-degree increase in the angle of sea-view depth is associated with a 1.7% higher price. The equivalent price effect for a one standard deviation increase in view breadth is just over €4,900 (Table 5.3). These picture and playground effects were independently significant, taking into account the correlation between living near the coast and having a view of the sea. The results were similar for rents, although the blue space premium on rents was generally lower than for sales. In both segments the willingness to pay for blue space amenities is greatest at the top end of the housing price distribution. For example, for housing in the top ventile, being within 100m of a beach is associated with a 92% price premium (applying the appropriate transformation to the coefficient of 0.65), roughly four times the average OLS premium of 17%. The chapter also documents differences across urban and rural markets, for view breadth as well as access to sand/shingle, and differences over time, with the price of the view amenity pro-cyclical and that of access to desirable coast counter-cyclical.

Various robustness strategies including: the use of LiDAR data, varying the level of spatial fixed effect; using spatio-temporal fixed effects; and using a proximity matched sample, largely give credence to the claim that the estimated implicit prices for sea views are unbiased and reliable. Investigation into the spatial distribution of sea views illustrated in Figure 4.3 reveals there is consistent variation with respect to distance from the coastline. The estimates for coastal recreational amenities may be more context specific, however.

8.1.2 Floods findings

The second empirical chapter related to floods looked at the extent to which flood risk affects housing prices in Ireland. The key finding is that information matters: house prices appear to respond to the release of new flood risk information, with the emergence of a significant price discount (3.1%) for properties located within a 1-in-100-year risk zone after the release of flood risk maps in 2011. This discount is not observed in areas that have been defended by flood relief schemes, suggesting that the public perception of these schemes is that they have been effective in reducing (or eliminating) the risk of flooding for protected areas. Indeed, the results suggest a short-lived premium after the construction of flood defences, possibly due to localised pent-up demand for houses in those previously at-risk areas. Evidence is also found that flood risk is borne disproportionately by dwellings in the lowest quartile of value (7.2% discount for flood risk in the bottom decile of the price distribution), and that the market's memory of flood events is short.

The fact that new information about flood risk was released in the middle of the sample period legitimises identification, because the estimates are unlikely to be biased by some unobserved process that is correlated with both flood risk and the severity of flood risk. In addition, a number of robustness checks – including varying the level of spatial fixed effect, clustering the error terms, and comparing estimates from different samples – largely confirm the reliability of the estimates for willingness to pay to avoid flood risk zones.

The chapter reports on a survey of actors in the housing market's attitudes to flood risk, which finds that the general public in Ireland is concerned about flooding, that those concerns have increased for many over the last 10 years, and that a large majority of people expect the problem to get worse in the coming decades. It also reveals a continuing information deficit in relation to flood risk. A quarter of those surveyed said they didn't know if flood risk was relevant for the areas in which they were looking. Of those who said they thought it was relevant, more than a third said they weren't aware of the risk in the specific areas in which they were looking to buy or rent.

The survey asked about the appropriate price discount for dwellings at risk of flooding. The results indicate a stated preference flood discount that is an order of magnitude larger than revealed preferences, at around 31% compared to 3.1% in the hedonic price models. The larger stated preference discount might partly reflect the nature of the methodology, for example in relation to salience of flood risk. But it could also be that the full welfare costs of flooding are still not reflected in Irish housing prices.

8.1.3 Green space findings

This study examined the relationship between urban green space and housing prices in Dublin. It updates existing work on this by Mayor et al. (2009; MLDT), which used data on transactions 2001-2006. In addition to more recent transactions, the dataset is sufficiently larger that a more appropriate level of spatial controls can be included, while the merger with Building Energy Ratings allows the inclusion of important dwelling characteristics. It finds that park space within 2km is an amenity valued by housing market participants, with a 10% increase in park space within 2km of a dwelling causing a 5.5% increase in price. This is largely in line with the MLDT estimate (6.7%). However, while MLDT find an almost one-for-one response of housing prices to non-park green space, twice as prevalent as park space, the analysis here shows no statistically significant relationship between the two. This difference between studies may stem from market conditions, which changed dramatically between 2001-2006 and the period since 2010, or from selection effects, with the MLDT database concentrated in higher value areas.

8.2 Policy conclusions

These studies demonstrate that environmental amenities offer significant flows of societal value, some of which are capitalised in the form of housing wealth. Specific policy recommendations stemming from the results of this research follow.

In relation to blue space amenities, policy makers may choose to draw on elements of these estimated values as a contribution to the costs of maintaining coastal amenities, for example by applying property taxes. Methods such as those used in this study can help inform local infrastructure cost–benefit trade-offs. For example, a practical use for the sea view depth measure developed in the thesis could be applied when assessing whether or not to build a sea wall that would limit the depth of sea views but also reduce future costs associated with coastal erosion.

There may also be planning implications associated with the finding that residential coastal proximity and views are highly valued. High-density development closer to coastlines might have significant economic and societal value if the benefits are not fully offset by flood risk and other negative factors.

The findings in relation to flood hazard have numerous implications for policymakers, including relating to flood risk management, insurance and flood defences, and for projections of future flood losses. Applying the estimated discounts and frequencies to a system with an average dwelling value of €300,000 gives a total effect of flood risk on housing of approximately €1.35bn, compared to an overall stock of wealth in residential real estate of approximately €520bn. As discussed in Section 6.3.4, this is likely a lower bound to the true flood discount and this figure also does not take into account other costs of flooding, such as damage to public infrastructure or commercial real estate.

The results present compelling evidence on the effectiveness of public investments in flood mitigation – both in terms of information provision and flood defences. But these two types of investments might be expected to have very different effects on future costs of flooding. Better information, and better dissemination of information, results in more awareness and a clear price signal, which should translate into less exposure to flooding in future, although the survey findings suggest there is still work to be done to translate scientific assessment of risk into public awareness. The heterogeneity of flood discount across the price distribution has implications for the allocation of flood defences in the context of distributional concerns. If lower income areas pay a heavier discount for flood risk, then perhaps there is a greater societal benefit to defending those areas from flood events. Flood defences – and the expectation of future investments in defences – might encourage development of flood-prone areas, with important implications for the future costs of flooding in a world with increasing flood risk.

The results of the green space analysis will be of use to local policymakers, as they confirm that a baseline minimum value of urban parks can be calculated using housing market data. The results show a statistically significant price premium for dwellings in the vicinity of parks: 10% more park space within 2km of a dwelling is associated with a 5.5% higher price. Overall, the results imply that Dublin's parks have a value of roughly €3.4bn capitalised into the city's housing stock, as of 2019.

Along with these policy contributions there are also a range of academic contributions arising from this work.

8.3 Contributions to the field

The thesis provides a number of contributions to the literature which vary in their originality and significance.

The WTP estimates generated in the thesis contribute to the related literature as they are, for two reasons: Firstly, this is the first time these data have been combined[39],

[39] With the exception of a small number of Irish studies such as Pilla et al. (2019) and Lyons (2013a)

and, secondly, the first time robust point estimates have been generated using a hedonic framework for these specific amenities in the context of Ireland.[40]

The primary methodological contribution in the blue space study relates to the novel measures of sea views that are developed. Reverse engineering the viewshed process allows for a once off computational expense with resulting viewshed data that can be applied to any dataset. The sea view depth measure is also unique to the literature to the best of the researcher's knowledge. It is also the first time that WTP has been identified for different categorisations of the coastline, informing preferences for cliffs and beaches, as well as sand/shingle classifications.

In the floods analysis the importance of including specific controls is demonstrated, when estimating the flood discount. In particular, while the omission of exact floor area may exaggerate the flood discount, the omission of 'blue space' amenities – in particular sea views/distance to beaches – may create a downward bias in estimated flood discounts. These controls have often been omitted from previous empirical analysis of flood discounts (Beltran et al., 2018a), but the results suggest their inclusion in future studies should be standard. The results also speak to the value of information provision as the capitalisation of the flood discount could be interpreted as the societal benefit of flood risk information. The comparison of stated and revealed preference estimates of flood capitalisation might be of interest to the broader theoretical field of non-market valuation. The inclusion of flood risk maps, flood events *and* flood defences makes this study quite novel in the literature.

In both the floods and the blue space analyses, there are several unique cross-over contributions. Firstly, there are results relating to the comparison of sale and rental price effects of interest. The ability to compare like for like data on sales and rental listings speaks to the uniqueness of the data and the ensuing results that contribute to the related literature. In both studies, the sale effect is greater than rental,

[40] With the exception of urban green spaces as in MLDT.

supporting the "lock-in" hypothesis (Lyons, 2013a) and opens up future avenues of research about the nature of household searches and their relationship to the market cycle.

Secondly, through the use of a transactions prices sub-sample, it is shown that list prices are a reliable proxy for transactional prices. Given the prevalence of flood risk in lower-income settings, where formal housing statistics are typically weaker, this is a useful finding for both researchers and policymakers.

Thirdly, the choice of SFE is an important one for the researcher to make to balance the trade-off between reducing OVB and increasing within variation. Few studies report their findings with varying levels of SFE's, the scale of the SFE's chosen in this study can be used a guide for future studies.

8.4 Potential limitations of the research

The methodologies and results in the thesis are not without their limitations. There are theoretical limitations of the hedonic model which is based on the assumption that people have perfect information about the market and there does not exist any moving costs. This is especially the case when using a nationwide sample which works under the assumption that people could freely choose from a set of houses all over the country. However, in practice work and family ties exert a strong influence on preventing people from moving far from their current jurisdiction. Long sample periods present similar issues in that people's preferences can change over time due to macroeconomic forces, which is inconsistent with the principles underlying the law of one price function, thus limiting the model's ability to translate hedonic prices into MWTP measures (Bishop et al. 2020). The size of the data facilitates a large amount of within variation (especially in the rental listings sample) at the smallest scale of SFE (census small area). While it can be argued that this effectively negates OVB whilst maintaining variation in the variables of interest, the true magnitude of the marginal value may extend beyond the scale of the SFE, and hence lead to an underestimation of the WTP when more granular SFE's are used (Abbott and Klaiber, 2011).

The difference between the objective and subjective measurement of the environment can also undermine identification (Schaeffer and Dissart, 2018). It is reasonable to assume that proximity measures of environmental amenities do not exactly mimic the perceived proximity of an environmental good and it may be interlinked with environmental views. For example, access to views might give a perception of being closer to an environmental amenity.

Measurement error in the blue space "picture" amenities is dealt with in detail in Section 4.2.1.2. In summary the reliability of the sea view simulations is bound by the resolution of the DSM which is used to generate them. Even though the results are largely confirmed in a specification using LiDAR data for a subset of the coastline, these are still just proxies for the true view at each location. While a number of robustness checks are undertaken, the results have their limitations. The findings are robust to the use of transaction prices (and the inclusion of additional controls), but it is clear that sample composition matters. Restricting the sample to start in 2010, rather than 2006, has an effect on some results – as does restricting the sample within Dublin to those listings that can be matched to a transaction. Taken together with the significant variation in amenity pricing over time, the results do not imply a stable price for these amenities, but one that is very much context-specific.

Similarly, with the results in the floods analysis, the volatility in the housing market during the years analysed may help internal validity and robustness of the results, they may also limit the external validity, as housing systems with less dramatic mismatches between supply and demand may exhibit different relationship between (dis)amenities and housing prices than a system like Ireland's. Also, the datasets used have significant strengths and are largely consistent with each other but ultimately findings for the full period from 2006 rely on listings, while transactions data are limited to one city.

Despite these limitations I am confident that the research design based on the data available, was the best approach to uncovering WTP estimates.

8.5 Avenues for future research

Future research stemming from the thesis would be largely dictated by an increase in the data available. The *daft.ie* housing dataset is constantly being updated and improved, with greater richness of detail and an increasing number of listings linked to their inevitable transacted price and date. Not only would this improve the variation available to the researcher but also allow for different outcome variables such as time to sell and the difference between listed and sale price. Page views and enquiries would also be an interesting outcome variable to explore. They might proxy for shorter term adjustments in the hedonic price function. For example, there is anecdotal evidence of a rise in interest in coastal properties resulting from the COVID-19 pandemic. More detailed phrase finding analysis of the text of the *daft.ie* ads can lead to more robust measures of various types of environmental views ("mountain views", "lake views", etc).

Improved data managing and location accuracy of the *daft.ie* dataset may provide the ability to identify repeat sales in the data, thus allowing for the use of a difference-in-difference style analysis, broadening the potential scope of the data.

There are possible ways to improve the measurement of sea views by using more detailed LiDAR analysis in combination with a more rigorous phrase finding strategy from the text of the advertisement. GIS techniques could be used to identify the perimeter around a dwelling to see which pixel has the *best* sea view (that isn't on the roof), taking into account the number of stories in the dwelling. Thereby negating pixels that are on the opposite of the sea-facing side of the dwelling and don't have any view potential. This in combination with searching for phrases such as "sea view(s)", "Atlantic view(s)", "view(s) of the ocean", etc, (as opposed to simply "views"), might significantly reduce measurement error.

In terms of the floods analysis there are numerous avenues to explore drawing on different spatial data available in Ireland. The allocation of flood defences is something that was left unexplained in the analysis. Incorporating a political-economy equation into the analysis might lend explanatory power to the model and better inform flood defence strategy. The use of official climate change scenario maps from the OPW would be of interest for future work. Although it is found that current flood risk is capitalised into house prices, this does not necessarily mean that future flood risk will be too. These data are also publicly available and also released in the middle of the sample period. Analysing the effect of their release would be interesting from a climate change perspective. Alternatively, it would be interesting to combine planning permissions data with future climate change scenario maps to see if development is responding to the science on future flood risk scenarios or is it largely being ignored.

There is a much more work to do in the green space analysis, with numerous avenues having been explored already, but they are very much in a preliminary stage. These future avenues for research in the green space analysis were discussed in more detail in Section 7.4., and relate to the use of a second-stage hedonic analysis to uncover non-marginal WTP estimates for green space as well as the demand for the attributes of green spaces, given enough variation in green space characteristics in the data.

Other broader and more expansive research questions stem from the work in the thesis. For example, the results of quantile regressions suggest there is an unequal access to environmental amenities, with the upper end of the market driving up the premiums associated with environmental amenities. Conversely, results in the floods analysis suggest that flood risk is also borne unequally, and properties in the lower end of the housing market face relatively larger price discounts. Residential properties in the already developed coastal urban areas are limited in supply and prohibitively expensive, therefor new development may require re-zoning, so that not just the wealthy can accrue the benefits of being close to the sea while at the same time close to work. This is especially true in the cases of lock downs as a result of the COVID-19 pandemic, where access to environmental amenities which have been shown to improve mental health, are unequally distributed across society.

8.6 Final word

The purpose of the thesis is to investigate how environmental amenities and dis-amenities affect house prices in Ireland. How they affect house prices speaks directly to people's preferences for the environment, as underpinned by economic theory and confirmed by a wealth of empirical evidence. Given the current context of climate change and the rapid depletion of environmental ecosystems, it is becoming increasingly important to better understand people's preferences and behaviours with respect to the environment. The thesis contributes to this pool of empirical evidence by using unique and rich data and incorporating well-established and robust methodologies. It is clear from these empirical investigations that blue space and green space amenities are capitalised in Irish house prices as well as flood risk. It is hoped that the results of this research will have real world implications in how decision makers manage the environment, and how planners and policy makers prepare for future flood risk resulting from climate change.

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Appendix

Blue Space

Appendix A. Descriptive statistics and additional figures

Blue Space Appendix, Table A 1: Type 1 and Type 2 errors for sea view simulation

Sales

		innerscore>0		
		0	1	Total
"views"	0	126,085	103,369	229,454
	1	18,325	24,166	42,491
	Total	144,410	127,535	271,945

Rentals

		innerscore>0		
		0	1	Total
"views"	0	187,712	243,734	431,446
	1	14,600	28,911	43,511
	Total	202,312	272,645	474,957

Note the above table displays the type 1 and type 2 errors for the calculation of sea views. A type 1 error in this instance would be the computer simulation estimates that at least one inner sea point is visible from a dwelling but the terms "views" is not mentioned in the text of the ad. Similarly, a type 2 error in this instance would be when "views" is mentioned in the text of the ad but 3D simulation doesn't account for any inner sea point being visible

Blue Space Appendix, Table A 2: List of, and descriptive statistics, for continuous variables

Continuous Variables

	VARIABLES	N	mean	sd	min	p25	p50	p75	max
Sales listings	Listed Sale Price*	271,866	€297,024	€207,129	€30,000	€170,000	€250,000	€355,000	€2,000,000
	Distance to nearest CBD*	271,866	23,849	27,859	0.393	4,635	11,046	33,410	138,632
	Distance to Major Road*	271,866	2,040	3,058	0.0177	422.4	1,027	2,235	37,418
	Distance to Primary School*	271,866	738.8	740.8	0.0905	309.4	513.5	858.2	9,966
	Distance to secondary School*	271,866	1,973	2,849	2.578	484	833.2	1,804	29,310
	% Unemployed	271,866	10.71	5.594	0	6.557	9.845	13.88	43.88
	% with Degree	271,866	11.36	6.966	0	6.154	10.11	15.42	50
	Seaview Breadth*	271,866	0.177	0.758	0	0	0	0	20.92
	Seaview Depth (degrees)	271,866	7.387	32.08	0	0	0	0	449

Seaview Breadth >0	24,165	83.11	72.69	1	22	69	122	449
Seaview Depth >0 (degrees)	23,562	2.05	1.68	0.06	0.87	1.55	2.65	20.92

	VARIABLES	N	mean	sd	min	p25	p50	p75	max
Sales Transactions	Transacted Sale Price*	38,523	€358,795	€217,468	€30,000	€220,000	€301,000	€430,000	€2,000,000
	Distance to Nearest CBD*	38,523	7,906	5,349	72.93	4,074	7,047	10,767	31,226
	Distance to Major Road*	38,523	1,191	1,223	0.0968	384.1	864.8	1,622	8,942
	Distance to Primary School*	38,523	467.3	267.2	10.42	273.2	422.1	607.7	3,075
	Distance to Secondary School*	38,523	739.2	577.5	30.93	396.8	613.6	882.5	8,778
	% Unemployed	38,523	8.843	5.019	0	5	7.965	11.72	40.86
	% with Degree	38,523	14.36	8.236	0	7.853	13.64	19.55	45.45
	Floor Area m^2*	38,523	99.37	41.61	14.03	72.72	91.76	116.4	726.3
	Water Efficiency*	38,523	82.49	14.36	0.65	75	79.2	90.5	417
	Space Efficiency*	38,523	82.17	17.61	0.65	73	79.1	90.4	553
	Building Area m^2*	38,523	264.1	847.6	8.581	50.94	67.32	106.7	45,141
	Building Age	38,523	42.33	32.28	1	16	34	61	258
	Seaview Breadth*	38,523	9.831	41.76	0	0	0	0	426
	Seaview Depth (degrees)	38,523	0.0958	0.474	0	0	0	0	11.89
	Seaview Breadth >0	3,037	124.70	88.30	1	51	115	189	426
	Seaview Depth >0 (degrees)	2,992	1.23	1.22	0.14	0.55	0.91	1.43	11.89

	VARIABLES	N	mean	sd	min	p25	p50	p75	max
Rental Listings	Listed Annual Rent*	475,129	€13,641	€7,548	€2,086	€9,000	€12,000	€16,200	€108,000
	Distance to Nearest CBD*	475,129	14,790	22,477	3.47	2,209	5,690	13,259	138,034
	Distance to Major Road*	475,129	1,269	1,982	0.00102	282.5	680.8	1,453	35,691
	Distance to Primary School*	475,129	561.1	501.1	1	261.6	439	688.3	10,081
	Distance to Secondary School*	475,129	1,147	1,804	2.51	373.2	609.9	1,027	28,079
	% Unemployed	475,129	10.12	5.868	0	5.578	8.989	13.48	43.88
	% with Degree	475,129	14.83	8.382	0	8.333	13.79	20.51	66.67
	Seaview Breadth*	475,129	0.0852	0.485	0	0	0	0	14.7
	Seaview Depth (degrees)	475,129	7.002	34.32	0	0	0	0	430
	Seaview Breadth >0	28,923	115.02	83.23	1	47	103	176	430
	Seaview Depth >0 (degrees)	28,500	1.42	1.42	0.05	0.53	0.98	1.66	14.70

