Picture and Playground: Valuing Coastal Amenities

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Picture and Playground: Valuing Coastal Amenities*

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Abstract

As the world continues to urbanise, understanding housing market preferences can help planners accommodate city growth. Housing is a bundle of both structural attributes and locational amenities, with "blue space" coastal amenities including both aesthetic (picture) and recreational (playground) services. We examine the effect of these different amenities, applying novel measure of views, suitable for large datasets, to almost 500,000 real estate listings, covering both sale and rental markets in Ireland, 2006-2017. We find that proximity to beaches and similar shorelines is rewarded in both sale and rental markets, as is breadth and depth of sea-views. There is no evidence that urban price premiums differ from rural ones. However, there is clear evidence that sale price premiums are typically larger than their rental equivalents. In addition, sale price premiums are larger in times of falling prices, a finding consistent with "property ladder" effects in tighter markets.

JEL codes: Q5, R21, R31, R58

Keywords: Hedonic House Price Model, Coastal Valuation, Market Cycles, Urban Planning, Blue Flag Beach

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1. Introduction

The world is becoming increasingly urban. By 2050, it is expected that two thirds of humans will live in cities and, combined with aggregate population growth, the population of the world's cities will grow from roughly 4 billion currently to 6.5 billion (UN 2014). Accommodating that growth will involve planning by public and private sectors, to match new housing supply to demand. Therefore, understanding consumer preferences in relation to housing is very relevant for policymakers today. Natural amenities, such as coastline, offer significant utility to households and, for that reason, can act as an anchor for city development (Lee and Lin, 2018).

This paper examines in detail the impact "blue space" coastal amenities have on the value of housing, both sale and rental, in different market conditions, using a large dataset of almost 500,000 real estate listings in Ireland, 2006-2017. It distinguishes between the aesthetic (picture) and recreational (playground) amenities offered by coastal features and finds clear evidence that both are rewarded in the housing market. It does this by using a unique continuous measure of sea views based on 3D GIS simulation, in combination with detailed distance-based measures to particular types of coastline. It directly compares the sale and rental effects, finding sale effects to be larger in magnitude in almost all cases. It also compares effects across very different market conditions, finding strong evidence of counter-cyclical amenity prices, with the relative price of proximity to coast and of sea views greatest in a falling market.

Rosen (1974) provides the theoretical framework for thinking about price differentials as indications of willingness to pay for attributes that are bundled in complex goods, such as housing. A substantial literature, starting with Shabman and Bertelson (1972) and Conner et al (1973), has found distance to coast to have a significant effect on housing values. A more recent literature has examined the impact of views; see, for example, Benson et al. (1997) and Bond et al. (2002). GIS techniques, which allow a continuous rather than categorical measure of view, are increasingly used, although studies such as Samarasinghe and Sharp (2008) for New Zealand and Wallner (2012) for Australia rely, however, on relatively small samples during a single year.

Some work has examined the relationship between housing market cycles and amenity valuation. Stein (1995) suggests that, with down-payment constraints, a market where the most valuable properties are bought by those trading up will be more volatile, as a negative shock to prices would limit effective demand at the top end of the market. Case & Mayer (1996), however, found the opposite to be the case, with the premium attached to homes in high-quality school districts falling during the housing boom they examine. Lyons (2013) identifies two competing mechanisms: a "lock-in" effect that would drive pro-cyclical pricing of amenities, and a "property ladder" effect, which would mean counter-cyclical pricing. "Lock-in" effects would apply where, recognising the inelasticity of the supply of amenities, buyers during housing booms scramble to 'lock in' access to those amenities, pushing up the relative price of high-value housing. Conversely, with "property ladder" effects, expectations of capital gains during a boom would mean buyers place greater importance to having any property, even one with poor amenities, than at other points in the cycle. Bourassa et al. (2005) and Hansen et al. (2013) find evidence of procyclical premiums for a coastal view, consistent with excess demand for amenities that are fixed in supply (a "lock-in" effect).