*Note the above table displays descriptive statistics for the continuous variables included in model specifications from the analysis, for the three main samples: sales listings, sales transactions, and rental listings, all within 10km of the coastline of Ireland. Variables marked with a * undergo a natural log transformation in regressions.*

Blue Space Appendix, Table A 3: List of, and descriptive statistics for, categorical variables

		Sales listings		Sales Transactions		Rental Listings	
		N	**%**	**N**	**%**	**N**	**%**
Property Type							
Apartment		29,760	10.95%	7,609	19.75%	226,489	**47.69%**
Terraced		49,327	18.14%	9,234	23.97%	N/A	
End-of Terrace		17,981	6.61%	3,721	9.66%	N/A	
Bungalow		12,755	4.69%	930	2.41%	N/A	
Detached		66,266	24.37%	2,990	7.76%	N/A	
Duplex		3,065	1.13%	822	2.13%	N/A	
Townhouse		4,623	1.70%	453	1.18%	N/A	
Semi-Detached		88,089	32.40%	12,764	33.13%	N/A	
House		N/A		N/A		18,676	**3.93%**
Flat		N/A		N/A		228,821	**48.18%**
Studio		N/A		N/A		915	**0.19%**
Total		271,866	100.00%	38,523	100.00%	474,901	100.00%
Property Size (Bedroom:Bathroom)							
	11	7,798	2.87%	2,050	5.32%	86,105	**18.13%**
	12	215	0.08%	37	0.10%	1,669	**0.35%**
	13	25	0.01%			42	**0.01%**
	14	7	0.00%			13	**0.00%**
	15	1	0.00%			1	**0.00%**
	16	0	0.00%			1	**0.00%**
	21	30,597	11.25%	6,402	16.62%	98,852	**20.82%**
	22	17,028	6.26%	3,830	9.94%	80,041	**16.85%**
	23	1,314	0.48%	196	0.51%	3,814	**0.80%**
	24	20	0.01%	3	0.01%	29	**0.01%**
	25	0	0.00%			2	**0.00%**
	26	2	0.00%			1	**0.00%**
	27	0	0.00%	0		2	**0.00%**
	31	57,513	21.15%	8,943	23.21%	47,721	**10.05%**
	32	41,691	15.34%	5,771	14.98%	52,984	**11.16%**
	33	23,745	8.73%	2,981	7.74%	28,844	**6.07%**
	34	897	0.33%	120	0.31%	1,180	**0.25%**
	35	27	0.01%	3	0.01%	20	**0.00%**
	36	4	0.00%			6	**0.00%**
	37	1	0.00%			2	**0.00%**
	41	12,776	4.70%	1,323	3.43%	9,298	**1.96%**

		Sales listings		Sales Transactions		Rental Listings	
	42	26,173	9.63%	2,708	7.03%	23,904	**5.03%**
	43	27,003	9.93%	2,413	6.26%	22,235	**4.68%**
	44	5,810	2.14%	367	0.95%	4,343	**0.91%**
	45	922	0.34%	50	0.13%	758	**0.16%**
	46	128	0.05%	7	0.02%	58	**0.01%**
	47	7	0.00%			5	**0.00%**
	51	1,707	0.63%	113	0.29%	777	**0.16%**
	52	4,582	1.69%	423	1.10%	3,760	**0.79%**
	53	6,375	2.34%	489	1.27%	4,633	**0.98%**
	54	3,706	1.36%	216	0.56%	2,544	**0.54%**
	55	1,357	0.50%	60	0.16%	989	**0.21%**
	56	375	0.14%	15	0.04%	226	**0.05%**
	57	60	0.02%	3	0.01%	42	**0.01%**
Phrase (Dummy)							
”balcony”		19,152	7.04%	5,147	13.36%	67,993	**14.32%**
”bay_window”		30,959	11.39%	4,468	11.60%	4,627	**0.97%**
”conservatory”		10,036	3.69%	1,390	3.61%	5,886	**1.24%**
”deck”		24,953	9.18%	3,667	9.52%	14,413	**3.03%**
”double_glaze”		71,284	26.22%	10,383	26.95%	20,200	**4.25%**
”edwardian”		542	0.20%	171	0.44%	308	**0.06%**
”ensuite”		78,656	28.93%	10,010	25.98%	97,437	**20.52%**
”fireplace”		121,983	44.87%	19,766	51.31%	29,987	**6.31%**
”frenchdoors”		18,837	6.93%	2,839	7.37%	4,781	**1.01%**
”garage”		38,544	14.18%	5,733	14.88%	14,891	**3.14%**
”garden”		182,114	66.99%	29,349	76.19%	156,521	**32.96%**
”georgian”		1,757	0.65%	198	0.51%	3,778	**0.80%**
”granny_flat”		1,591	0.59%	184	0.48%	524	**0.11%**
”highceilings”		5,480	2.02%	1,256	3.26%	5,090	**1.07%**
”jacuzzi”		6,411	2.36%	688	1.79%	3,849	**0.81%**
”mews”		1,572	0.58%	289	0.75%	3,125	**0.66%**
”patio”		82,259	30.26%	11,254	29.21%	44,689	**9.41%**
”period”		7,745	2.85%	1,853	4.81%	10,011	**2.11%**
”redbrick”		7,250	2.67%	2,004	5.20%	2,250	**0.47%**
”sash”		2,230	0.82%	444	1.15%	1,539	**0.32%**
”securitygates”		983	0.36%	219	0.57%	2,659	**0.56%**
”solar”		3,198	1.18%	201	0.52%	1,419	**0.30%**
”sunroom”		14,847	5.46%	1,612	4.18%	5,141	**1.08%**
”terrace”		57,544	21.17%	10,363	26.90%	49,051	**10.33%**
”tripleglaze”		1,081	0.40%	206	0.53%	557	**0.12%**
”underfloor”		4,274	1.57%	672	1.74%	5,924	**1.25%**
”utility”		80,398	29.57%	8,363	21.71%	46,709	**9.84%**
”victorian”		2,473	0.91%	552	1.43%	2,067	**0.44%**

	Sales listings		Sales Transactions		Rental Listings	
”walkinwardrobe”	11,632	4.28%	927	2.41%	6,171	**1.30%**
”wetroom”	5,541	2.04%	1,263	3.28%	1,898	**0.40%**
river_views (<75m &"views"==1)	1,418	0.52%	217	0.60%	2,599	**0.55%**
lake_views (<75m &"views"==1)	271	0.10%	72	0.20%	920	**0.19%**
Golf Course						
>1k (Base)	214,032	78.73%	29,676	77.03%	387,870	81.67%
500m-1k	33,862	12.46%	5,135	13.33%	52,699	11.10%
250m-500m	13,486	4.96%	2,163	5.61%	19,470	4.10%
100m-250m	6,430	2.37%	1,058	2.75%	9,423	1.98%
<100m	4,056	1.49%	491	1.27%	5,667	1.19%
Powerlines						
>1k (Base)	219,560	80.76%	31,583	81.98%	412,593	86.88%
500m-1k	27,429	10.09%	3,635	9.44%	32,813	6.91%
250m-500m	12,574	4.63%	1,636	4.25%	14,898	3.14%
100m-250m	7,519	2.77%	1,057	2.74%	8,768	1.85%
<100m	4,784	1.76%	612	1.59%	6,057	1.28%
Mixed Woodlands						
>1k (Base)	234,898	86.40%	31,287	81.22%	419,551	88.34%
500m-1k	24,004	8.83%	4,853	12.60%	36,552	7.70%
250m-500m	8,146	3.00%	1,521	3.95%	11,087	2.33%
100m-250m	3,153	1.16%	590	1.53%	5,210	1.10%
<100m	1,665	0.61%	272	0.71%	2,729	0.57%
Deciduous Woodlands						
>1k (Base)	204,323	75.16%	29,182	75.75%	372,202	78.37%
500m-1k	39,133	14.39%	6,227	16.16%	59,117	12.45%
250m-500m	16,453	6.05%	1,917	4.98%	24,540	5.17%
100m-250m	7,575	2.79%	922	2.39%	12,273	2.58%
<100m	4,382	1.61%	275	0.71%	6,997	1.47%
Conifer Woodlands						
>1k (Base)	224,849	82.71%	36,348	94.35%	416,600	87.72%
500m-1k	25,310	9.31%	1,253	3.25%	31,306	6.59%
250m-500m	11,321	4.16%	542	1.41%	14,525	3.06%
100m-250m	6,629	2.44%	265	0.69%	8,182	1.72%
<100m	3,757	1.38%	115	0.30%	4,516	0.95%
Nature Reserve						
>1k (Base)	262,215	96.45%	34,765	90.24%	451,409	95.05%
500m-1k	5,148	1.89%	2,065	5.36%	12,882	2.71%
250m-500m	2,604	0.96%	1,017	2.64%	6,219	1.31%
100m-250m	1,396	0.51%	522	1.36%	3,095	0.65%
<100m	503	0.19%	154	0.40%	1,524	0.32%
Canals						
>500m (base)	257,266	94.63%	33,917	88.04%	421,534	88.76%

	Sales listings		Sales Transactions		Rental Listings	
250m-500m	9,557	3.52%	3,022	7.84%	34,314	7.23%
100m-250m	3,125	1.15%	952	2.47%	11,603	2.44%
<100m	1,918	0.71%	632	1.64%	7,678	1.62%
Rivers						
>500m (base)	214,124	78.76%	32,088	83.30%	346,170	72.89%
250m-500m	36,925	13.58%	4,211	10.93%	75,330	15.86%
100m-250m	12,023	4.42%	1,212	3.15%	27,213	5.73%
<100m	8,794	3.23%	1,012	2.63%	26,416	5.56%
Lakes						
>500m (base)	260,754	95.91%	36,859	95.68%	441,477	92.96%
250m-500m	8,422	3.10%	1,214	3.15%	25,166	5.30%
100m-250m	1,855	0.68%	264	0.69%	4,661	0.98%
<100m	835	0.31%	186	0.48%	3,825	0.81%
Transitional water-body sand/shingle						
>500m (base)	255,681	94.05%	38,349	99.55%	448,953	94.54%
250m-500m	11,070	4.07%	149	0.39%	16,532	3.48%
100m-250m	2,962	1.09%	24	0.06%	4,979	1.05%
<100m	2,153	0.79%	1	0.00%	4,665	0.98%
Blue Space Variables						
Cliffs						
>500m (base)	267,277	98.31%	38,183	99.12%	471,655	99.32%
250m-500m	3,557	1.31%	288	0.75%	2,719	0.57%
100m-250m	716	0.26%	30	0.08%	494	0.10%
<100m	316	0.12%	22	0.06%	261	0.05%
Beaches						
>500m (base)	268,982	98.94%	38,327	99.49%	471,912	99.37%
250m-500m	2,264	0.83%	142	0.37%	2,466	0.52%
100m-250m	419	0.15%	41	0.11%	527	0.11%
<100m	201	0.07%	13	0.03%	224	0.05%
Coastal Sand/Shingle						
>500m (base)	247,587	91.07%	35,615	92.45%	436,259	91.86%
250m-500m	16,289	5.99%	2,031	5.27%	26,138	5.50%
100m-250m	4,867	1.79%	593	1.54%	7,309	1.54%
<100m	3,123	1.15%	284	0.74%	5,423	1.14%
Flood Risk Variable						
0	133,942	49.27%	20,714	53.77%	188,727	39.74%
No flood defences or before construction						
1. (500-200m)	65,214	23.99%	8,730	22.66%	113,281	23.85%
2. (200-100m)	29,118	10.71%	3,393	8.81%	55,688	11.73%
3. (<100m from low flood risk zone)	33,164	12.20%	4,182	10.86%	77,902	16.40%
4. (inside low risk zone)	4,983	1.83%	722	1.87%	19,849	4.18%
5. (inside medium or high zone)	4,288	1.58%	293	0.76%	16,411	3.46%

	Sales listings		Sales Transactions		Rental Listings	
After construction of flood defence						
6. (500-200m)	54	0.02%	24	0.06%	104	0.02%
7. (200-100m)	14	0.01%	3	0.01%	77	0.02%
8. (<100m from low flood risk zone)	309	0.11%	60	0.16%	780	0.16%
9. (inside low risk zone)	578	0.21%	296	0.77%	1,916	0.40%
10. (inside medium or high zone)	202	0.07%	106	0.28%	394	0.08%
Total	**271,866**	**100.00%**	**38,523**	**100.00%**	**474,901**	**100.00%**
Year Quarter						
2006Q1	1,060	0.39%	0		2,121	0.45%
2006Q2	2,322	0.85%	0		2,412	0.51%
2006Q3	3,960	1.46%	0		2,664	0.56%
2006Q4	3,944	1.45%	0		1,778	0.37%
2007Q1	6,324	2.33%	0		2,000	0.42%
2007Q2	6,081	2.24%	0		2,706	0.57%
2007Q3	6,483	2.38%	0		3,202	0.67%
2007Q4	5,133	1.89%	0		2,908	0.61%
2008Q1	5,433	2.00%	0		3,030	0.64%
2008Q2	5,600	2.06%	0		3,944	0.83%
2008Q3	4,876	1.79%	0		5,056	1.06%
2008Q4	2,841	1.05%	0		4,641	0.98%
2009Q1	3,031	1.11%	0		5,566	1.17%
2009Q2	3,724	1.37%	0		5,786	1.22%
2009Q3	3,325	1.22%	0		5,935	1.25%
2009Q4	2,143	0.79%	0		3,955	0.83%
2010Q1	2,941	1.08%	327	0.85%	4,405	0.93%
2010Q2	4,271	1.57%	450	1.17%	11,963	2.52%
2010Q3	5,010	1.84%	513	1.33%	20,576	4.33%
2010Q4	3,134	1.15%	421	1.09%	15,112	3.18%
2011Q1	4,435	1.63%	263	0.68%	17,305	3.64%
2011Q2	5,196	1.91%	344	0.89%	19,184	4.04%
2011Q3	4,634	1.70%	475	1.23%	20,980	4.42%
2011Q4	2,990	1.10%	522	1.36%	14,492	3.05%
2012Q1	3,813	1.40%	386	1.00%	16,268	3.43%
2012Q2	4,163	1.53%	501	1.30%	17,517	3.69%
2012Q3	3,978	1.46%	607	1.58%	17,628	3.71%
2012Q4	3,142	1.16%	818	2.12%	12,243	2.58%
2013Q1	3,877	1.43%	420	1.09%	13,594	2.86%
2013Q2	5,243	1.93%	603	1.57%	12,529	2.64%
2013Q3	4,806	1.77%	930	2.41%	13,430	2.83%
2013Q4	3,414	1.26%	1,074	2.79%	9,185	1.93%
2014Q1	4,459	1.64%	682	1.77%	9,549	2.01%
2014Q2	6,699	2.46%	865	2.25%	10,655	2.24%
2014Q3	6,052	2.23%	1,248	3.24%	11,244	2.37%

	Sales listings		Sales Transactions		Rental Listings	
2014Q4	4,705	1.73%	1,423	3.69%	8,305	1.75%
2015Q1	6,632	2.44%	1,238	3.21%	9,780	2.06%
2015Q2	8,169	3.00%	1,222	3.17%	9,754	2.05%
2015Q3	6,928	2.55%	1,537	3.99%	10,259	2.16%
2015Q4	4,475	1.65%	1,511	3.92%	7,914	1.67%
2016Q1	6,350	2.34%	1,098	2.85%	8,529	1.80%
2016Q2	8,292	3.05%	1,230	3.19%	8,961	1.89%
2016Q3	7,336	2.70%	1,691	4.39%	9,496	2.00%
2016Q4	4,880	1.80%	1,737	4.51%	8,192	1.72%
2017Q1	6,871	2.53%	1,229	3.19%	8,873	1.87%
2017Q2	8,540	3.14%	1,356	3.52%	8,776	1.85%
2017Q3	8,432	3.10%	1,739	4.51%	9,074	1.91%
2017Q4	6,886	2.53%	1,925	5.00%	7,839	1.65%
2018Q1	7,407	2.72%	1,484	3.85%	8,215	1.73%
2018Q2	10,579	3.89%	1,535	3.98%	8,512	1.79%
2018Q3	10,002	3.68%	1,859	4.83%	9,221	1.94%
2018Q4	6,845	2.52%	1,970	5.11%	7,866	1.66%
2019Q1	0	0.00%	1,259	3.27%	0	0.00%
2019Q2	0	0.00%	31	0.08%	0	0.00%
Total	**271,866**	**100%**	**38,523**	**100.00%**	**474,901**	**100.00%**
BER Data						
New or Second-hand						
New Dwelling	N/A		355	0.92%	N/A	
Second-Hand Dwelling	N/A		38,168	99.08%	N/A	
stories						
0	N/A		6	0.02%	N/A	
1	N/A		8,939	23.20%	N/A	
2	N/A		25,936	67.33%	N/A	
3	N/A		3,568	9.26%	N/A	
4	N/A		68	0.18%	N/A	
5	N/A		6	0.02%	N/A	
Insulation Type						
Masonry	N/A		24,157	62.71%	N/A	
Mixed Masonry/Timber	N/A		13,610	35.33%	N/A	
Timber	N/A		756	1.96%	N/A	
Glazing						
Double/Triple	N/A		521	1.35%	N/A	
Double	N/A		25,558	66.34%	N/A	
None	N/A		2	0.01%	N/A	
Single/Double/Triple	N/A		120	0.31%	N/A	

	Sales listings		Sales Transactions		Rental Listings	
Single/Double	N/A		9,298	24.14%	N/A	
Single/Triple	N/A		31	0.08%	N/A	
Single	N/A		2,816	7.31%	N/A	
Triple	N/A		177	0.46%	N/A	
Fuel type						
Electricity	N/A		5,746	14.92%	N/A	
Gas	N/A		29,082	75.49%	N/A	
Oil	N/A		3,424	8.89%	N/A	
Solid Fuel	N/A		271	0.70%	N/A	
BER rating	N/A			0.00%	N/A	
A2	N/A		24	0.06%	N/A	
A3	N/A		154	0.40%	N/A	
B1	N/A		167	0.43%	N/A	
B2	N/A		809	2.10%	N/A	
B3	N/A		2,119	5.50%	N/A	
C1	N/A		2,869	7.45%	N/A	
C2	N/A		3,584	9.30%	N/A	
C3	N/A		4,078	10.59%	N/A	
D1	N/A		5,093	13.22%	N/A	
D2	N/A		5,457	14.17%	N/A	
E1	N/A		3,677	9.54%	N/A	
E2	N/A		3,410	8.85%	N/A	
F	N/A		3,674	9.54%	N/A	
G	N/A		3,408	8.85%	N/A	
Total	**0**	**0%**	**38,523**	**100.00%**	**0**	**0%**

<u>**Rental Data**</u>

Rental Dummy Variables

	Sales listings		Sales Transactions		Rental Listings	
Cable television					204,675	43.10%
Central heating					382,417	80.53%
Dishwasher					243,938	51.37%
Dryer					364,691	76.79%
Garden					156,568	32.97%
House alarm					290,375	61.14%
Internet					137,736	29.00%
Microwave					269,894	56.83%
Parking					158,822	33.44%
Pets allowed					211,166	44.47%
Washing machine					316,152	66.57%
Wheelchair access					26,872	5.66%
Lettings agent						

	Sales listings	Sales Transactions	Rental Listings	
Yes			313,578	66.03%
Has Price Chaged			58,345	12.29%
Lease (months)				
0			21,704	4.57%
3			5,216	1.10%
6			26,044	5.48%
9			5,902	1.24%
12			415,049	87.40%
24			823	0.17%
36			391	0.08%
Rent allowance				
0			289,237	60.90%
1			148,883	31.35%
2			37,009	7.79%
Furnished				
0			1,182	0.25%
1			429,587	90.46%
2			19,492	4.10%
3			24,868	5.24%
Bed single (bedroom number : number of single beds)				
10			83,162	17.51%
11			4,708	0.99%
20			149,580	31.50%
21			31,363	6.60%
22			1,884	0.40%
30			37,073	7.81%
31			87,523	18.43%
32			5,410	1.14%
33			807	0.17%
40			18,392	3.87%
41			27,908	5.88%
42			12,747	2.68%
43			1,049	0.22%
44			543	0.11%
50			4,770	1.00%
51			4,629	0.97%
52			2,521	0.53%
53			674	0.14%
54			173	0.04%

		Sales listings	Sales Transactions	Rental Listings	
	55			213	0.04%
Total				**474,901**	**100.00%**

Note the above table displays frequencies and percentages of the total sample for the categorical variables included in model specifications from the analysis, for the three main samples: sales listings, sales transactions, and rental listings, all within 10km of the coastline of Ireland.