This paper contributes to the literature in three respects. Firstly, it develops a new methodology for calculating breadth and depth of views, which can be used in large datasets, where viewshed analysis can still involve prohibitive computational costs. Secondly, it is the first to directly compare the housing price effects of aesthetic and recreational amenities offered by the coastline. Thirdly, it is also the first paper to directly compare sale and rental price effects of coastal amenities. It finds that proximity to shingle and beaches (including Blue Flag beaches) is systematically rewarded in both sale and rental markets, as is the depth and breadth of the sea view. It also finds that sale price effects are typically larger in magnitude than rental price effects, and sale premiums are larger in times of falling prices, a finding consistent with "property ladder" effects in tighter markets.

The rest of the paper is structured as follows. The next section describes the data used in this study and the new technique used for calculating sea-views in large datasets, while Section 3 outlines the methodology and empirical specifications used. Section 4 presents and discusses the results of the core specification, for both sale and rental properties, which contains all properties within 10km of the coast, as well as numerous robustness checks, including straight-line coast, LiDAR data and a sample with nearest-neighbour treatment-control matching. It also presents results by time period, while the final section concludes.

2. Data

2.1 Real Estate Listings

The main source for property-related data was the daft.ie listings website. The information in the dataset includes: listed price (sale or rental); structural attributes (number of bedrooms/bathrooms, property type); location (and level of accuracy); time of listing; and the text of the ad. The parent company of daft.ie estimates that its coverage of both sales and rentals is above 95% of the Irish market. The dataset includes listings from Q1 2006 to Q2 2017. Only listings with the highest level of location accuracy and within 10 kilometres of the coastline were included in the final dataset. This left a final sales sample of 159,591 and a rental sample of 339,764.The basic attributes of the listings, in relation to size and location, are given in Table 1.

The dataset is unique in the hedonic housing price literature for two main reasons. The first is the size of the dataset (just under 0.5 million observations) relative to the Irish market (the country had 2 million dwellings in the 2011 and 2016 Censuses), and also compared to other hedonic housing price studies worldwide. In a review of 69 studies of willingness to pay for environmental amenities, 1996-2006, Kuminoff et al. (2010) find that fewer than one in four had samples greater than 10, 000 observations and fewer than 10% covered an entire country. Secondly, aside from other work using the same dataset (Lyons 2013), there is no other published work on environmental amenities using a dataset that includes both rentals and sales.

Table 1: Dataset size, by cohort (building-level accuracy only, <10 km to coastline)

Category	Cohort	Sales		Rentals	
		N	%	N	%
Size	One-bedroom	4,772	3.0	68,218	20.1
	Two-bedroom	29,411	18.4	130,976	38.5
	Three-bedroom	71,782	45.0	90,263	26.6
	Four-bedroom	42,910	26.9	41,181	12.1
	Five-bedroom	10,716	6.7	9,126	2.7
Region	Dublin	65,905	41.3	210,264	61.9
	Other cities	16,645	10.4	38,623	11.4
	Leinster	29,576	18.5	38,907	11.5
	Munster	33,198	20.8	36,074	10.6
	Connacht/Ulster	14,221	8.9	15,815	4.7
Total		159,591		339,774	

The use of listed prices is well-established in the housing economics literature. For example, Shiller's dataset of long-run housing prices for the U.S. relies on newspaper listings for the period 1934-53, with similar usage of listed prices for the rental sector (and CPI) for the pre-WW1 period (Margo 1996; Officer & Williamson 2018; Shiller 2005). In the Irish housing market, listed prices are not in any way legally privileged. A seller may state that they require offers "in excess of" or "in the region of" the list price, but they are for information only and set after agreement between the seller and their estate agent. As most homes in Ireland are sold through an agent, issues relating to homeowner-assessed values, as raised by, for example, Banzhaf & Farooque (2012), are not an issue. Research exploring the relationship between list and transaction prices in Ireland during this period finds a very strong correlation between the two (Lyons 2018).

In relation to dwelling attributes, four principal dimensions of attribute are included: size, type, time listed on the market and location. The measure of size used in the dataset is number of bedrooms and number of bathrooms, with only properties of between one and five bedrooms included. (Size in square metres is not a widely used metric by consumers in Ireland and consequently, the majority of sales listings and all rental listings do not include this information.) To capture a property's size, indicator variables are included for number of bedrooms (one to five) and then number of bathrooms relative to number of bedrooms. For rental properties, the occupancy of each bedroom is also known and this is measured by number of single bedrooms out of the total number of bedrooms.

The most fundamental distinction within dwelling type is between apartments and houses. Within apartments, there are additional variables for duplexes (in sales) and "flats" (in rentals; referring to parts of houses that have been subdivided for rental accommodation). For houses, there is additional information in the sales segment: terraced, semi-detached, detached and bungalow. These are all captured with categorical variables.

Categorical variables by quarter are included to reflect the trend in property prices over time. A frequently absent feature of hedonic models is the extent to which time and other attributes interact. Thus, the analysis includes interactions between different phases of the market and coastal dimensions of the data.

In addition to size, type, and time, a wider range of further controls is included, using the text of the ad. Phrases were searched within the ad and categorical variables generated to indicate the possible presence of an attribute based on it being mentioned. These variables include a property's aspect (south or south-west facing), age (period, Edwardian, Victorian or Georgian), condition (whether the property has been recently refurbished or renovated), whether the property is in a cul-de-sac/no-through-road, various types of rooms (utility room, conservatory, granny-flat, walk-in wardrobe, wet room), features related to energy efficiency (underfloor heating, fireplace, solar panels, double-glazing) and other features (balcony, bay windows, Jacuzzi, fitted wardrobes, en-suite, garage, French doors, high or corniced ceilings, and branded kitchen appliances).

The most important phrase related to this research is the term "views". This is a simple dummy variable indicating whether the term "views" is mentioned in the text of the ad. We use this dummy variable as a robustness check on the various GIS measures of sea views which we develop later in the paper. The *a priori* assumption being made is that any property with a view would mention it in the text of the ad as it would be a selling point to buyers. Use of a more detailed LiDAR sample allows us to relax this assumption in a robustness check.

The final three controls relate to location: micro-market, Census 'Small Area', and the dwelling's exact location. All properties are located within the one of 276 local micro-markets. These micro-markets were developed by the Daft.ie website and reflect the lowest geographical units with sufficient volume of listings on a quarterly basis to allow reliable estimation of price trends by location. These micro-markets nest within counties, cities and – within Dublin, the largest city – its 25 postal districts. These fixed effects are designed to capture the impact on price of area-specific factors that are not captured by other variables.

In addition, we use the property's physical coordinates, converted from the listing address into *xy* coordinates using the quasi-official Geodirectory service. As these are converted using manually-entered addresses, only listings where building-level accuracy is returned are included in the analysis here. This is motivated by the nature of the study, which uses 3D viewshed simulation, but has a significant effect on the dataset, as it means that almost 1.5 million listings are excluded.

By using the *xy* coordinates, it is possible to add more granular neighbourhood characteristics from Census data. This is done at the level of the 'Small Area', an official division of the country into over 18,000 units, with an average of 100 dwellings in each. 2011 census attributes included in the baseline empirical specifications are the local unemployment rate and the percentage of people with a college degree, as a time-invariant index of neighbourhood quality.

The final locational controls are distance-based. These include distance to (source in brackets): closest CBD; Dublin's CBD; primary & post-primary schools (Department of Education); transport nodes, including motorway, national primary, national secondary (Ordnance Survey Ireland, [OSi]); and 'green' amenities, including golf courses (GUI), forests, rivers, lakes and transitional water bodies (OSi & EPA) and mountains with an elevation of >300m (OSi).

2.2 Coastal Amenities

The focus of this research is on recreational and aesthetic coastal amenities. To capture recreational amenities, the coast of Ireland is split into four different categories[1]: cliffs, beach, coastal sand/shingle, and Blue Flag beaches, described in more detail below. Closer proximity to these coastal categories implies a higher potential for associated recreation. Euclidean distance to nearest category was generated for each listing. The three sources of the data on coastal categories were: for regular coastline, Ordnance Survey Ireland (OSi); for the location of Blue Flag sites, the Environmental Protection Agency (EPA) and *An Taisce*; and, for cliffs, the National Parks and Wildlife Services (NPWS).