Blue Space Appendix Table A 4: Spatial fixed effects by number of units/observations within units

Sales listings sample

Fixed Effect	*Number of spatial units in sample*	*Mean Number of Observations Within Spatial Unit*	*Median Number of Observations Within Spatial Unit*
Local Market	54	9,724	9,370
Micro-Market	335	2,010	1,338
Electoral Division	1,617	724	390
Small Area	11,558	37	31

Sales transactions sample (Dublin)

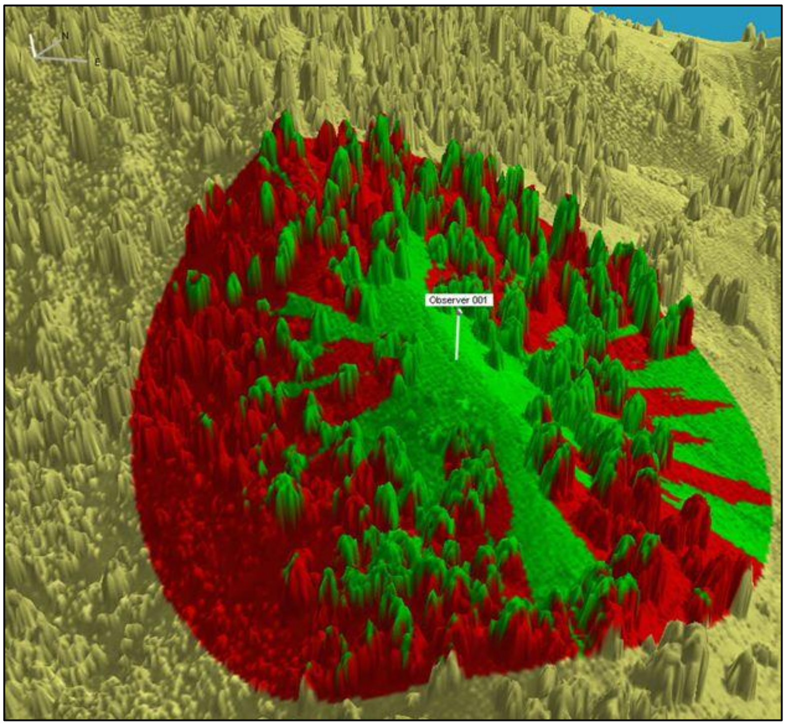
Fixed Effect	*Number of spatial units in sample*	*Mean Number of Observations Within Spatial Unit*	*Median Number of Observations Within Spatial Unit*
Local Market	26	2,201	1,853
Micro-Market	116	577	435
Electoral Division	318	235	145
Small Area	4,487	12	11

Rental listings sample

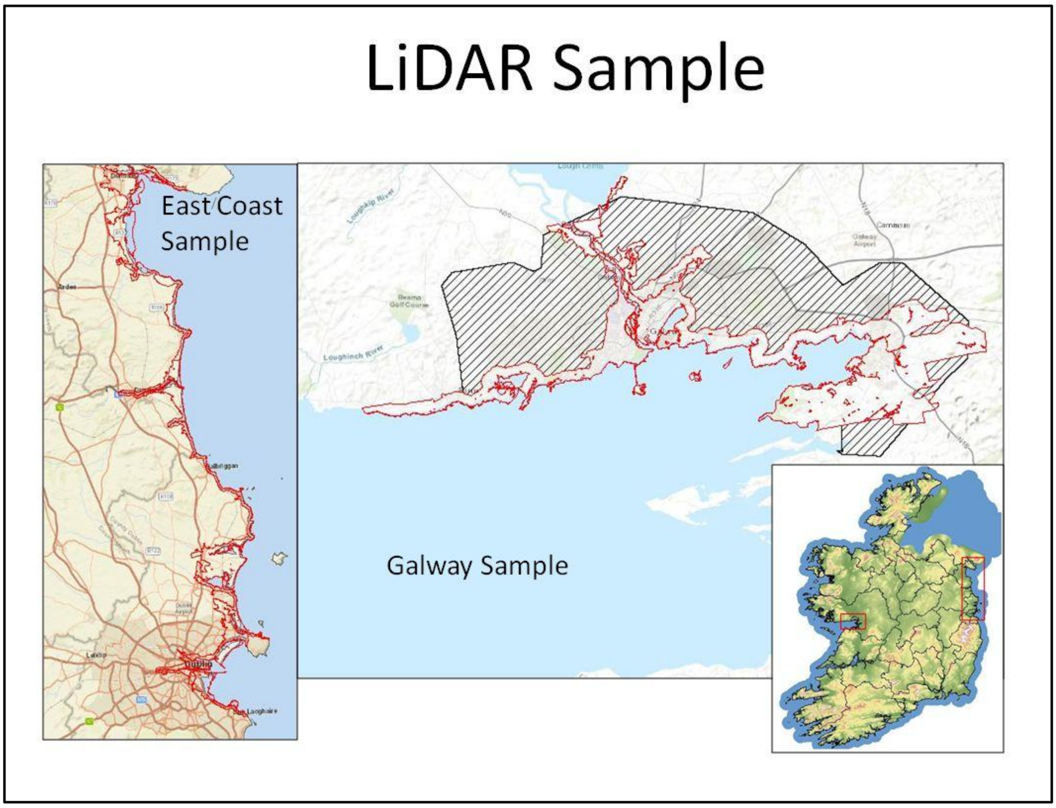
Fixed Effect	*Number of spatial units in sample*	*Mean Number of Observations Within Spatial Unit*	*Median Number of Observations Within Spatial Unit*
Local Market	54	17,654	15,935
Micro-Market	353	4,834	3,176
Electoral Division	1,528	1,520	1,172
Small Area	11,171	175	86

Note: The table above gives an indication of the within variation of the level of SFE in terms of the number of observations, used in the analysis. Three primary samples are reported: sales listings, sales transactions, and rental listings. All samples are restricted to within 10km of the coastline, as specified in the text.

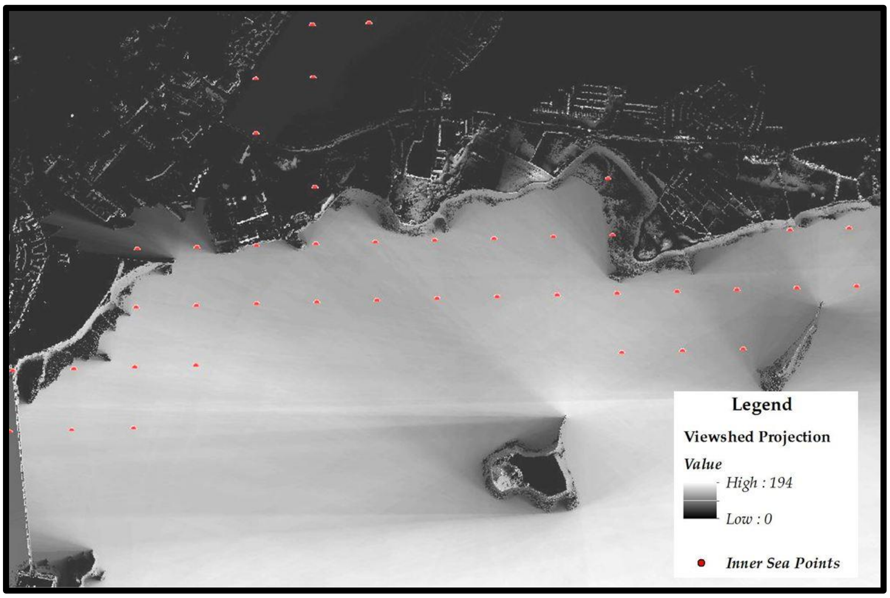
Blue Space Appendix, Figure A 1: Example of 3D viewshed simulation (green = visible, red= not visible)



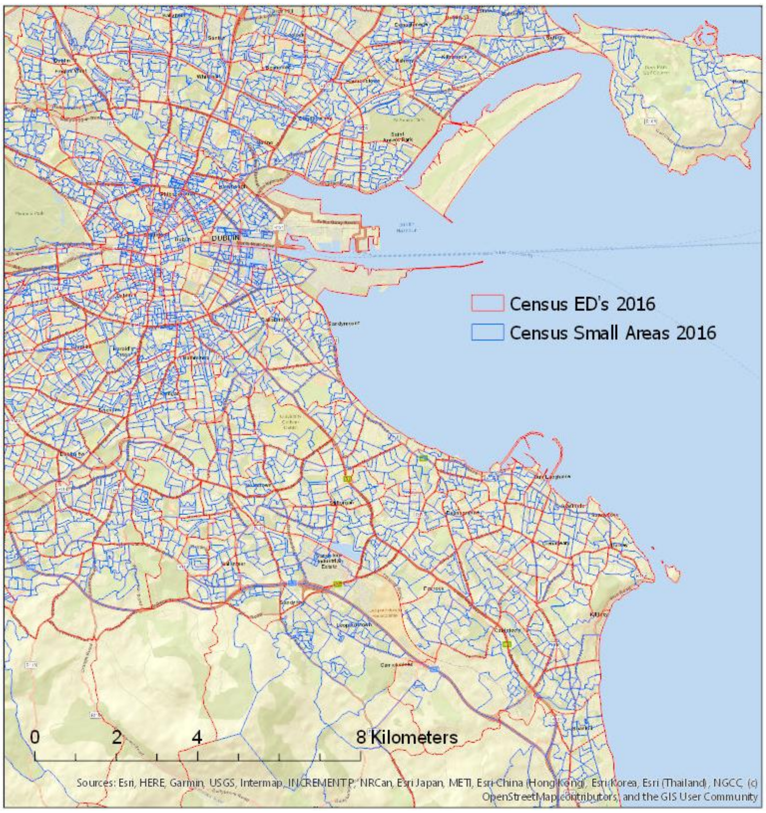
Blue Space Appendix, Figure A 2: LiDAR Sample Areas (shaded area in Galway represents OPW's inland flood risk sub-sample)



Blue Space Appendix Figure A 3: Example of LiDAR detail in inner point viewshed projection on Galway city coastline



Blue Space Appendix Figure A 4: Census 2016 ED and small area boundaries for Dublin area



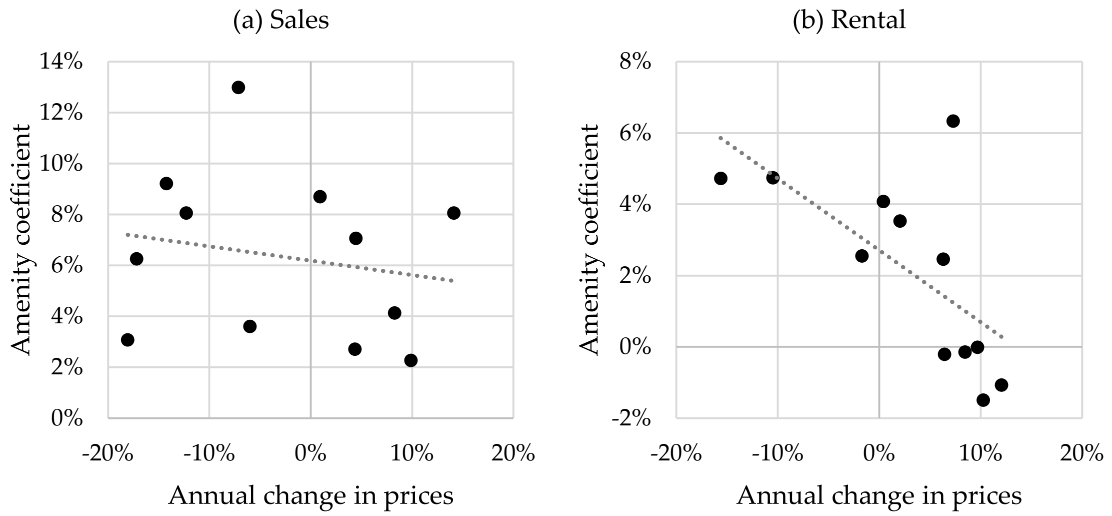
Note: The above figure shows boundary outlines for electoral districts and small areas, the primary levels of SFE used in the analysis.

Blue Space Appendix Figure A 5: Extent of PRIME 2 data

Note: The above figure displays the extent of PRIME 2 data available.

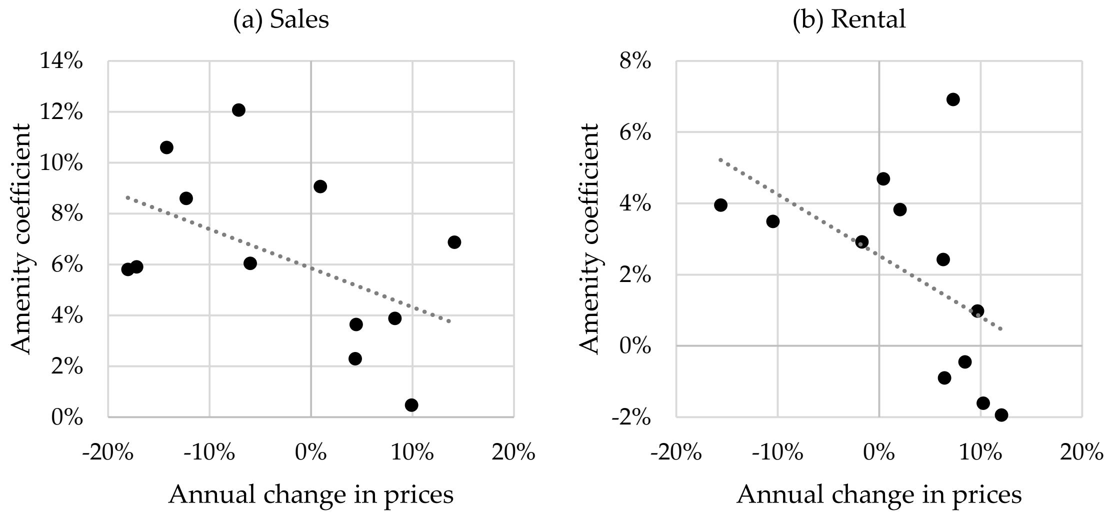
Appendix B. Additional figures for Section 5.3.3

Blue Space Appendix, Figure B 1: Scatterplot of coefficients by year and annual change in listed prices: >250m to sand/shingle amenity, sale and rental datasets



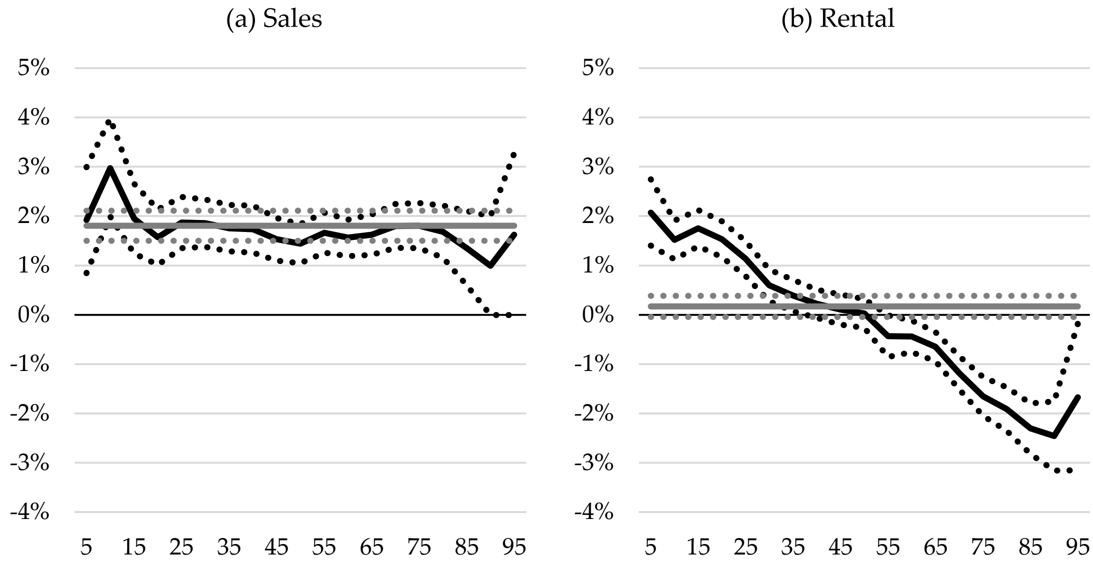
Note: This figure shows, for the coefficients on the relevant amenity, by year, together with the change in housing prices in that year, by segment.

Blue Space Appendix, Figure B 2: Scatterplot of coefficients by year and annual change in listed prices: >250m to any non-transitional coastline, sale and rental datasets



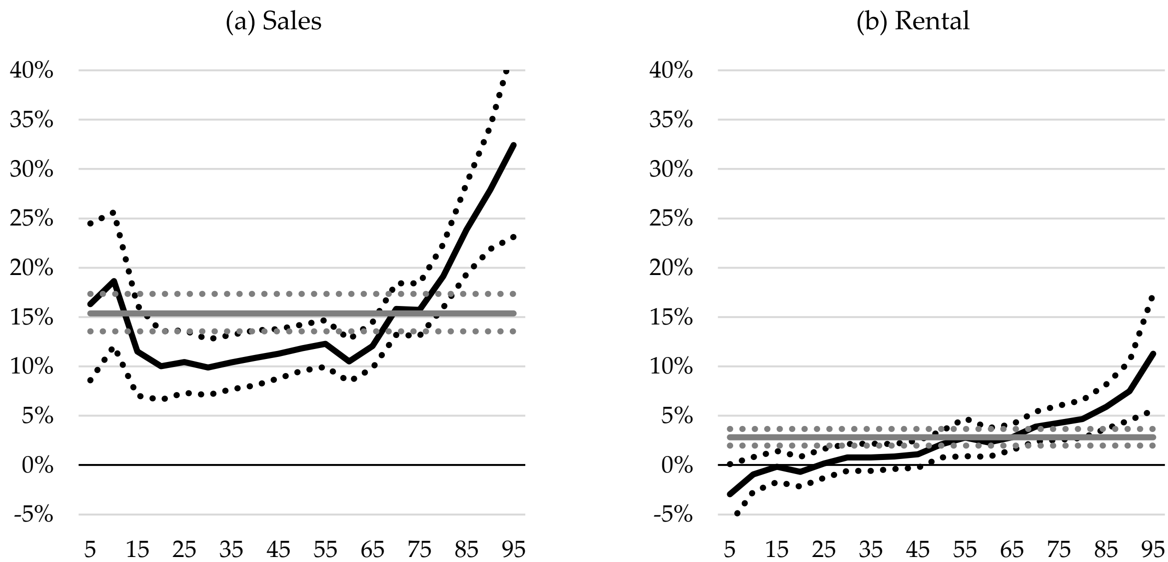
Note: This figure shows, for the coefficients on the relevant amenity, by year, together with the change in housing prices in that year, by segment.