1. **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.
2. **Cliffs:** Cliffs arguably 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 at cliffs.
3. **Beach:** Beaches provide numerous valuable ecosystems and recreational services. The OSi's classification of a beach is one which has sand above the high tide line. This classification means that some sites effectively used as recreational beaches are classified as "sand/shingle" by the OSi. Just over 10% of the coastline is classified as beach.
4. **Coastal Sand/Shingle:** This classification of coast accounts for almost 78% of the coastline of Ireland. This broad classification includes rocky reefs,

[1]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.

boulders, shingle and sand. Many small coves/tidal flats with beach-like qualities are amalgamated into this classification and therefore the value of small unknown beach sites cannot be distinguished on a countrywide level.

5. **Blue Flag sites:** The Blue Flag is a certification by the Foundation for Environmental Education that a beach or marina meets its stringent standards for water quality, safety, beach management, and information provision (Blue Flag Programme, 2006). Blue Flag status is intended to serve as an important quality signal and is therefore a possible determinant of the recreational value of such beaches.

To capture aesthetic amenities provided by the coast, spatial analysis is required, as the dataset does not provide information on whether the house has a view of the sea (or other features). The only indication within the dataset as to whether the listing has a view or not is if the term "views" is mentioned in the text of the ad. However, using viewshed analysis, i.e. combining the *xy* coordinate with local topographical data, we utilise 3D simulation to determine a property's view. In other words, given the spatial topography of an area, it is possible to calculate the areas visible from a certain point; an example is given in Appendix Figure 1.

The reliability of these viewshed simulations is based on the detail of the Digital Surface Model (DSM). We use two separate sources for a DSM of Ireland. The first is the OSi's contour line data, which is mapped in 10-meter elevation intervals but does not take into account surface objects. Converting this into raster format gives an output of a model of Ireland in 10x10 meter blocks. This model of Ireland assumes a smooth landscape without buildings, individual trees (forests are accounted for) and other potential objects which may block a property's view.

The limitations of the DSM mean that there is some measurement error in viewshed calculations. For that reason, Light Detection and Ranging (LiDAR) data was obtained for a sample area, covering Galway city and a large section of the east coast (see Appendix Figure 2). LiDAR is a remote sensing method that uses light in the form of a pulsed laser to measure ranges to the Earth. It is, in effect, a much more detailed digital representation of the surface of the earth. As it includes buildings and trees, it gives a more realistic viewshed output, although at the expense of more intense computer processing (see Appendix Figure 3). LiDAR data was obtained from the Office of Public Works[2] (OPW) as a 2-meter resolution DSM for a sample area. The OPW originally generated this data for the purposes of coastal and inland flood risk assessment; as such the sample is mainly confined to low elevation areas which are close to the coastline.

Developing a measure of sea view

A number of previous studies developed non-categorical measures of sea view, including Benson et al. (1998), Sharp (2008), Hamilton and Morgan (2010), and Wallner (2012). To measure the area of water visible from a property, the viewshed for that property was related to the sea and the scope and extent of the sea view was measured. This was done property-by-property and was possible given the small datasets used in their studies. Both the absolute size of this dataset and its large geographical scope make such techniques unfeasible.

To get around this computational constraint, the process is reversed. The measure of view for each listing is calculated by filling the sea with evenly distributed points, at different levels of concentration based on their distance from the coast. Three buffers were created from the coastline (coastal and transitional water bodies) out to sea:

1. To capture the area close to the shoreline, an inner buffer stretching 500 meters out to sea is filled with evenly distributed points spaced 250 meters apart. The maximum visible radius is 10.5 kilometres.[3]
2. To capture open sea views, a further (middle) buffer stretching from 500m to 5km out to sea is filled with evenly distributed points spaced 500 meters apart. The maximum visible radius is 15 kilometres.
3. Lastly, for robustness, an outer buffer 5km-10km out to sea is filled with points spaced 500 meters apart. The maximum visible radius is 20 kilometres.

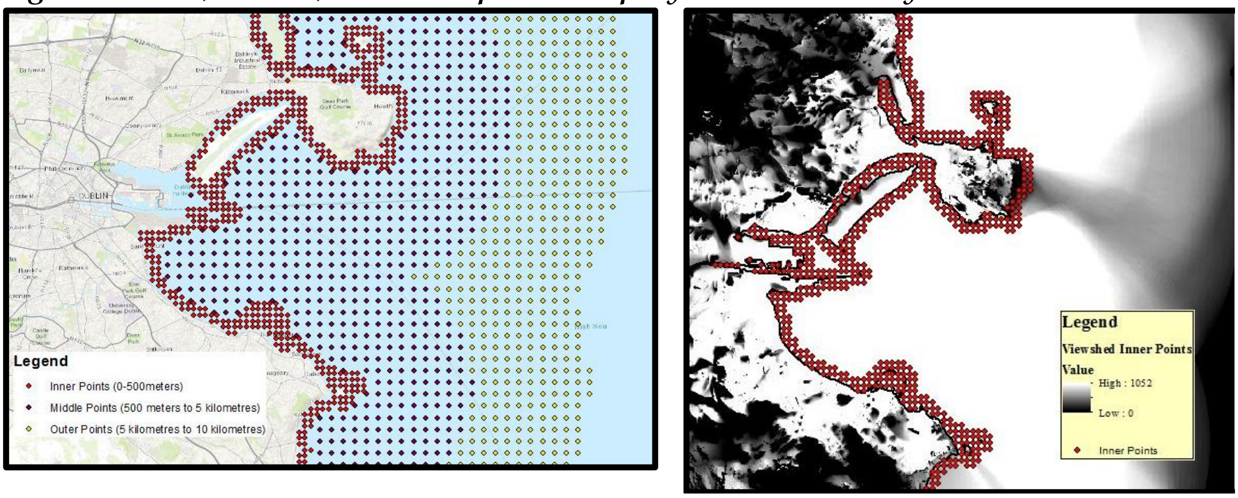
Viewsheds from the perspective of each of these sea points are generated and aggregated together and the sea points viewsheds projected onto the land. This produces 10-meter resolution rasters representing, for each pixel on land, the number of inner, middle and outer sea points visible from that location. The greater the number of sea points visible from a location on land, the greater the area of sea

[2] LiDAR data in Ireland is not publicly available and it was only under special permission that we were able to obtain the data for a sub section of Ireland (see appendix). Ideally, we would like to use LiDAR for the whole sample but this was not possible.

[3]As our sample is within 10km of the coast, the maximum visible radius for each buffer is the distance to the coast plus distance to the outer boundary of the buffer. Each viewshed simulation is from the perspective of 1.8 meters off the ground which represents the average eye level of a person standing.

can be seen from that point. The three buffers are shown in the left-hand panel of Figure 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.

Figure 1: Inner, middle, and outer points displayed in Dublin bay

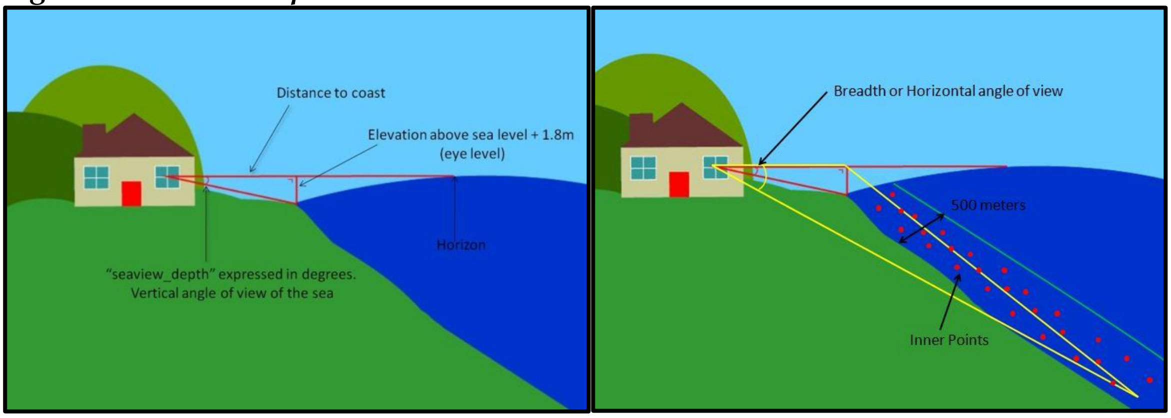


The above methodology captures in particular the (horizontal) breadth of the sea view but may not capture as accurately the (vertical) depth of the view. This is due to the fact that a large sea surface area from a bird's eye perspective will not always have the same visual impact when perspectives are 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 2 gives an illustration of the horizon angle measured in degrees.