Blue Space Appendix, Figure B 3: Coefficients and 95% confidence intervals for quantile regressions: view-depth amenity, sale and rental datasets



Note: This figure shows the estimated coefficients and associated 95% confidence intervals for quantile regressions on the same amenity across sale and rental segments, with standardised axes.

Blue Space Appendix, Figure B 4: Coefficients and 95% confidence intervals for quantile regressions: >100m to sand/shingle amenity, sale and rental datasets



Note: This figure shows the estimated coefficients and associated 95% confidence intervals for quantile regressions on the same amenity across sale and rental segments, with standardised axes.

Blue Space Appendix, Table C 1: Robustness checks for listed sale prices, 2006-2018

Specification	Proximity matched		Straight Coast		LiDAR		Baseline	
Level of spatial FE	ED	SA	ED	SA	ED	SA	ED	SA
Dependent Variable: natural log of the listed sale price								
Playground Variables								
Sand/Shingle								
500 - 200m	0.022	0.024	0.003	-0.004	-0.019	-0.013	0.024	0.030
	2.1	1.4	0.5	-0.5	-3.0	-1.3	6.8	5.3
200 - 100m	0.038	0.081	-0.005	-0.003	-0.028	-0.006	0.045	0.063
	2.7	3.4	-0.5	-0.2	-2.9	-0.4	7.3	7.2
<100m	0.133	0.183	0.061	0.085	0.072	0.080	0.143	0.154
	7.5	6.4	4.1	4.1	4.8	3.8	17.0	13.5
Beaches								
500 - 200m	0.009	0.042	-0.021	0.013	0.033	0.092	-0.020	0.025
	0.5	1.2	-1.9	0.7	1.6	2.6	-2.2	1.8
200 - 100m	0.212	0.181	0.044	0.038	0.064	0.170	0.075	0.089
	5.4	3.2	1.6	1.1	1.9	3.5	3.7	3.5
<100m	0.167	0.150	0.117	0.079	0.115	0.176	0.172	0.197
	3.7	2.2	2.7	1.3	2.6	2.4	5.7	5.7
Cliffs								
500 - 200m	0.000	-0.017	-0.039	-0.034	-0.137	-0.135	-0.009	0.011
	0.0	-0.6	-4.4	-2.2	-4.2	-3.0	-1.4	1.1
200 - 100m	0.001	-0.034	0.058	0.046	-0.125	-0.161	0.020	0.021
	0.1	-0.8	2.2	1.5	-3.2	-3.0	1.4	1.1
<100m	0.155	0.116	0.003	0.027	-0.188	-0.205	0.030	0.038
	3.4	2.0	0.1	0.5	-3.6	-2.0	1.2	1.4
Picture Variables								
Seaview breadth	0.005	0.002	0.017	0.015	0.013	0.016	0.014	0.013
	3.2	1.4	9.9	7.7	3.9	4.9	17.6	14.9
Seaview depth	0.013	0.018	0.013	0.013	0.014	0.007	0.018	0.017
	4.0	4.2	4.1	3.2	6.2	2.5	11.7	10.1
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	15,309	15,309	45,293	45,293	30,628	30,628	271,866	271,866
R-squared	0.824	0.882	0.804	0.835	0.837	0.867	0.809	0.84
rmse	0.279	0.256	0.261	0.243	0.252	0.232	0.268	0.25
Number of absorbed SFE	741	3,753	204	1,711	136	1,415	1,617	11,558

Notes: Robust t-statistics reported below coefficients. Columns show different levels of SFE denoted at header, while controls include location, dwelling and time listed on the market, as discussed in the text. Robust t-statistics are reported in columns 1-4 while clustered t-statistics are reported in columns 5-8.

Blue Space Appendix, Table C 2 : Robustness checks for listed rental prices, 2006-2018

Specification	Proximity matched		Straight Coast		LiDAR		Baseline	
Level of spatial FE	ED	SA	ED	SA	ED	SA	ED	SA
Dependent Variable: natural log of the listed rental price								
Playground Variables								
Sand/Shingle								
500 - 200m	0.002	0.022	-0.006	-0.001	-0.026	-0.001	-0.012	0.002
	0.3	1.3	-2.1	-0.2	-8.7	-0.2	-6.2	0.6
200 - 100m	-0.016	-0.004	0.005	0.001	-0.022	-0.001	-0.002	0.002
	-1.3	-0.2	1.0	0.1	-5.0	-0.2	-0.5	0.3
<100m	0.008	0.024	0.006	0.011	0.018	0.030	0.028	0.017
	0.6	1.0	1.0	1.1	2.9	3.4	6.7	2.6
Beaches								
500 - 200m	0.005	0.001	0.013	0.049	0.014	0.023	0.012	0.042
	0.3	0.0	2.2	4.4	1.2	0.8	2.3	4.1
200 - 100m	0.015	-0.030	0.014	0.043	0.043	0.080	0.018	0.044
	0.6	-0.6	1.2	2.4	2.5	2.0	2.0	2.9
<100m	0.050	0.058	0.079	0.077	0.114	0.157	0.086	0.099
	1.5	0.8	3.4	2.9	4.5	3.1	5.3	4.8
Cliffs								
500 - 200m	-0.005	-0.002	-0.022	-0.004	-0.068	-0.066	-0.003	0.009
	-0.3	-0.1	-4.1	-0.4	-4.7	-3.0	-0.7	1.1
200 - 100m	0.008	0.020	-0.021	0.000	-0.074	-0.092	0.012	0.029
	0.2	0.4	-1.4	0.0	-3.8	-3.5	0.8	1.7
<100m	-0.059	-0.012	0.006	0.132	-0.151	-0.107	-0.014	0.013
	-1.7	-0.2	0.1	1.6	-3.6	-1.0	-0.8	0.6
Picture Variables								
Seaview breadth	0.007	0.008	0.006	0.003	0.008	0.009	0.010	0.010
	7.7	7.5	5.3	2.8	4.2	4.8	23.3	21.1
Seaview depth	0.001	0.002	0.016	0.018	0.005	0.000	0.002	0.002
	0.3	0.5	6.3	6.2	6.5	0.3	1.5	1.6
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Observations	17,376	17,376	65,841	65,841	99,505	99,505	474,901	474,901
R-squared	0.852	0.888	0.816	0.833	0.831	0.846	0.855	0.87
rmse	0.196	0.184	0.171	0.165	0.187	0.18	0.174	0.166
Number of absorbed SFE	532	2,963	190	1,667	136	1,435	1,524	11,163

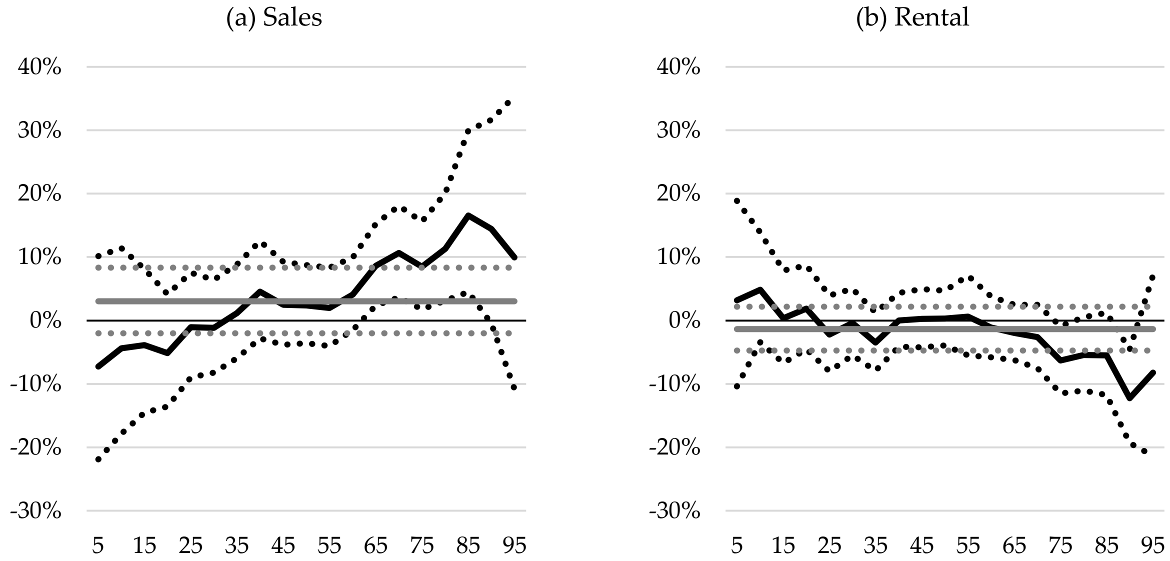
Notes: Robust t-statistics reported below coefficients. Columns show different levels of SFE denoted at header, while controls include location, dwelling and time listed on the market, as discussed in the text. Robust t-statistics are reported in columns 1-4 while clustered t-statistics are reported in columns 5-8.

Blue Space Appendix, Table C 3: Robustness checks for transacted sale prices, 2010-2018

Sample description	Prox matched	Straight Coast	LiDAR	Main results
Level of spatial fixed effect	ED	ED	ED	ED
Dependent Variable: natural log of the transacted sale price				
Playground Variables				
Sand/Shingle				
500 - 200m	0.020	-0.011	0.005	0.008
	0.8	-0.8	0.4	0.9
200 - 100m	0.061	-0.024	0.121	0.017
	1.8	-1.0	1.5	1.3
<100m	0.052	-0.049	0.089	0.084
	1.1	-1.1	0.7	4.4
Beaches				
500 - 200m	0.053	0.014	0.051	0.025
	1.2	0.5	1.2	1.1
200 - 100m	0.097	0.109	0.044	0.119
	2.0	3.3	0.3	3.3
<100m	0.119	0.135	0.244	0.226
	1.1	1.3	1.3	2.2
Cliffs				
500 - 200m	-0.003	-0.021	-0.034	-0.044
	0.0	-1.1	-1.7	-2.9
200 - 100m	-0.042	-0.067	-0.127	-0.083
	-0.4	-1.2	-1.4	-2.3
<100m		-0.147	0.059	-0.113
		-1.9	0.5	-1.8
Picture Variables				
Seaview breadth	0.003	0.023	-0.008	0.008
	1.2	3.3	-0.8	5.2
Seaview depth	0.005	-0.005	0.015	0.004
	0.4	-0.4	2.3	0.7
Controls	YES	YES	YES	YES
Standard Errors	Robust	Robust	Robust	Robust
Observations	2,561	2,874	33,181	38,523
R-squared	0.914	0.917	0.892	0.889
rmse	0.179	0.165	0.174	0.179
Number of absorbed SFE	238	25	305	318

Notes: Robust t-statistics reported below coefficients. Columns show results for different outcome variables, regressors and samples, as discussed in the text.

Blue Space Appendix, Figure C 1: Coefficients and 95% confidence intervals for quantile regressions: >100m to cliff amenity, sale and rental datasets



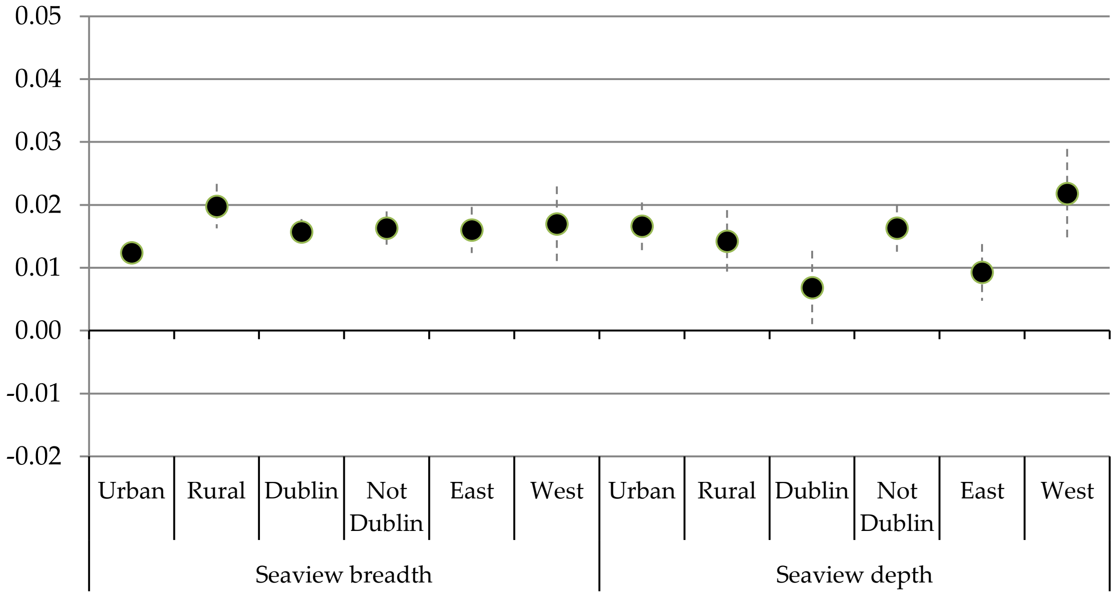
Note: This figure shows the estimated coefficients and associated 95% confidence intervals for quantile regressions on the same amenity across sale and rental segments, with standardised axes.

Blue Space Appendix, Table C 4: Baseline specifications by property types

Specification	Apartment/ Duplex		Terraced/End-of/Townhouse		Detached/ Bungalow		1-2 Bedrooms		3 Bedrooms		>3 Bedrooms	
Level of spatial FE	ED	SA	ED	SA	ED	SA	ED	SA	ED	SA	ED	SA
Dependent Variable: natural log of the listed sale price												
Playground Variables												
Sand/Shingle												
500 - 200m	0.047	0.034	0.009	-0.024	0.021	0.032	0.005	0.010	0.030	0.031	0.033	0.038
	3.7	1.8	1.2	-1.6	4.8	4.8	0.6	0.7	5.5	3.4	5.8	4.3
200 - 100m	0.056	0.068	-0.001	-0.032	0.057	0.076	0.013	0.034	0.037	0.051	0.076	0.090
	3.2	2.5	-0.1	-1.3	7.3	7.1	0.9	1.4	3.8	3.6	7.6	6.3
<100m	0.117	0.089	0.130	0.085	0.146	0.166	0.102	0.104	0.119	0.124	0.180	0.203
	5.5	2.5	6.8	2.5	13.3	11.9	6.1	3.6	8.7	6.5	12.4	10.4
Beaches												
500 - 200m	-0.088	-0.158	-0.040	-0.018	-0.015	0.036	-0.044	0.008	-0.045	0.013	0.023	0.065
	-2.8	-2.3	-2.1	-0.4	-1.3	2.2	-1.9	0.2	-3.0	0.5	1.6	2.9
200 - 100m	0.001	0.005	-0.024	0.036	0.085	0.103	-0.001	0.116	0.061	0.052	0.096	0.119
	0.0	0.1	-0.5	0.5	3.6	3.6	0.0	1.9	1.7	1.2	3.0	2.8
<100m	0.860		0.070	0.180	0.191	0.202	0.011	0.090	0.135	0.163	0.271	0.241
	21.7		1.2	1.4	5.5	5.2	0.2	1.2	2.5	2.1	5.8	4.3
Cliffs												
500 - 200m	-0.103	0.078	-0.001	0.009	0.003	0.012	-0.063	-0.055	0.013	-0.001	-0.010	-0.007
	-4.1	1.5	-0.1	0.2	0.3	1.0	-3.6	-1.7	1.2	-0.1	-0.9	-0.4
200 - 100m	0.136	0.328	0.060	-0.031	0.011	0.006	0.034	-0.016	0.042	0.033	0.014	0.003
	2.2	3.6	1.7	-0.6	0.7	0.3	0.8	-0.3	1.8	1.0	0.7	0.1
<100m	-0.049	0.190	-0.012	-0.175	0.079	0.062	-0.121	-0.092	0.128	0.116	0.038	0.000
	-1.0	2.0	-0.1	-1.4	2.8	2.0	-2.4	-1.1	2.8	2.4	1.1	0.0
Picture Variables												
Seaview breadth	0.020	0.020	0.015	0.011	0.012	0.010	0.015	0.013	0.016	0.012	0.013	0.010
	12.8	12.2	8.0	5.7	10.5	7.8	9.8	8.1	11.3	7.6	9.5	6.5
Seaview depth	0.000	-0.005	0.019	0.022	0.020	0.019	0.020	0.016	0.017	0.018	0.015	0.016
	0.1	-0.9	4.7	4.5	11.1	9.1	5.0	3.2	6.9	6.3	6.8	5.7
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	32,825	32,825	71,931	71,931	167,110	167,110	57,007	57,007	123,878	123,878	90,981	90,981
R-squared	0.828	0.882	0.843	0.877	0.799	0.835	0.803	0.859	0.807	0.852	0.795	0.847
rmse	0.256	0.224	0.244	0.226	0.266	0.247	0.272	0.245	0.24	0.218	0.273	0.248
Number of absorbed SFE	717	3,990	954	6,787	1,608	10,380	1,404	7,696	1,539	10,604	1,570	9,667

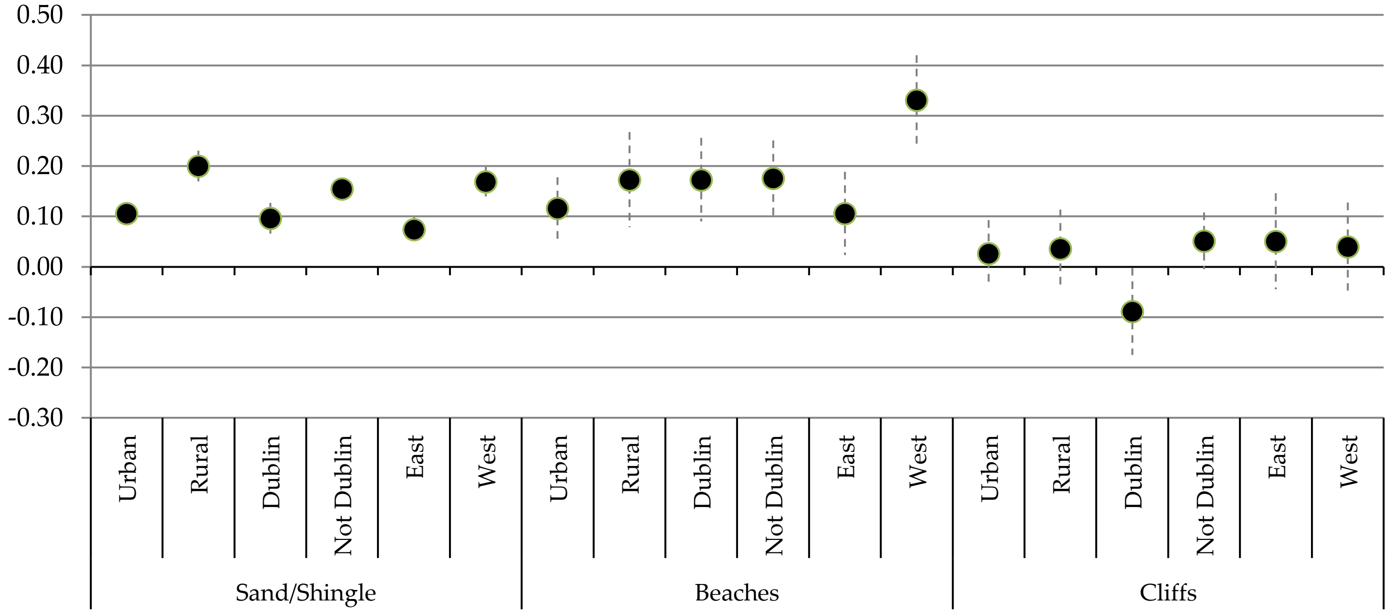
Notes: Robust t-statistics reported below coefficients. Columns show different levels of SFE denoted at header, while controls include location, dwelling and time listed on the market, as discussed in the text.