Given the countrywide DEM is smooth and does not take into account objects which may block a house's view, in particular buildings and trees, it is likely to overstate the number of sea points which can be seen in reality[4]. To make these scores more robust, only listings which mention the term *views* in the text of the ad are given an inner or middle score; if there is no mention of *views* in the text of the listing, its score will be zero. An alternative, using LiDAR data that captures the built environment and other factors that may affect the view, is discussed in the robustness checks.

[4] See appendix table 7 for Type 1 and Type 2 errors comparing the views term and the GIS view measure.

Figure 2: Seaview depth and breadth



Thus, three continuous measures of coastal/sea view are included for each listing. These "picture" variables included in the specification are: *seaview_breadth* (the log of the inner views score), *seaview_distant* (the log of the middle views score[5]), and *seaview_depth*(the horizon angle). These are calculated for each listing, *i*, as follows:

1. $seaview\_breadth_i = \ln(innerscore_i) * 'views'_i$

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

2. $seaview\_distant_i = \ln(middlescore_i) * 'views'_i$

$$Where: seaview\_distant_i = 0 \; if \; middlescore_i = 0 \mid innerscore_i > 0$$

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

$$Where: eye\ level_i = (elevation_i + 1.8),$$
$$seaview\_depth_i = 0 \; if \; 'views'_i = 0 \mid innerscore_i = 0$$

3. Empirical Framework

3.1 Baseline Specification

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 green spaces or the coast). The error term, ε, reflects the gap

[5] To avoid co linearity with *innerviews*, seaview distant takes a value of 0 if innerscore >0. We are purely capturing listings which can only see the middle area and not the inner area.

between the predicted value 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:

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

Where: $price_i$ refers to sale or (monthly) 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 local market fixed effects; X'_{4i} to a vector of location-specific control amenities (including distance to schools, transport networks and golf courses); and X'_{5i} represents our regressors of interest, a vector of variables capturing coast-specific amenities. To account for possible heteroscedasticity, robust standard errors are used when calculating statistical significance.[6]

The coast amenities variables are split into aesthetic and recreational categories. The three "picture" variables included, reflecting a view of the shore and the breadth and depth of the view of the sea, are as defined above. In addition, four "playground" variables are included. Four distance categories (1km-0.5km, 0.5km-0.25km, 0.25km-100m, and <100m, the base being a distance of >1km) to each of the following types of coastline are included: coastal shingle, beach, Blue Flag sites, and cliffs.

3.2 Empirical Strategy

For both sales and rental segments, this baseline specification is applied to five main samples, which differ by geographical coverage. The core sample covers all property listings nationwide within 10 kilometres of the coastline. This restriction of distance to coastline was put in place, as properties sufficiently far away from the coastline are unlikely to benefit from the various coastal categories.

The second sample is one that covers only areas with relatively straight coastlines. The purpose of this sample is to rigorously test the system of measuring views that is used. Other sectors of coastline, such as those with bays or inlets, may be offering amenities, such as view of a skyline and landscapes on the opposite side of the bay.

[6] In addition, mention is made in Section 4 if statistical significance differs substantively when clustered standard errors are used instead.

To examine this, sections of coastline which were identified geographically as being "straight" with no major bays or inlets were used to select listings (see Appendix figure 3). The straight coast sample was similar in the fraction in urban areas to the countrywide sample (85% vs. 82% in the full sample).

The third geographical sample used was the LiDAR sample. This was also used to test the view measure variables using a more detailed digital surface model. The measures of shore view, and sea view breadth and depth, are as given above, but, given the higher resolution, the 'views' interaction term was dropped.

The baseline analysis was carried out on two further samples, urban and rural listings respectively, to examine the heterogeneity of the price effects by market. Theoretical priors could go either way. For example, if coastline offers an amenity that is fixed in value, this may be smaller (in percentage) for more valuable urban properties. Conversely, if such natural amenities are luxury goods, this may be reflected in a larger urban premium for these amenities.

3.3 Other Specifications

In addition to these ten core specifications (five each for sales and rental listings), three additional sets of specifications were employed:

1. The first interacts categorical variables for each year (2006-2017) with each amenity, in order to examine the effect of the coastal amenities over time. During the period covered, Ireland's property market went from a credit-fuelled bubble (ending in 2007) to a sharp crash (to 2013), before price started to rise again due to strong demand and weak supply.
2. Secondly, for ease of exposition and comparability with previous studies, categorical formulations of the regressors of interest are also used.
3. Quartiles of sea-view breadth are used in one specification to test the reliability of the measure.