Blue Space Appendix, Figure C 2: Coefficients and 95% confidence intervals for geographical regions: View based amenities, sales dataset



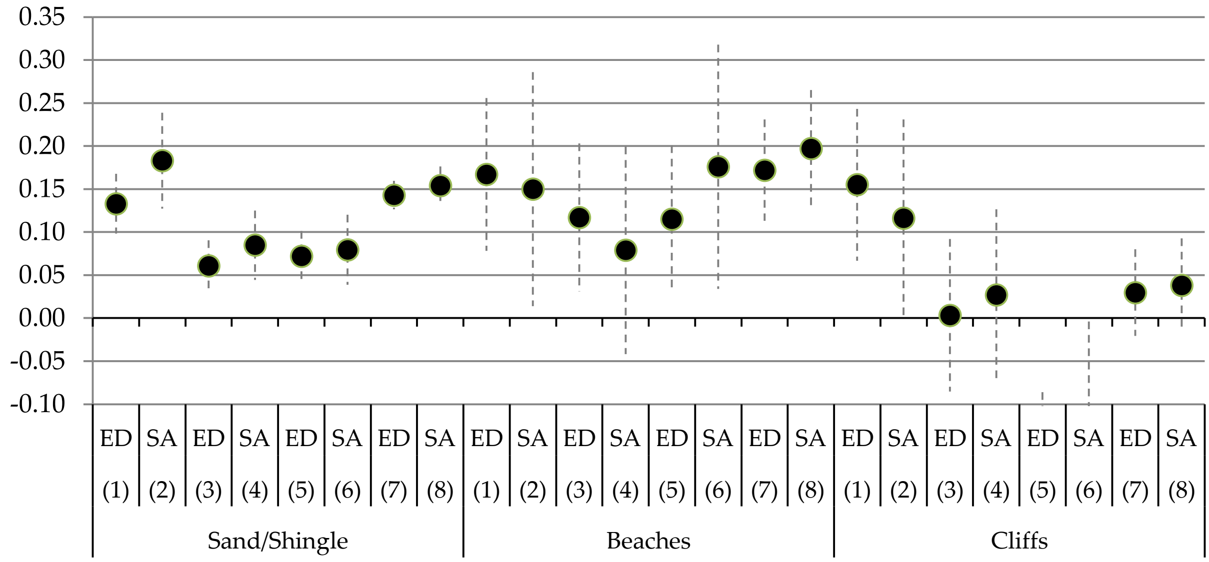
Note: This figure shows, for the specifications discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the two view based blue-space amenities.

Blue Space Appendix, Figure C 3: Coefficients and 95% confidence intervals for geographical regions: distance-based amenities (within 100m), sales dataset



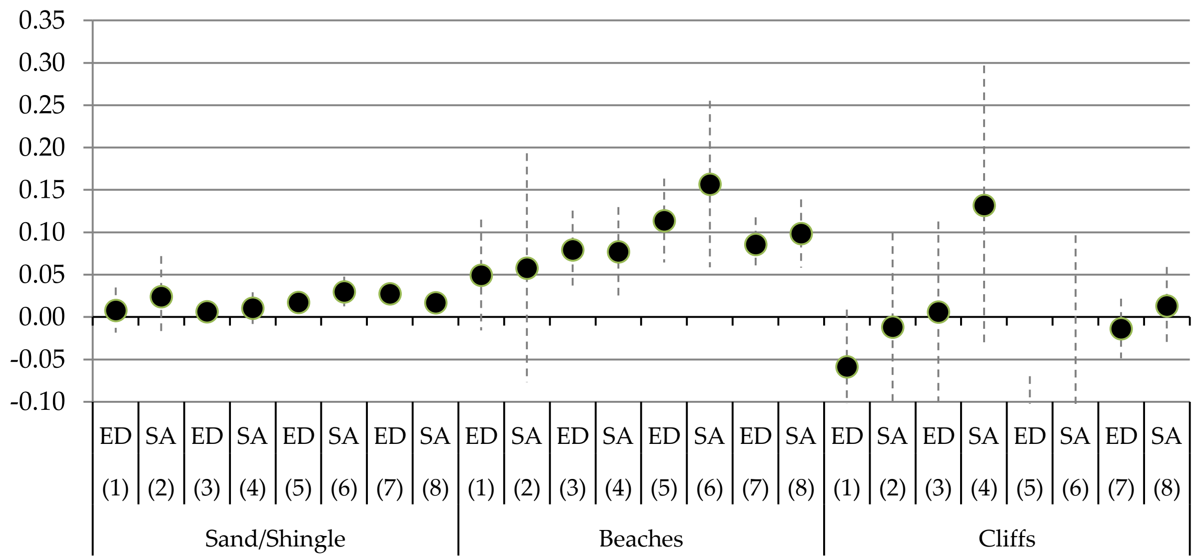
Note: This figure shows, for the specifications discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the three distance-based blue-space amenities.

Blue Space Appendix, Figure C 4: Coefficients and 95% confidence intervals for robustness checks: distance-based amenities (within 100m), sales listings dataset



Note: This figure shows, for the specifications discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the three distance-based blue-space amenities.

Blue Space Appendix, Figure C 5: Coefficients and 95% confidence intervals for robustness checks: distance-based amenities (within 100m), rental listings dataset



Note: This figure shows, for the specifications discussed in the text, the estimated coefficients and associated 95% confidence intervals, for the three distance-based blue-space amenities.

Blue Space Appendix, Table C 5: Additional Robustness checks

Specification	Baseline	(1)	(2)	(3)	(4)	(5)	(6)
Level of spatial FE	ED	ED	ED	ED	ED	ED	ED
Dependent Variable: natural log of the listed sale price							
Playground Variables							
Sand/Shingle							
500 - 200m	0.024	0.026	0.026	0.026	0.024	0.023	0.022
	6.8	7.4	7.2	7.1	6.6	6.5	6.3
200 - 100m	0.045	0.047	0.054	0.055	0.045	0.042	0.042
	7.3	7.8	8.7	8.9	7.3	6.9	6.9
<100m	0.143	0.146	0.164	0.160	0.143	0.139	0.134
	17.0	17.6	19.3	18.9	17.0	16.6	16.0
Beaches							
500 - 200m	-0.020	-0.023	-0.017	-0.011	-0.020	-0.020	-0.015
	-2.2	-2.5	-1.8	-1.1	-2.1	-2.1	-1.6
200 - 100m	0.075	0.076	0.082	0.089	0.077	0.076	0.081
	3.7	3.8	3.9	4.3	3.8	3.7	4.0
<100m	0.172	0.185	0.183	0.179	0.172	0.170	0.167
	5.7	6.3	6.0	5.9	5.8	5.7	5.6
Cliffs							
500 - 200m	-0.009	-0.003	-0.002	0.014	-0.011	-0.009	0.003
	-1.4	-0.5	-0.2	2.0	-1.7	-1.3	0.4
200 - 100m	0.020	0.021	0.036	0.059	0.017	0.021	0.043
	1.4	1.4	2.5	4.1	1.2	1.5	3.0
<100m	0.030	0.030	0.047	0.066	0.027	0.032	0.053
	1.2	1.2	1.8	2.5	1.0	1.3	2.0
Blue Flag Beaches							
500 - 200m					0.013		
					1.4		
200 - 100m					0.029		
					1.5		
<100m					0.019		
					0.8		
Picture Variables							
Seaview breadth	0.014	0.013	-0.001	0.005	0.013	0.014	0.022
	17.6	16.4	-1.3	8.2	14.9	17.5	37.5
Seaview depth	0.018	0.019	0.015		0.017	0.018	
	11.7	12.6	12.2		10.0	11.8	
Seaview Distant					0.011		
					6.0		
Controls	YES	YES	YES	YES	YES	YES	YES
Observations	271,866	271,866	271,866	271,866	271,866	271,866	271,866
R-squared	0.809	0.822	0.808	0.808	0.809	0.809	0.809
rmse	0.268	0.259	0.269	0.269	0.268	0.268	0.269
Number of absorbed	1,617	1,617	1,617	1,617	1,617	1,617	1,617

Notes: Robust t-statistics reported below coefficients. Columns show different levels of SFE denoted at header, while controls include location, dwelling and time listed on the market, as discussed in the text.

Blue Space Appendix, Table C 6: Formal tests of parameter equality between models from Table 5.4

Model comparisons	(1) & (2)	(4) & (5)	(1) & (7)
Playground Variables			
Sand/Shingle			
500 - 200m	0.01	0.03	0.01
200 - 100m	0.00	0.03	0.02
<100m	0.01	0.04	0.04
Beaches			
500 - 200m	0.01	0.06	0.04
200 - 100m	0.01	0.03	0.03
<100m	0.07	0.02	0.04
Cliffs			
500 - 200m	0.01	0.04	0.03
200 - 100m	0.01	0.08	0.07
<100m	0.00	0.10	0.11
Picture Variables			
Seaview breadth	0.00	0.00	0.00
Seaview depth	0.00	0.01	0.01

Note: The above t-values correspond to the difference of estimated parameters dependent on model specification based on a hypothesis test that the difference between estimated coefficients is equal to zero. This is based on the following formula: For models i and k, the computed t- value, t_{ik} , between two identical parameters,

$$= \frac{\widehat{\beta_i} - \widehat{\beta_k}}{\sqrt{\widehat{\beta_i}^{SE(\widehat{\beta_i})} + \widehat{\beta_k}^{SE(\widehat{\beta_k})}}}$$

Floods

Appendix A: Data

A.1 Flood events

Floods Appendix, Table A 1.: Frequency of flood event variables

Flood events measure		Sales Listings	Sales Transactions	Rentals Listings
Flooding within 100-250m of dwelling	None	269,726	37,216	463,904
	More than 30 years	302	41	2,277
	10-30 years	2,425	318	8,848
	5-10 years	2,614	522	6,568
	2-5 years	2,523	468	6,110
	Less than 2 years	1,291	167	5,779
Flooding within 100m of dwelling	More than 30 years	1,665	293	5,023
	10-30 years	2,460	329	8,359
	5-10 years	907	140	3,924
	2-5 years	686	118	2,297
	Less than 2 years	283	31	1,687
Total sales		284,882	39,643	514,776

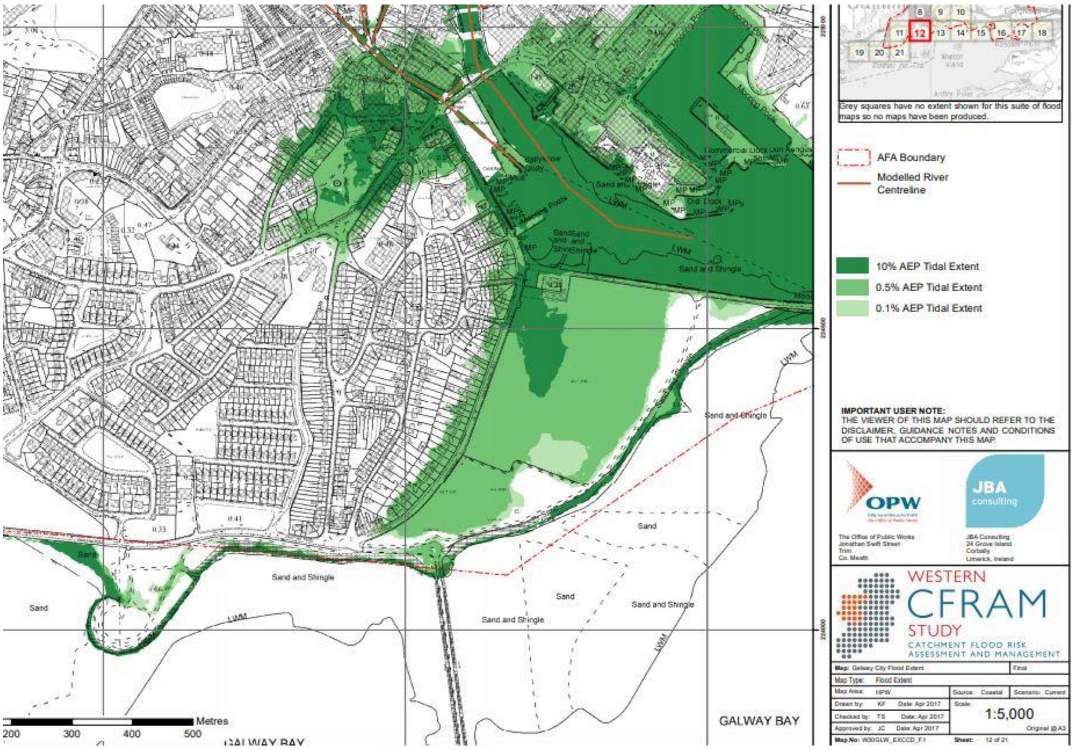
Note: The table shows the frequency of observations in each of the 11 categories related to exposure to past flood events, as described in the text, for three samples: sale listings (2006-2018), sale transactions (2010-2018) and rental listings (2006-2018).

Floods Appendix, Table A 2: Breakdown of urban/rural split by listings sample compared with Eircodes

	Sales Listings			Rental Listings		
	Urban	Rural	Total	Urban	Rural	Total
Floods Sample						
Eircode within AFA	1,147,049	121,578	1,268,627	1,147,049	121,578	1,268,627
	90%	10%		90%	10%	
Daft final within AFA	264,019	20,863	284,882	469,685	45,091	514,776
	93%	7%		91%	9%	
Discrepancy	**1%**			**0%**		
Daft final within AFA, > year 2010	174,273	16,431	190,704	353,389	36,964	390,353
	91%	9%		91%	9%	
Discrepancy	**0%**			**0%**		
Blue Space Sample (<10k from coastline)						
Eircode	997,917	380,967	1,378,884	997,917	380,967	1,378,884
	72%	28%		72%	28%	
Daft Final	221,285	50,660	271,945	412,487	62,698	475,185
	81%	19%		87%	13%	
Discrepancy	**4%**			**7%**		

Note: The above table shows the urban/rural breakdown of the daft.ie sales and listings samples used in the preferred specifications in Chapters 5 and 6. These are compared to the same geographical breakdown of the corpus of residential Eircodes in Ireland as explained in section 3.2. The discrepancy rows are the difference in the daft.ie listings sample percentages and the Eircode percentages divided by 2.

Floods Appendix, Figure A 1: CFRAM Example



Note: The above figure is an example of the publicly available CFRAM maps which can be accessed at floodinfo.ie. The CFRAM maps are of the highest precision at 2 meter resolution making it possible to distinguish e.g. individual dwellings at risk and not at risk on the same street or in the same housing estate.

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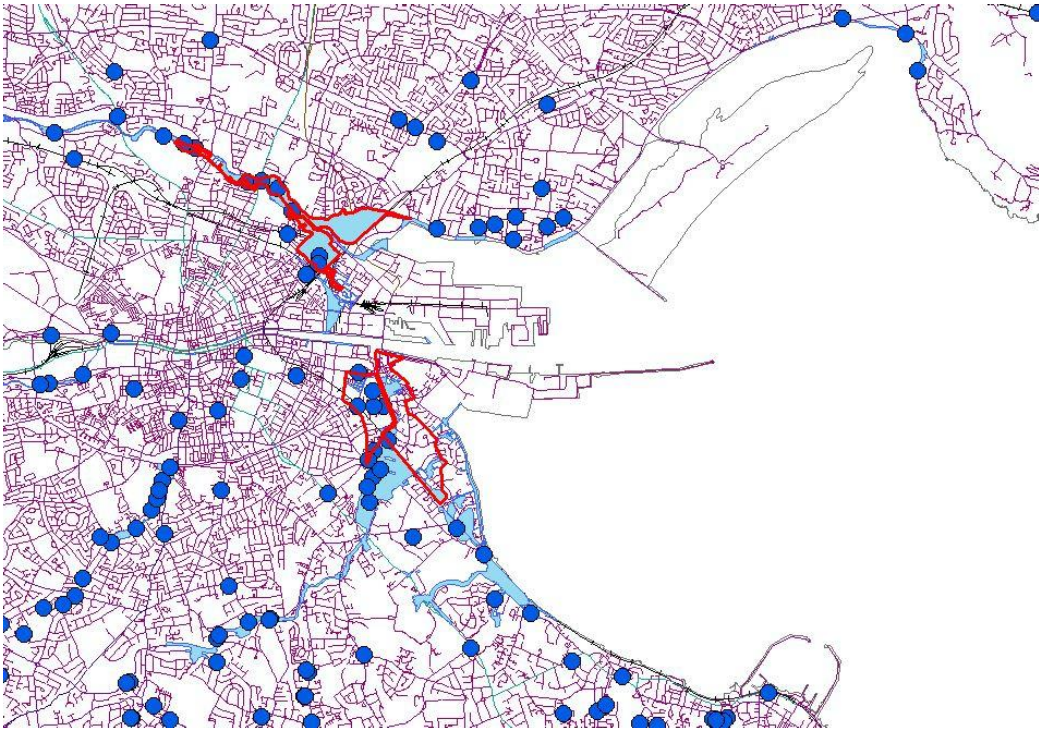
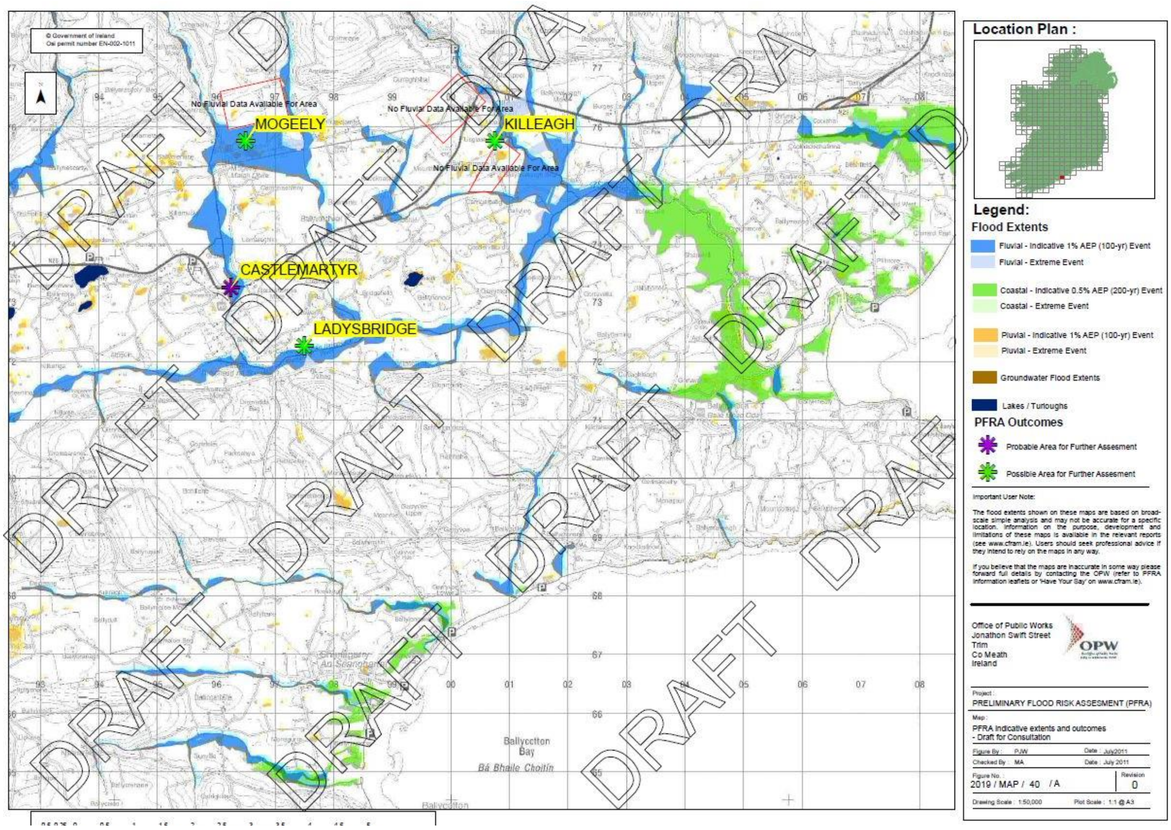
Floods Appendix, Figure A 2: Flood events and flood defences



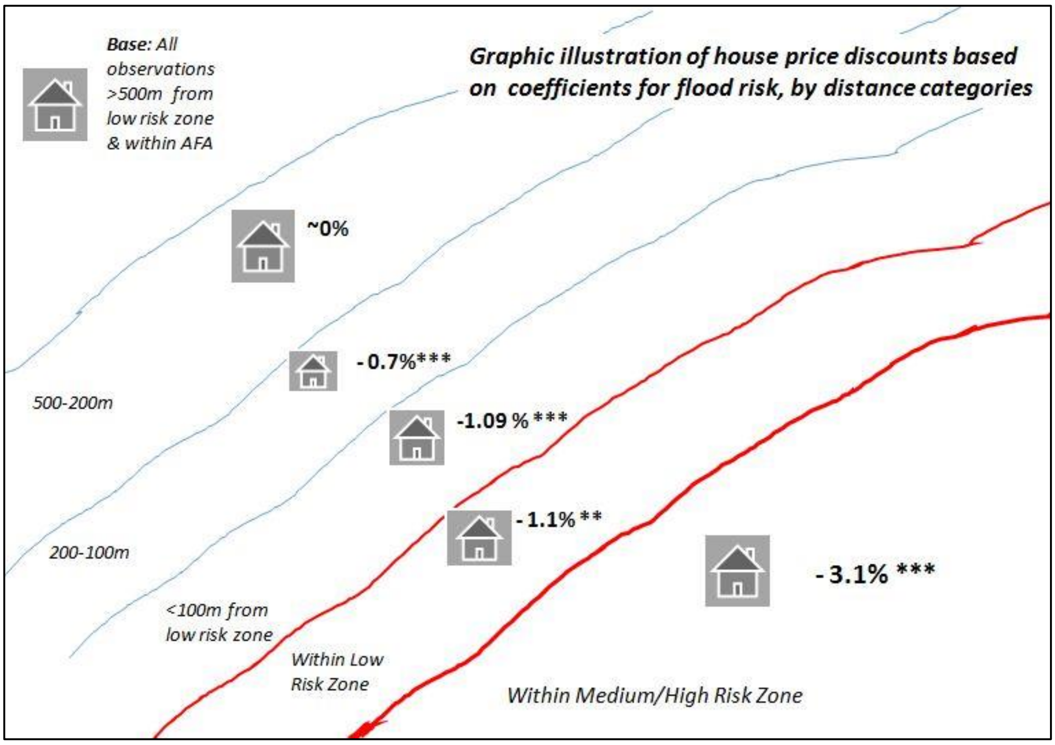
Note: The above figure displays flood event points (blue dots), flood event extents (blue polygons), and areas protected by flood defences (red outlines) for the Dublin area.

Floods Appendix, Figure A 3: PFRA map example



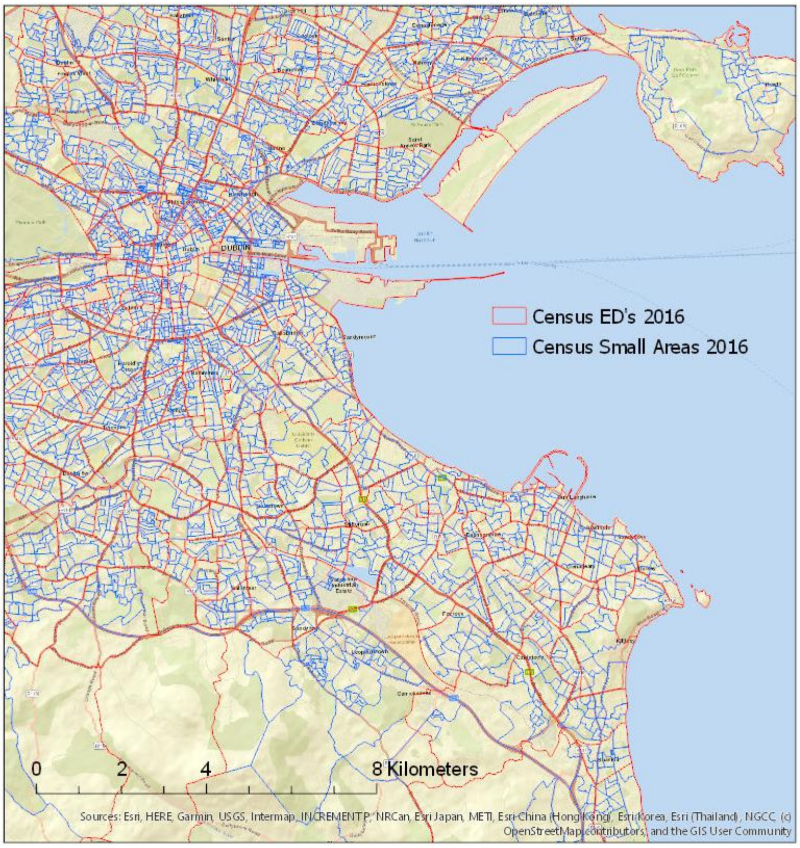
Note: The above figure displays the extent of the PFRA flood risk areas as described in the text. These maps were made publicly available in 2011 at a high enough resolution to identify individual dwellings. PFRA maps had a national coverage but with varied levels of resolution. These were then replaced by the CFRAM maps in 2014, an example of which can be seen in Floods Appendix, Figure A 1.

Floods Appendix, Figure A 4: Illustration of flood discount by distance



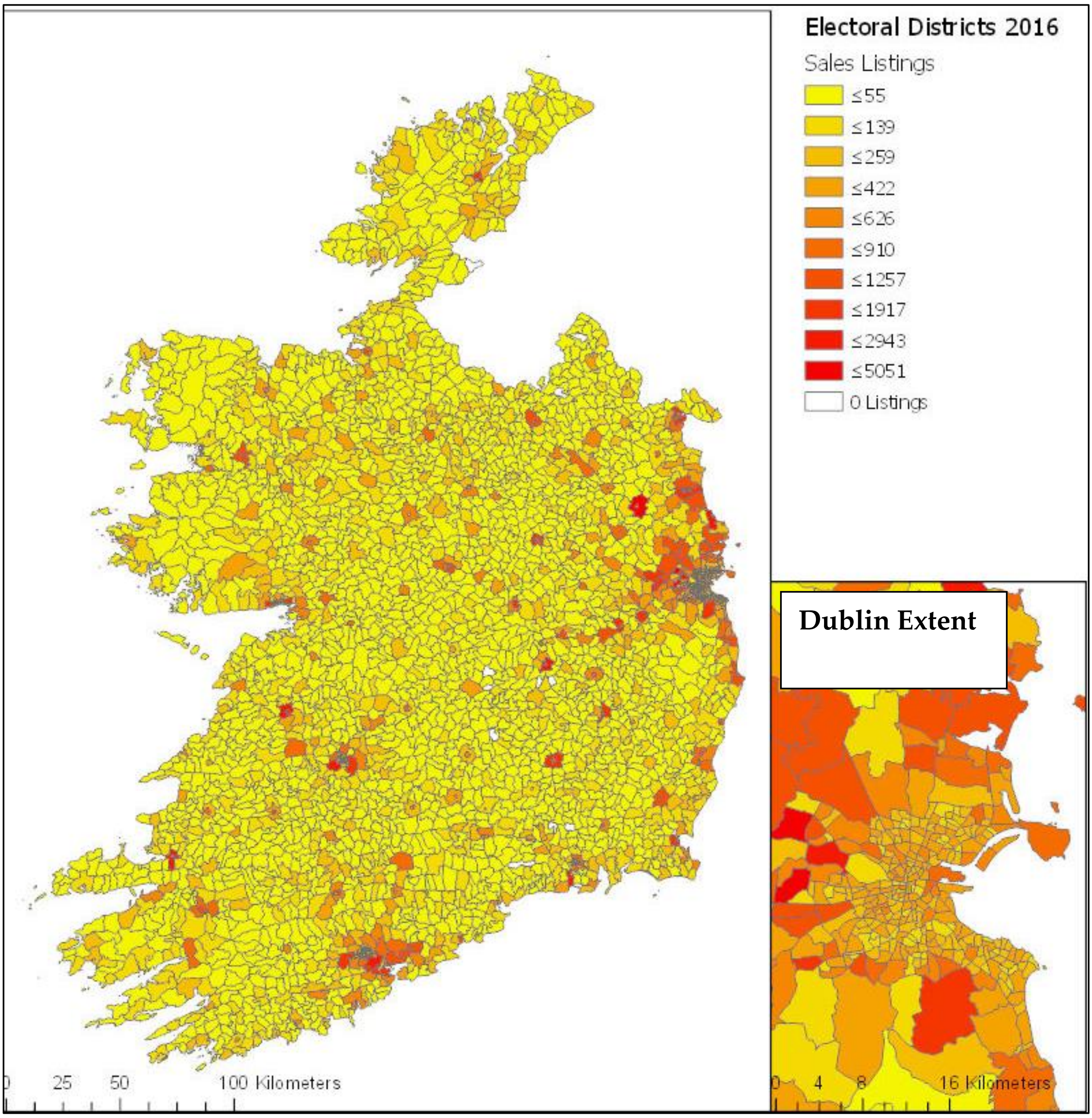
Note: The above figure spatially illustrates the results of the main specification for flood risk from the sales listings sample from Table 6.1in the main text.

Floods Appendix, Figure A 5: Census 2016 ED and small area boundaries for Dublin area



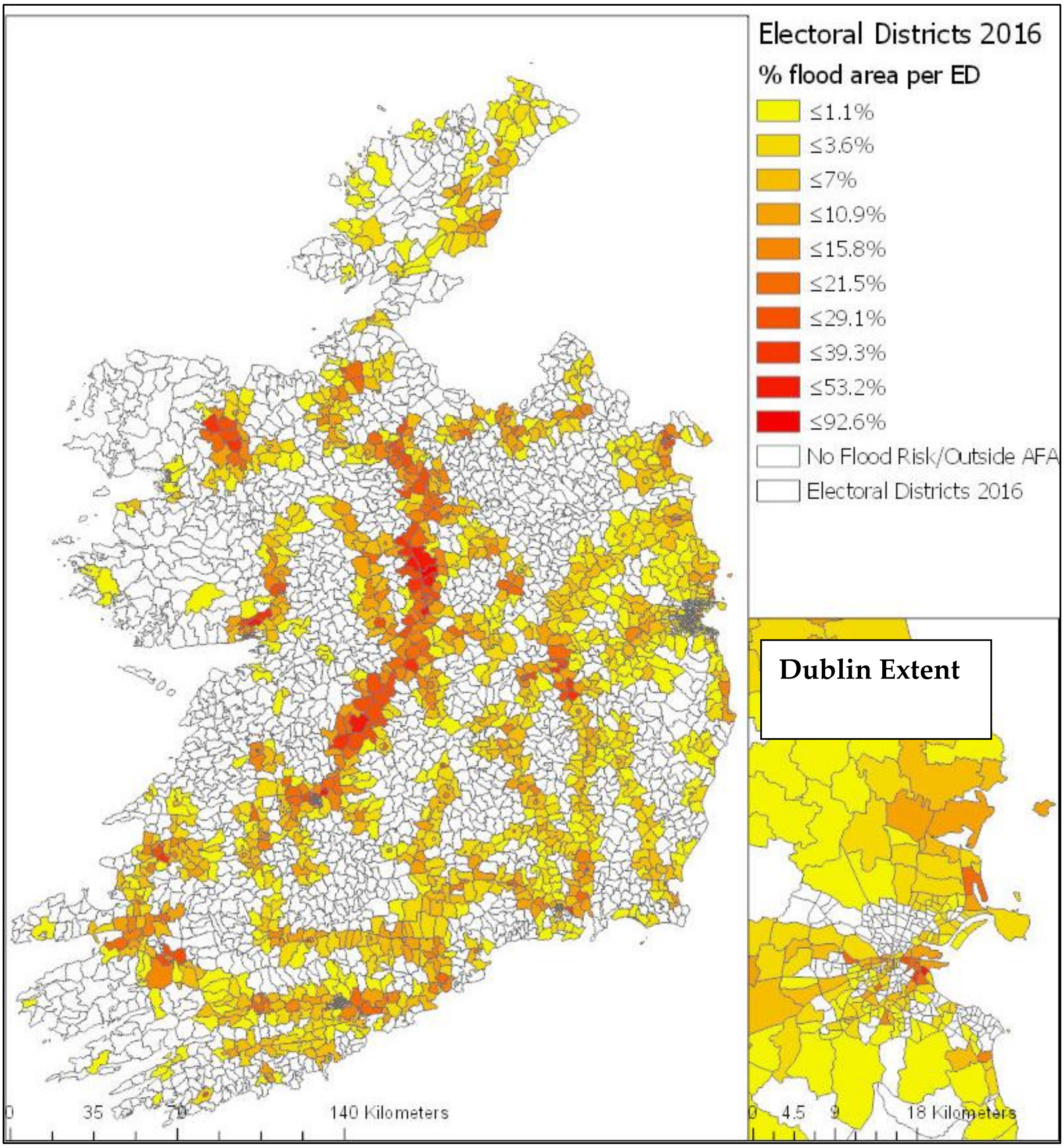
Note: The above figure shows boundary outlines for electoral districts and small areas, the primary levels of SFE used in the analysis.

Floods Appendix, Figure A 6: Distribution of sales listings per ED



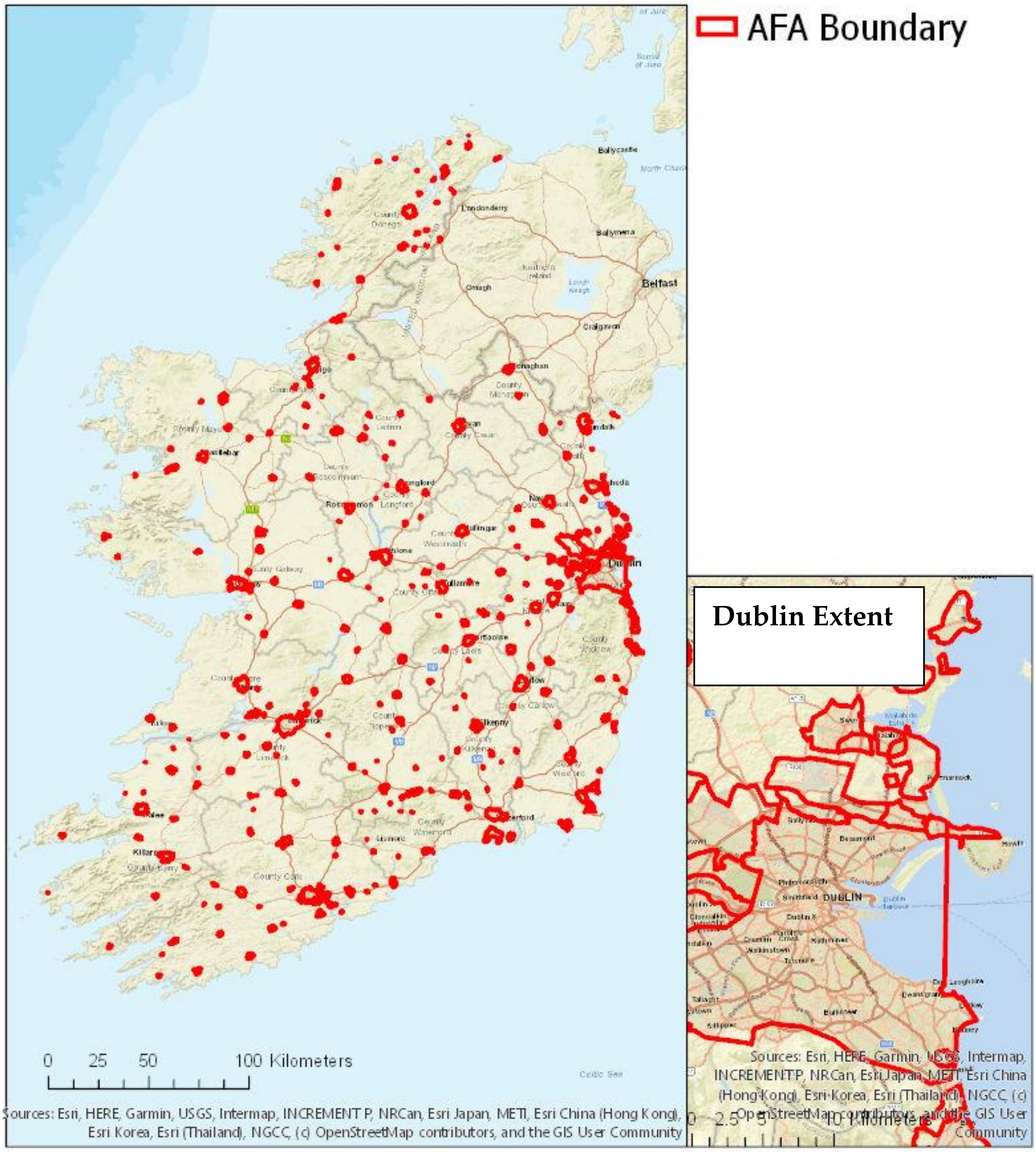
Note: The above figure displays the number of sales listings per electoral district.

Floods Appendix, Figure A 7: Distribution of flood risk per ED



Note: The above figure displays the percentage of electoral district area which is classified as a medium/high coastal/fluvial flood risk zone from the CFRAM dataset. Blank ED's either have no flood risk or are outside AFA boundaries.