Table 2. Regression results from hedonic model of listed sales prices, 2006-2017

	Country-wide	Straight Coast	LiDAR	Urban	Rural
Dependent Variable: natural log of the listed sale price					
Playground Variables					
Sand/Shingle					
1km - 500m	0.0374***	0.0378***	0.0255***	0.0399***	0.0219**
500m - 250m	0.0550***	0.0547***	0.0277***	0.0544***	0.0554***
250m - 100m	0.0597***	0.0539***	0.0636***	0.0499***	0.0727***
<100m	0.149***	0.119***	0.174***	0.127***	0.174***
Non-Blue Flag Beach					
1km - 500m	0.0063	0.00553	0.0374***	-0.00634	0.0409***
500m - 250m	-0.0229***	-0.0338***	0.0452***	-0.0388***	0.0425**
250m - 100m	0.0337***	0.00278	0.0595***	0.0173	0.0651**
<100m	0.112***	0.0678*	0.103***	0.0975***	0.151***
Blue Flag Beach					
1km - 500m	0.0110*	0.0281***	0.0411***	0.0122*	-0.0111
500m - 250m	0.0564***	0.0799***	0.0719***	0.0397***	0.0415
250m - 100m	0.0892***	0.149***	0.105***	0.0685***	0.106**
<100m	0.0688**	0.103**	0.135***	0.0998***	0.065
Cliffs					
1km - 500m	-0.0258***	-0.0178**	0.0106	-0.0468***	0.0237*
500m - 250m	-0.0254***	-0.0609***	-0.143***	-0.0496***	0.0355**
250m - 100m	0.0238*	0.0137	-0.153***	0.017	0.019
<100m	0.0564*	-0.0327	-0.250***	0.0267	0.100**
Picture Variables					
Seaview breadth	0.0143***	0.0162***	0.0142***	0.0126***	0.0166***
Seaview (distant)	0.0110***	0.0120***	-0.000491	0.00938***	0.0122***
Seaview depth	0.0196***	0.0194***	0.00944***	0.0185***	0.0182***
Controls	YES	YES	YES	YES	YES
Observations	159,472	37,056	23,777	131,066	28,406
R-Squared	0.798	0.797	0.831	0.83	0.668
RMSE	0.28	0.267	0.259	0.258	0.35

Notes: Robust t-statistics in parentheses. Columns shows different samples, while controls include location, dwelling and time listed on the market, as discussed in the text. The results are largely robust to switching to clustering the error terms at the county level. A single asterisk (*) indicates significant at 10%, a double asterisk (**) indicates significant at 5% and a triple asterisk (***) indicates significant at 1%.

4. Results

4.1 Baseline Results

Tables 2 and 3 present the regression output, for the five sales and rental samples respectively, for the seven coastal variables of interest.[7] Due to the log-log nature of the specification for the 'picture' variables, the coefficients can be interpreted as elasticities. For the 'playground' variables the distance to the coastal feature was categorised into four distance bins, with the base being any listing >1km from the coastal feature.[8]

Regarding playground variables, a clear hierarchy emerges across the sale and rental specifications. In all ten empirical specifications, proximity to the sand/shingle category (which includes smaller beaches), has the largest positive effect on sale prices but somewhat less on rental prices. Similarly, close proximity to cliffs has a small positive effect. Proximity to beaches, whether Blue Flag or otherwise, has a positive effect on sale/rental prices in almost all cases, although the relative magnitude of the two categories varies by sample and segment. Unless otherwise specified, the percentage price effects (converting the coefficient in log terms into percentages) below (sale or rental) are for comparing a property <100m away to one >1km away (i.e. comparing the closest distance category to the base).