Floods Appendix, Figure A 8: AFA boundaries



Note: The above figure displays boundaries of the "Areas of Further Assessment" (AFAs), which define the geographic scope of the samples used in the *baseline (preferred) specifications.*

Floods Appendix, Table A 3: Continuous Variables frequencies

Sales Listings 2006-18

VARIABLES	N	mean	sd	min	p25	p50	p75	max
Listed Sale Price*	284,954	276,167	195,393	30,000	158,000	235,000	335,000	2.00E+06
Distance to Primary school*	284,954	587	409.1	0.414	297.4	483.7	759.8	6,306
Distance to Secondary school*	284,954	1,150	1,621	2.578	446.4	733.7	1,210	19,887
Distance to CBD*	284,954	28,930	29,039	0.393	5,110	15,409	44,046	130,428
Distance to major road*	284,954	1,466	2,103	0.0177	345.5	798.5	1,684	29,257
% unemployed	284,936	11.55	6.05	0	6.993	10.73	15.06	56.28
% with degree	284,861	11.07	6.914	0	5.882	10	15	50
Distance to coastline*	284,954	19,546	23,123	0.226	2,756	8,964	29,075	91,916
Dist. trans. Waters*	284,954	12,633	19,080	0	1,085	3,844	15,380	85,652
Sea view (see section 4.2.2)	284,954	0.00637	0.0371	0	0	0	0	0.544

Sales Transactions 2011-18

VARIABLES	N	mean	sd	min	p25	p50	p75	max
Transacted Sale price*	36,341	361,951	218,513	31,276	222,000	305,000	435,000	2.00E+06
Floor area (m^2)*	36,341	99.22	41.88	11.59	72.18	91.46	116.4	726.3
Main water heating efficiency	36,070	82.76	14.89	30	75.4	79.4	90.5	417
Main space heating efficiency	36,070	82.57	19.39	30	75	79.2	90.4	566
Building age	36,341	41.61	32.3	-4	15	32	61	258
Building area*	36,341	151.4	670.1	0	50.22	64.34	86.46	45,141
Distance to CBD*	36,341	1,184	1,226	0.0968	377.3	856.8	1,610	8,942
Distance to major road*	36,341	7,998	5,395	72.93	4,069	7,156	10,969	31,226
Distance to primary school*	36,341	470.9	272.7	10.42	274.2	424	611.7	3,075
Distance to secondary school*	36,341	754.1	597.8	34.58	400.5	622.4	895.6	8,778
% unemployed	36,341	8.845	5.012	0	5	7.975	11.73	40.86
% with degree	36,341	14.51	8.247	0	8	13.79	19.79	45.45
Distance to coastline*	36,341	5,138	4,216	5.713	1,734	4,000	7,162	20,947
Distance transitional waters*	36,341	4,048	2,930	6.859	1,475	3,356	6,556	15,419
Sea view (see section 4.2.2)	36,338	0.0101	0.0452	0	0	0	0	0.613

Rental Listings 2011-18

VARIABLES	N	mean	sd	min	p25	p50	p75	max
Listed Rent (annual)*	390,353	13,269	7,804	2,086	8,340	11,400	15,642	108,000
Distance to primary school*	390,353	523	362.7	1	264.9	440.6	680.3	6,298
Distance to secondary school*	390,353	879.7	1,171	2.51	370.3	606.8	972.1	19,836
Distance to CBD*	390,353	20,477	26,670	3.47	2,350	7,361	29,757	130,386
Distance to major road*	390,353	1,062	1,512	0.00102	253.2	618.8	1,254	29,256
% unemployed	390,353	10.85	6.227	0	6.04	9.836	14.43	56.28
% with degree	390,322	14.43	8.408	0	7.826	13.19	19.88	66.67
Distance to coastline*	390,353	14,139	19,980	0.0637	2,014	5,170	14,318	91,823
Dist. trans. Waters*	390,353	8,577	15,859	0	642.1	2,021	7,152	85,802
Sea view (see section 4.2.2)	390,353	0.00614	0.035	0	0	0	0	0.551

*Note the above table displays descriptive statistics for the continuous variables included in model specifications from the analysis, for the three main samples: sales listings, sales transactions, and rental listings. Variables marked with a * undergo a natural log transformation in regressions.*

Floods Appendix, Table A 4: Frequency of categorical variables

		Sales Listings 2011-18		Sales Transactions 2011-18		Sales Listings 2006-18		Rental Listings 2011-18	
Property Type									
Apartment		30,039	15.75%	7,681	21.14%	33,231	11.66%		49.50%
Terraced		34,871	18.28%	8,531	23.47%	53,907	18.92%	N/A	
End-of Terrace		13,346	7.00%	3,456	9.51%	19,336	6.79%	N/A	
Bungalow		7,351	3.85%	836	2.30%	10,678	3.75%	N/A	
Detached		34,243	17.95%	2,829	7.78%	51,901	18.21%	N/A	
Duplex		2,664	1.40%	853	2.35%	3,029	1.06%	N/A	
Townhouse		3,490	1.83%	438	1.21%	5,550	1.95%	N/A	
Semi-Detached		64,772	33.95%	11,717	32.24%	107,322	37.66%	N/A	
House		N/A		N/A		N/A			3.47%
Flat		N/A		N/A		N/A			46.80%
Studio		N/A		N/A		N/A			0.23%
Total		**190,776**	**100%**	**36,341**	**100%**	**284,954**	**100%**	**390,353**	**100%**
Property Size									
	11	6,898	3.62%	2,039	5.61%	8,146	2.86%	69847	17.89%
	12	202	0.11%	41	0.11%	249	0.09%	1391	0.36%
	13	17	0.01%			31	0.01%	48	0.01%
	14	5	0.00%			17	0.01%	12	0.00%
	15	1	0.00%			1	0.00%	1	0.00%
	16	0	0.00%			0	0.00%	1	0.00%
	21	23,317	12.22%	6,030	16.59%	31,869	11.18%	83049	21.28%
	22	15,482	8.12%	3,875	10.66%	18,131	6.36%	67889	17.39%
	23	1,213	0.64%	205	0.56%	1,565	0.55%	3456	0.89%
	24	13	0.01%	3	0.01%	18	0.01%	29	0.01%
	25	0	0.00%			0	0.00%	2	0.00%
	26	1	0.00%			1	0.00%	1	0.00%
	27	0	0.00%	0		0	0.00%	2	0.00%
	31	35,435	18.57%	7,987	21.98%	61,424	21.56%	36358	9.31%
	32	29,235	15.32%	5,457	15.02%	44,635	15.66%	43270	11.08%
	33	18,066	9.47%	2,904	7.99%	26,248	9.21%	25534	6.54%
	34	635	0.33%	126	0.35%	803	0.28%	889	0.23%
	35	18	0.01%	3	0.01%	21	0.01%	20	0.01%
	36	3	0.00%			3	0.00%	7	0.00%
	37	2	0.00%			2	0.00%	2	0.00%
	41	7,238	3.79%	1,163	3.20%	14,301	5.02%	6987	1.79%
	42	18,001	9.44%	2,526	6.95%	27,788	9.75%	19330	4.95%
	43	19,569	10.26%	2,288	6.30%	28,016	9.83%	19096	4.89%
	44	3,891	2.04%	389	1.07%	4,883	1.71%	3183	0.82%
	45	492	0.26%	50	0.14%	588	0.21%	473	0.12%
	46	50	0.03%	6	0.02%	66	0.02%	30	0.01%

	Sales Listings 2011-18		Sales Transactions 2011-18		Sales Listings 2006-18		Rental Listings 2011-18	
47	1	0.00%			4	0.00%	6	0.00%
51	829	0.43%	103	0.28%	1,919	0.67%	545	0.14%
52	2,840	1.49%	385	1.06%	4,391	1.54%	2812	0.72%
53	4,111	2.15%	462	1.27%	5,741	2.01%	3586	0.92%
54	2,265	1.19%	218	0.60%	2,942	1.03%	1767	0.45%
55	718	0.38%	63	0.17%	875	0.31%	565	0.14%
56	199	0.10%	15	0.04%	243	0.09%	139	0.04%
57	29	0.02%	3	0.01%	33	0.01%	26	0.01%
Phrase (Dummy)								
"balcony"	16,816	8.81%	5,208	14.33%	18,543	6.51%	56,497	14.47%
"bay_window"	23,122	12.12%	4,204	11.57%	33,402	11.72%	3,765	0.96%
"conservatory"	5,202	2.73%	1,266	3.48%	8,041	2.82%	3,802	0.97%
"deck"	14,269	7.48%	3,447	9.49%	23,394	8.21%	10,720	2.75%
"double_glaze"	46,892	24.58%	9,650	26.55%	73,574	25.82%	17,105	4.38%
"edwardian"	418	0.22%	154	0.42%	535	0.19%	234	0.06%
"ensuite"	56,845	29.80%	9,623	26.48%	81,595	28.63%	81,701	20.93%
"fireplace"	86,136	45.15%	18,233	50.17%	125,783	44.14%	24,959	6.39%
"frenchdoors"	13,462	7.06%	2,692	7.41%	18,400	6.46%	3,749	0.96%
"garage"	24,914	13.06%	5,224	14.37%	36,429	12.78%	11,926	3.06%
"garden"	125,408	65.74%	27,462	75.57%	188,785	66.25%	126,964	32.53%
"georgian"	1,159	0.61%	186	0.51%	1,641	0.58%	2,765	0.71%
"granny_flat"	944	0.49%	162	0.45%	1,323	0.46%	395	0.10%
"highceilings"	4,156	2.18%	1,227	3.38%	5,064	1.78%	4,127	1.06%
"jacuzzi"	3,808	2.00%	642	1.77%	5,449	1.91%	2,955	0.76%
"mews"	1,247	0.65%	274	0.75%	1,543	0.54%	2,422	0.62%
"patio"	57,123	29.94%	10,563	29.07%	83,819	29.41%	36,588	9.37%
"period"	5,637	2.95%	1,713	4.71%	7,340	2.58%	7,732	1.98%
"redbrick"	5,226	2.74%	1,881	5.18%	7,361	2.58%	1,737	0.44%
"sash"	1,610	0.84%	406	1.12%	2,027	0.71%	1,210	0.31%
"securitygates"	729	0.38%	214	0.59%	940	0.33%	2,182	0.56%
"solar"	2,351	1.23%	249	0.69%	2,617	0.92%	989	0.25%
"sunroom"	7,760	4.07%	1,505	4.14%	11,067	3.88%	3,199	0.82%
"terrace"	41,326	21.66%	9,724	26.76%	62,384	21.89%	39,934	10.23%
"tripleglaze"	1,102	0.58%	229	0.63%	1,136	0.40%	524	0.13%
"underfloor"	2,675	1.40%	663	1.82%	3,313	1.16%	4,466	1.14%
"utility"	54,966	28.81%	7,998	22.01%	79,798	28.00%	39,760	10.19%
"victorian"	1,769	0.93%	507	1.40%	2,273	0.80%	1,553	0.40%
"walkinwardrobe"	6,602	3.46%	939	2.58%	8,585	3.01%	4,688	1.20%
"wetroom"	4,330	2.27%	1,201	3.30%	4,914	1.72%	1,626	0.42%

	Sales Listings 2011-18		Sales Transactions 2011-18		Sales Listings 2006-18		Rental Listings 2011-18	
river_views (<75m &"views"==1)	1,367	0.72%	212	0.58%	1,632	0.57%	2,606	0.67%
lake_views (<75m &"views"==1)	233	0.12%	74	0.20%	255	0.09%	834	0.21%
Golf Course								
>1k (Base)	151,366	79.34%	27,792	76.48%	226,827	79.60%	320,861	82.20%
500m-1k	23,645	12.39%	4,908	13.51%	35,146	12.33%	43,280	11.09%
250m-500m	8,988	4.71%	2,080	5.72%	13,379	4.70%	15,455	3.96%
100m-250m	4,518	2.37%	1,073	2.95%	6,472	2.27%	7,228	1.85%
<100m	2,259	1.18%	488	1.34%	3,130	1.10%	3,529	0.90%
Powerlines								
>1k (Base)	157,827	82.73%	29,631	81.54%	232,872	81.72%	337,335	86.42%
500m-1k	18,320	9.60%	3,521	9.69%	28,794	10.10%	29,882	7.66%
250m-500m	7,414	3.89%	1,593	4.38%	11,868	4.16%	11,821	3.03%
100m-250m	4,556	2.39%	1,004	2.76%	7,165	2.51%	6,888	1.76%
<100m	2,659	1.39%	592	1.63%	4,255	1.49%	4,427	1.13%
Mixed Woodlands								
>1k (Base)	167,044	87.56%	29,581	81.40%	250,241	87.82%	350,272	89.73%
500m-1k	14,918	7.82%	4,508	12.40%	21,823	7.66%	25,257	6.47%
250m-500m	5,508	2.89%	1,442	3.97%	8,216	2.88%	8,544	2.19%
100m-250m	2,198	1.15%	547	1.51%	3,184	1.12%	4,212	1.08%
<100m	1,108	0.58%	263	0.72%	1,490	0.52%	2,068	0.53%
Deciduous Woodlands								
>1k (Base)	140,184	73.48%	27,502	75.68%	208,752	73.26%	300,226	76.91%
500m-1k	29,975	15.71%	5,856	16.11%	45,429	15.94%	52,248	13.38%
250m-500m	12,743	6.68%	1,853	5.10%	19,294	6.77%	22,552	5.78%
100m-250m	5,361	2.81%	878	2.42%	7,736	2.71%	10,348	2.65%
<100m	2,513	1.32%	252	0.69%	3,743	1.31%	4,979	1.28%
Conifer Woodlands								
>1k (Base)	160,897	84.34%	34,236	94.21%	240,350	84.35%	344,510	88.26%
500m-1k	17,947	9.41%	1,253	3.45%	27,161	9.53%	27,881	7.14%
250m-500m	6,848	3.59%	508	1.40%	10,179	3.57%	10,355	2.65%
100m-250m	3,563	1.87%	236	0.65%	5,121	1.80%	5,142	1.32%
<100m	1,521	0.80%	108	0.30%	2,143	0.75%	2,465	0.63%
Nature Reserve								
>1k (Base)	183,935	96.41%	32,782	90.21%	276,333	96.97%	372,875	95.52%
500m-1k	3,719	1.95%	1,964	5.40%	4,693	1.65%	9,246	2.37%
250m-500m	1,799	0.94%	962	2.65%	2,272	0.80%	4,764	1.22%
100m-250m	944	0.49%	483	1.33%	1,221	0.43%	2,407	0.62%
<100m	379	0.20%	150	0.41%	435	0.15%	1,061	0.27%
Canals								
>1k (Base)	162,436	85.14%	27,746	76.35%	244,472	85.79%	302,209	77.42%
500m-1k	13,599	7.13%	4,214	11.60%	20,185	7.08%	39,562	10.13%
250m-500m	7,734	4.05%	2,333	6.42%	10,872	3.82%	25,226	6.46%
100m-250m	4,804	2.52%	1,414	3.89%	6,626	2.33%	15,468	3.96%

		Sales Listings 2011-18			Sales Transactions 2011-18		Sales Listings 2006-18		Rental Listings 2011-18	
<100m		2,203	1.15%		634	1.74%	2,799	0.98%	7,888	2.02%
Rivers										
>1k (Base)		97,061	50.88%		24,098	66.31%	144,400	50.67%	184,762	47.33%
500m-1k		40,773	21.37%		6,077	16.72%	63,254	22.20%	81,476	20.87%
250m-500m		27,316	14.32%		3,377	9.29%	40,834	14.33%	57,796	14.81%
100m-250m		16,442	8.62%		1,818	5.00%	24,146	8.47%	38,784	9.94%
<100m		9,184	4.81%		971	2.67%	12,320	4.32%	27,535	7.05%
Lakes										
>1k (Base)		166,383	87.21%		30,931	85.11%	249,200	87.45%	322,861	82.71%
500m-1k		16,216	8.50%		3,748	10.31%	24,408	8.57%	41,193	10.55%
250m-500m		5,255	2.75%		1,064	2.93%	7,444	2.61%	16,208	4.15%
100m-250m		2,195	1.15%		402	1.11%	3,061	1.07%	6,860	1.76%
<100m		727	0.38%		196	0.54%	841	0.30%	3,231	0.83%
Flood Variables										
Risk										
	0	65,210	34.18%		19,322	53.17%	98,418	34.54%		32.01%
Before defence or no defence										
1. (500-200m)		55,160	28.91%		8,236	22.66%	84,961	29.82%		25.72%
2. (200-100m)		27,032	14.17%		3,300	9.08%	40,529	14.22%		13.83%
3. (<100m from low risk)		33,182	17.39%		4,079	11.22%	47,546	16.69%		19.65%
4. (inside low risk)		4,792	2.51%		663	1.82%	6,776	2.38%		3.92%
5. (inside med or high)		4,025	2.11%		268	0.74%	5,290	1.86%		3.88%
After defence										
6. (500-200m)		54	0.03%		24	0.07%	54	0.02%		0.03%
7. (200-100m)		20	0.01%		3	0.01%	20	0.01%		0.02%
8. (<100m from low risk)		373	0.20%		57	0.16%	388	0.14%		0.25%
9. (inside low risk)		720	0.38%		287	0.79%	763	0.27%		0.61%
10. (inside med or high)		208	0.11%		102	0.28%	209	0.07%		0.10%
Events										
	0	178,891	93.77%		34,075	93.76%	269,795	94.68%		90.28%
250 m radius from listing (base										
1. (>30years)			92	0.05%	23	0.06%	302	0.11%	1,075	0.28%
2. (10-50 years)		1,854	0.97%		294	0.81%	2,426	0.85%		1.32%
3. (5-10 years)		1,993	1.04%		489	1.35%	2,614	0.92%		1.17%
4. (2-5 years)		2,059	1.08%		450	1.24%	2,524	0.89%		1.44%
5. (<2 years)		1,078	0.57%		145	0.40%	1,291	0.45%		1.34%
100m radius from listing										
6. (>30years)			1,340	0.70%	283	0.78%	1,665	0.58%	3,998	1.02%
7. (10-50 years)		2,043	1.07%		301	0.83%	2,461	0.86%		1.63%
8. (5-10 years)		633	0.33%		134	0.37%	907	0.32%		0.66%

	Sales Listings 2011-18		Sales Transactions 2011-18		Sales Listings 2006-18		Rental Listings 2011-18	
9. (2-5 years)	548	0.29%	117	0.32%	686	0.24%		0.49%
10. (<2 years)	245	0.13%	30	0.08%	283	0.10%		0.37%
Year Quarter								
2006Q1	0		0		1,252	0.44%	0	
2006Q2	0		0		2,830	0.99%	0	
2006Q3	0		0		4,663	1.64%	0	
2006Q4	0		0		4,613	1.62%	0	
2007Q1	0		0		7,787	2.73%	0	
2007Q2	0		0		7,849	2.75%	0	
2007Q3	0		0		8,098	2.84%	0	
2007Q4	0		0		6,255	2.20%	0	
2008Q1	0		0		6,450	2.26%	0	
2008Q2	0		0		6,537	2.29%	0	
2008Q3	0		0		5,518	1.94%	0	
2008Q4	0		0		3,159	1.11%	0	
2009Q1	0		0		3,514	1.23%	0	
2009Q2	0		0		3,953	1.39%	0	
2009Q3	0		0		3,710	1.30%	0	
2009Q4	0		0		2,405	0.84%	0	
2010Q1	0		0		3,232	1.13%	0	
2010Q2	0		0		4,345	1.52%	0	
2010Q3	0		0		4,890	1.72%	0	
2010Q4	0		0		3,118	1.09%	0	
2011Q1	4,506	2.36%	20	0.06%	4,506	1.58%		4.82%
2011Q2	4,957	2.60%	138	0.38%	4,957	1.74%		5.35%
2011Q3	4,559	2.39%	319	0.88%	4,559	1.60%		5.73%
2011Q4	2,822	1.48%	422	1.16%	2,822	0.99%		4.00%
2012Q1	3,836	2.01%	333	0.92%	3,836	1.35%		4.48%
2012Q2	3,982	2.09%	445	1.22%	3,982	1.40%		4.85%
2012Q3	3,832	2.01%	549	1.51%	3,832	1.34%		4.82%
2012Q4	3,214	1.68%	796	2.19%	3,214	1.13%		3.34%
2013Q1	3,774	1.98%	397	1.09%	3,774	1.32%		3.75%
2013Q2	5,140	2.69%	584	1.61%	5,140	1.80%		3.47%
2013Q3	4,695	2.46%	902	2.48%	4,695	1.65%		3.71%
2013Q4	3,440	1.80%	1,076	2.96%	3,440	1.21%		2.56%
2014Q1	4,481	2.35%	666	1.83%	4,481	1.57%		2.65%
2014Q2	6,549	3.43%	860	2.37%	6,549	2.30%		2.94%
2014Q3	6,102	3.20%	1,228	3.38%	6,102	2.14%		3.04%
2014Q4	4,924	2.58%	1,420	3.91%	4,924	1.73%		2.27%

	Sales Listings 2011-18		Sales Transactions 2011-18		Sales Listings 2006-18		Rental Listings 2011-18	
2015Q1	6,759	3.54%	1,242	3.42%	6,759	2.37%		2.70%
2015Q2	8,028	4.21%	1,224	3.37%	8,028	2.82%		2.67%
2015Q3	7,229	3.79%	1,556	4.28%	7,229	2.54%		2.77%
2015Q4	4,735	2.48%	1,541	4.24%	4,735	1.66%		2.15%
2016Q1	6,463	3.39%	1,122	3.09%	6,463	2.27%		2.32%
2016Q2	8,177	4.29%	1,268	3.49%	8,177	2.87%		2.46%
2016Q3	7,235	3.79%	1,721	4.74%	7,235	2.54%		2.54%
2016Q4	4,911	2.57%	1,776	4.89%	4,911	1.72%		2.19%
2017Q1	7,112	3.73%	1,254	3.45%	7,112	2.50%		2.36%
2017Q2	8,405	4.41%	1,379	3.79%	8,405	2.95%		2.39%
2017Q3	8,500	4.46%	1,770	4.87%	8,500	2.98%		2.43%
2017Q4	6,865	3.60%	1,960	5.39%	6,865	2.41%		2.12%
2018Q1	7,567	3.97%	1,515	4.17%	7,567	2.66%		2.21%
2018Q2	10,385	5.44%	1,566	4.31%	10,385	3.64%		2.30%
2018Q3	10,257	5.38%	1,902	5.23%	10,257	3.60%		2.48%
2018Q4	7,335	3.84%	2,020	5.56%	7,335	2.57%		2.12%
2019Q1	0	0.00%	1,285	3.54%	0	0.00%	0	0.00%
2019Q2	0	0.00%	31	0.09%	0	0.00%	0	0.00%
Total	190,776	100%	36,341	100.00%	284,954	100.00%	390,323	100%

BER Data

New or Second-hand		
New Dwelling	435	1.20%
Second-Hand Dwelling	35,906	98.80%
stories		
0	3	0.01%
1	8,830	24.30%
2	24,031	66.13%
3	3,408	9.38%
4	64	0.18%
5	5	0.01%
Insulation Type		
Masonry	21,954	60.41%
Mixed Masonry/Timber	13,626	37.49%
Timber	751	2.07%
Glazing		
Double/Triple	521	1.43%
Double	24,467	67.33%
None	1	0.00%
Single/Double/Triple	116	0.32%
Single/Double	8,564	23.57%
Single/Triple	30	0.08%

	Sales Listings 2011-18		Sales Transactions 2011-18		Sales Listings 2006-18		Rental Listings 2011-18	
Single			2,468	6.79%				
Triple			174	0.48%				
Fuel type								
Electricity			5,483	15.09%				
Gas			27,199	74.84%				
Oil			3,159	8.69%				
Solid Fuel			229	0.63%				
BER rating				0.00%				
A2			39	0.11%				
A3			242	0.67%				
B1			185	0.51%				
B2			855	2.35%				
B3			2,116	5.82%				
C1			2,803	7.71%				
C2			3,457	9.51%				
C3			3,896	10.72%				
D1			4,756	13.09%				
D2			5,050	13.90%				
E1			3,392	9.33%				
E2			3,112	8.56%				
F			3,351	9.22%				
G			3,087	8.49%				
Total	0	0%	36,341	100.00%				
<u>Rental Data</u>								
Rental Dummy Variables								
Garden							263,416	67.48%
Parking							251,114	64.33%
Central heating							80,358	20.59%
House alarm							167,746	42.97%
Cable television							231,959	59.42%
Washing machine							134,083	34.35%
Dryer							104,626	26.80%
Dishwasher							202,119	51.78%
Microwave							172,476	44.18%
Pets allowed							229,718	58.85%
Wheelchair access							369,677	94.70%
Internet							281,559	72.13%
Lettings agent								
Yes							118,168	30.27%

	Sales Listings 2011-18	Sales Transactions 2011-18	Sales Listings 2006-18	Rental Listings 2011-18	
Lease (months)					
0				17,141	4.39%
3				4,568	1.17%
6				21,178	5.43%
9				4,582	1.17%
12				341,686	87.53%
24				779	0.20%
36				419	0.11%
Rent allowance					
0				254,399	65.17%
1				110,890	28.41%
2				25,064	6.42%
Furnished					
0				1,491	0.38%
1				354,649	90.85%
2				15,342	3.93%
3				18,871	4.83%
Bed single					
10				67,556	17.31%
11				3,744	0.96%
20				126,621	32.44%
21				26,410	6.77%
22				1,397	0.36%
30				28,442	7.29%
31				72,806	18.65%
32				4,198	1.08%
33				634	0.16%
40				13,244	3.39%
41				24,361	6.24%
42				10,323	2.64%
43				805	0.21%
44				372	0.10%
50				3,192	0.82%
51				3,578	0.92%
52				1,902	0.49%
53				495	0.13%
54				134	0.03%
55				139	0.04%

Appendix B: Additional results

Floods Appendix, Table B 1: Main specification on all three datasets

	Sale Listings Post-2010	Rental Listings Post-2010	Sale Transactions Post-2010
Level of Fixed Effect	**Census ED**	**Census ED**	**Census ED**
No flood defences			
500m-200m away	-0.001	0.003	0.003
	-0.3	3.2	0.9
200m-100m away	-0.007	0.005	-0.003
	-2.9	4.3	-0.6
<100m from low risk	-0.011	0.008	-0.012
	-4.2	6.2	-2.4
Inside low risk	-0.011	0.009	-0.027
	-2.1	4.5	-2.7
Inside medium/high	-0.031	-0.002	-0.062
	-4.9	-1.0	-4.2
After flood defences			
500m-200m away	-0.041	0.065	-0.068
	-1.2	4.2	-1.4
200m-100m away	-0.011	0.004	0.060
	-0.2	0.3	1.1
<100m from low risk	-0.011	-0.011	-0.037
	-0.7	-1.8	-1.4
Inside low risk	-0.024	0.002	-0.042
	-1.7	0.3	-2.3
Inside medium/high	0.097	0.023	0.027
	4.9	2.1	1.0
Last flood event 100-250 metres from the dwelling			
More than 30 years	-0.036	-0.061	-0.052
	-0.9	-10.0	-0.9
10-30 years	-0.016	0.011	0.017
	-2.2	4.1	1.6
5-10 years	-0.008	-0.003	0.012
	-1.3	-1.0	1.6
2-5 years	0.015	0.015	0.013
	2.2	5.5	1.4
Less than 2 years	-0.027	-0.008	-0.036
	-2.6	-3.0	-1.6
Last flood event within 100 metres of the dwelling			
More than 30 years	-0.024	-0.002	-0.026
	-2.2	-0.6	-1.6
10-30 years	0.011	0.028	-0.010
	1.5	10.2	-0.6
5-10 years	-0.011	0.009	0.046
	-0.9	2.3	3.2
2-5 years	-0.011	-0.008	0.032
	-0.8	-2.0	1.7
Less than 2 years	-0.043	-0.004	-0.011
	-2.0	-1.0	-0.2
Controls	YES	YES	YES
Observations	190,635	390,301	35,922
R-squared	0.842	0.878	0.897
RMSE	0.263	0.169	0.172

Spatial units	1,020	1,003	322

Notes: Regression results show coefficients on various measures of flood risk and flood events, as discussed in the text, where the dependent variable is the natural log of the dwelling's listed sale price, listed rental price, and transacted sale price, respectively. Robust t-statistics are shown underneath each coefficient. Different columns show results using different samples as discussed in the text. Controls include dwelling characteristics, location amenities, and market conditions, as discussed in the text. Columns (1) and (2) here report extended results from the same specifications as reported in Columns (2) and (4) of Table 6.2 in the main text. Column (3) here reports extended results from the same specification as reported in Column (1) of Table 6.4 in the main text.

Floods Appendix, Table B 2: Additional robustness checks

Specification	(1)	(2)	(3)	(4)	(5)	(6)
No flood defences						
500m-200m away	-0.001	-0.001		-0.001	-0.007	-0.010
	-0.3	-0.3		-0.3	-4.2	-5.3
200m-100m away	-0.007	-0.007		-0.007	-0.008	-0.016
	-2.9	-2.9		-2.8	-3.4	-6.2
<100m from low risk	-0.011	-0.012		-0.010	-0.013	-0.019
	-4.2	-4.4		-3.7	-5.8	-7.1
Inside low risk	-0.011	-0.012		-0.010	-0.009	-0.017
	-2.1	-2.3		-1.8	-1.7	-2.9
Inside medium/high	-0.031	-0.032		-0.029	-0.026	-0.034
	-4.9	-5.1		-4.3	-7.7	-9.1
After flood defences						
500m-200m away	-0.041	-0.058		-0.042	-0.072	-0.088
	-1.2	-1.7		-1.2	-2.0	-2.7
200m-100m away	-0.011	-0.010		-0.008	-0.095	-0.079
	-0.2	-0.2		-0.2	-2.0	-1.7
<100m from low risk	-0.011	-0.013		-0.009	-0.046	-0.060
	-0.7	-0.9		-0.6	-2.5	-3.4
Inside low risk	-0.024	-0.026		-0.038	-0.095	-0.085
	-1.7	-1.9		-2.6	-4.6	-4.0
Inside medium/high	0.097	0.097		0.093	-0.014	-0.026
	4.9	4.9		4.2	-1.4	-2.6
Last flood event 100-250 metres from the dwelling						
More than 30 years	-0.036		-0.038	-0.038	-0.055	-0.034
	-0.9		-1.0	-1.0	-1.4	-0.9
10-30 years	-0.016		-0.018	-0.018	-0.015	-0.014
	-2.2		-2.5	-2.4	-2.1	-1.9
5-10 years	-0.008		-0.010	-0.027	-0.010	-0.007
	-1.3		-1.7	-2.9	-1.7	-1.2
2-5 years	0.015		0.014	-0.006	0.021	0.016
	2.2		1.9	-0.6	3.0	2.3
Less than 2 years	-0.027		-0.029	-0.028	-0.037	-0.027
	-2.6		-2.8	-2.1	-3.7	-2.6
Last flood event within 100 metres of the dwelling						
More than 30 years	-0.024		-0.029	-0.027	-0.003	-0.019
	-2.2		-2.6	-2.4	-0.3	-1.7
10-30 years	0.011		0.009	0.010	0.011	0.016
	1.5		1.2	1.3	1.5	2.1
5-10 years	-0.011		-0.014	-0.037	-0.015	-0.009
	-0.9		-1.1	-2.1	-1.2	-0.7
2-5 years	-0.011		-0.014	-0.054	-0.017	-0.008
	-0.8		-1.0	-2.9	-1.3	-0.6
Less than 2 years	-0.043		-0.047	-0.054	-0.053	-0.043
	-2.0		-2.2	-1.8	-2.6	-2.0
Controls	YES	YES	YES	YES	YES	YES
Observations	190,635	190,635	190,635	188,132	299,070	190,635
R-squared	0.842	0.842	0.842	0.841	0.798	0.842
RMSE	0.263	0.263	0.263	0.263	0.294	0.263
Spatial units absorbed	1,020	1,020	1,020	1,020	3,395	1,020

Notes: Regression results show coefficients on various measures of flood risk and flood events, as discussed in the text, where the dependent variable is the natural log of the dwelling's listed sale price. Robust t-statistics are shown underneath each *coefficient. Different columns show separate specifications as discussed in the text. Controls include dwelling characteristics, location amenities, and market conditions, as discussed in the text. Column (1) here is the same as Column (1) of Floods Appendix, Table B 1 above, for ease of comparison. The second and third columns here replicate Column (1) but omitting events (Column 2), or omitting flood risk (Column 3). Column (4) drops all observations that were affected by a major flood event in 2011. Approximately 2,500 observations were removed from the sample that were within 250m of that particular flood event based on flood event points, or observations that were within a flood event polygon related to that flood. The specifications reported in Columns (5) and (6) use flood risk data from the Preliminary Flood Risk Assessment (PFRA) maps. The variables are calculated in exactly the same way as described previously. Column (5) uses the full nationwide sample of sale listings, as the PFRA maps were not restricted to the AFA boundaries. Column (6) reports a specification where flood risk is defined using the PFRA maps, but restricting the sample to dwellings within AFAs.*

Floods Appendix, Table B 3: Border Discontinuity style analysis

	Baseline model	500m	Terraced and semi-detached	Terraced and semi-detached 500m
	(1)	(2)	(3)	(4)
No flood defences				
500m-200m away	-0.001		-0.005	
	-0.3		-2.3	
200m-100m away	-0.007	-0.007	-0.014	-0.008
	-2.9	-3.3	-4.6	-3.0
<100m from low risk	-0.011	-0.012	-0.012	-0.005
	-4.2	-4.9	-3.7	-1.8
Inside low risk	-0.011	-0.012	-0.012	-0.005
	-2.1	-2.3	-1.7	-0.7
Inside medium/high	-0.031	-0.034	-0.021	-0.016
	-4.9	-5.5	-2.3	-1.7
After flood defences				
Inside medium/high	0.097	0.096	0.144	0.149
	4.9	4.7	5.9	5.9
Controls	YES	YES	YES	YES
Observations	190,635	125,478	112,929	70,286
R-squared	0.842	0.828	0.865	0.849
RMSE	0.263	0.276	0.235	0.249
Spatial units absorbed	1,020	887	943	808

Notes: Regression results show coefficients on various measures of flood risk, as discussed in the text, where the dependent variable is the natural log of the dwelling's listed sale price. Robust t-statistics are shown underneath each coefficient. Different columns show separate specifications related to the border discontinuity style analysis, as discussed in the text. Controls include dwelling characteristics, location amenities, and market conditions, as discussed in the text. Column (1) replicates the *baseline model, as reported in Column (2) of Table 6.1 in the main text. Column (2) restricts the control group to dwellings no more than 500m away from a flood risk zone. Column (3) restricts the sample to terraced and semi-detached dwellings only. Column (4) restricts the sample both by dwelling type and by distance of control group dwellings from flood risk zones.*

Appendix C: Survey

Complete copy of survey (full list of survey questions)

1. Which of the following best describes the reason you visited *daft.ie* today?

   Interested in buying a property

   Interested in renting a property

   Looking to sell or rent out the property or the client's property

   Other, including general browsing or market research

2. What area(s) are you looking in?

   Drop down menu of 54 local markets

3. When choosing where to live, how important are the following factors:

   1 to 5 number scale very important to not important

   Proximity to Central business district of nearest city/town

   Proximity to Schools

   Proximity to Coastline

   Neighbourhood quality

   Proximity to Transport network (train stations etc)

   Proximity to Mountains

   No risk of flooding

   Proximity to Sports facilities (football pitch, golf course, etc)

   Proximity to Green spaces (parks, fields, etc)

   Proximity to Other inland blue spaces (rivers, lakes, canals, etc)

   Proximity to Forestry

   Proximity to Hospitals

4. Specifically thinking about the areas you are looking at, do you think flood risk is relevant to those areas?

Yes

No

Don't know

5. (Logical if yes to 4) Are you aware of the flood risk in the area in which you are searching, and for the properties you may be interested in?

Yes

No

6. (Logical if yes to 5) Please check the box which indicates the source from which you obtained the flood risk information

Local knowledge

Online resource

Ordinance survey maps

Property agency

Bank

Other (you may specify if you wish)

7. [logical yes to 5] Was it straightforward to find out the flood risk information for that particular location?

1. Straightforward
2. Somewhat straightforward
3. Difficult

8. [seen only if they answer no or dont know to 4 OR no to 5] Would you know where to look for flood risk information?

I know where the information is available.

I do not know where the information is available but I assume it would be easy to find.

I think it would be difficult to find.

9. [seen only if they answer no or dont know to 4 OR no to 5] Where would you look for flood risk information?

I would ask in the locality

I would look online

I would ask the estate agent

Other (optional specify)

10. Are you aware of the existence of publicly available flood risk maps for Ireland?

Yes

No

11. In the last 10 years has flood risk become:

More of a concern for you

Unchanged

Less of a concern for you

Not relevant

12. (Logical if answered less to 11)Please indicate the reasons why flood risk has become less of a concern for you.

I moved away from flood risky areas

Flood defences were installed

Flooding is less likely

I have new information

Other (specify optional)

13. (logic if answered "more" to 11) Please select the reasons for which flood risk has become more of a concern:

Flooding near me

Flooding near a friend or relative

Increased awareness of climate change

Flooding coverage in the media

Release of new information on flood risk in Ireland/locally

Other reason(s) (you may specify)

14. Split survey with 6 separate versions:

1. Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a flood risk zone, with a 1% (one in a hundred) chance of flooding per year and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price do you think the house in the flood risk zone should be?

   Scale bar 0 - €300,000

2. Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a 1% (one in a hundred) flood risk zone, roughly similar to a 25% chance of being flooded at least once over the course of a 30-year mortgage, and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price do you think the house in the flood risk zone should be?

   Scale bar 0 - €300,000

3. Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a flood risk zone, with a 0.1% (one in a thousand) chance of flooding per year and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price do you think the house in the flood risk zone should be?

   Scale bar 0 - €300,000

4. Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a 0.1% (one in a thousand) flood risk zone, roughly similar to a 3% chance of being flooded at least once over the course of a 30-year mortgage, and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price do you think the house in the flood risk zone should be?

   Scale bar 0 - €300,000

5. Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a flood risk zone, with a 10% (one in ten) chance of flooding per year and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price

do you think the house in the flood risk zone should be?

Scale bar 0 -€300,000

6. Consider two houses that are identical in every respect, including size, location, access to amenities etc. The only difference is that one house is in a 10% (one in ten) flood risk zone, roughly similar to a 96% chance of being flooded at least once over the course of a 30-year mortgage, and the other is not at risk of flooding. If the house which is not at risk of flooding is valued at €300,000, what price do you think the house in the flood risk zone should be?

Scale bar 0 - €300,000

15. Do you expect flood risk in Ireland to change by the year 2050?

Flood risk will increase
Flood risk will remain the same as today
Flood risk will decrease

16. Have you ever experienced flooding in a property you lived in, in the past?

Yes
No

17. Please rate the following types of flood in terms of their potential for property damage.

Highly Damaging, Somewhat Damaging, Not Damaging, Don't know

Coastal Flooding (Storm surge and high tides)
Fluvial Flooding (River bursting its banks)
Pluvial Flooding (Heavy accumulations of water due to rainfall)

18. Have flood defences been constructed/planned to be constructed in your area?

Yes

No

Don't know

19. To what extent to you agree/disagree with the following statements?

    1. "Man-made flood defences provide an adequate protection against flood risk."

       Strongly agree, agree, disagree, strongly disagree, don't know

    2. "Man-made flood defences reduce your enjoyment of an area, either visually or otherwise."

       Strongly agree, agree, disagree, strongly disagree, don't know

    3. "Flood defences should be funded by general taxation."

       Strongly agree, agree, disagree, strongly disagree, don't know

<u>Risk and budgetary related questions</u>

20. If you are considering buying a property, what type of buyer best describes you?

    First time buyer
    Upsizing
    Downsizing
    Looking for an investment property
    Other

21. If you are considering buying a property, will you be paying in cash or will you be getting a mortgage from a bank?

    Cash buy
    Mortgage

22. If you are planning to purchase a property, please indicate the price category which most closely corresponds to your available budget:

    30-100k

100-200k

200-300k

300-400k

400-500k

500-600k

600-700k

700-800k

800-900k

>900k

23. Considering the following periods, relative to today's house prices, do you think, in Ireland:

    1. In 1 years' time (prices will be: higher than today, the same as today, lower than today)
    2. In 5 years' time (prices will be: higher than today, the same as today, lower than today)
    3. In 10 years' time (prices will be: higher than today, the same as today, lower than today)

24. Do you have any of the following types of insurance? (Please check the box)

    Yes, No, Don't know

    Life insurance

    Health insurance

    Dental insurance

    Income protection cover

    Mobile phone insurance

25. If you were to receive one of the following payouts, which would you rather receive?

    €45 in three days' time.

    €70 in three months' time.

Demographics questions

26. Including you, how many people are in your household in the following age groups:

Below 5 years

5-15 years

Between 16-60 years old

Over 60 years old

27. What age are you?

28. What gender are you?

29. Which of the following best describes your level of education?

Primary level

Secondary level

Third level

Post-graduate education

30. Which category best describes your current work status?

Working full time

Working part time

Student

Home maker

Retired

Unemployed

Unable to work due to sickness or disability

Other