1. **Sand/shingle**: For a property 1km away from sand/shingle zone, compared to one <100m away, the sale price will be 15% higher (rent: 5.5% higher). The sale price effect is larger in the LiDAR (19%) and rural (19%) samples. Whereas the sale price premium is smaller in cities than elsewhere, (13.5% vs. 19%), the opposite is true in rents (6.4% vs. <0.01%). In the rental segment, the price effect is similar (~6.4%) in all but the rural sample.
2. **Beach**: The price of proximity to any beach which doesn't have a blue flag designation ranges from 7%-15% in the sales sample. However, in the rental sample, the only sample which estimates a positive and significant is the rural sample (5%), the country-wide, LiDAR and urban samples are negative and statistically significant.

[7] Due to space constraints, the tables in the main body of the text show coefficients only, with statistical significance at 10%, 5% and 1% denoted by asterisks. Tables with both coefficients and corresponding *t*-values are given in the Appendix.

[8] The choice of >1km as a base control was motivated by the geographical size of the micro market fixed effect areas. 1km radius is generally accepted as a "walkable" distance in amenity valuation literature.

Table 3. Regression results from hedonic model of listed rental prices, 2006-2017

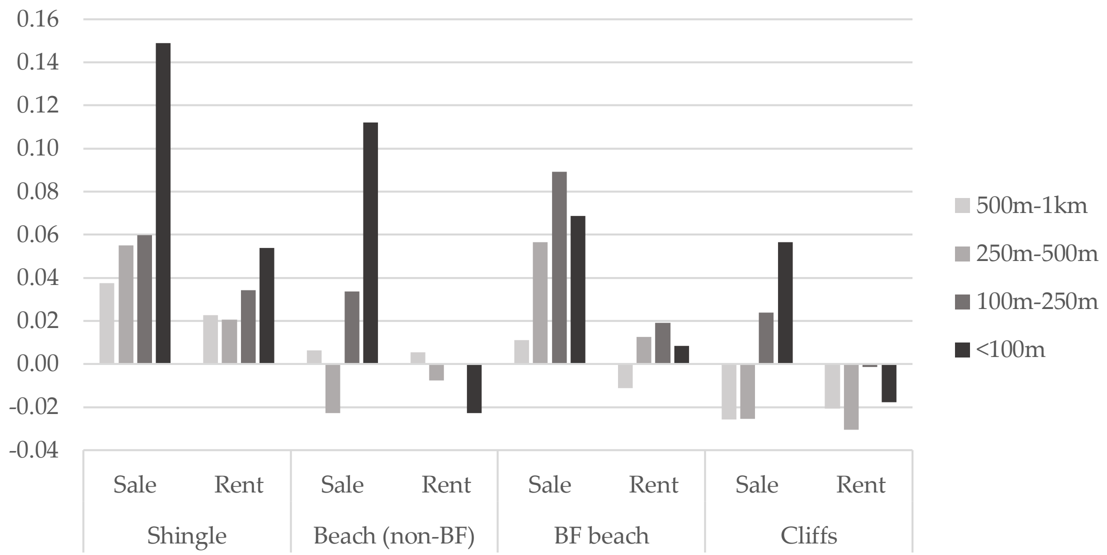
	Country-wide	Straight Coast	LiDAR	Urban	Rural
Dependent Variable: natural log of the listed monthly rental price					
Playground Variables					
Sand/Shingle					
1km - 500m	0.0228***	0.0202***	0.00771**	0.0186***	-0.000589
500m - 250m	0.0205***	0.0277***	-0.000131	0.0154***	0.0216***
250m - 100m	0.0342***	0.0575***	0.0143***	0.0406***	-0.0150*
<100m	0.0540***	0.0570***	0.0573***	0.0624***	0.00853
Non-Blue Flag Beach					
1km - 500m	0.00543**	-0.00256	0.0224***	0.00971***	0.0207*
500m - 250m	-0.00770**	-0.0156***	0.00749	-0.00652*	0.0501***
250m - 100m	0.000362	-0.0168***	0.0184**	-0.00517	0.0623***
<100m	-0.0229**	0.00893	-0.0357***	-0.0320***	0.0504**
Blue Flag Beach					
1km - 500m	-0.0112***	0.0209***	0.0333***	-0.0171***	0.0204**
500m - 250m	0.0127**	0.0387***	-0.00348	0.00948	0.0399**
250m - 100m	0.0192*	0.0575***	0.0387**	0.0102	0.0846**
<100m	0.0084	0.105***	-0.00454	-0.00294	0.144**
Cliffs					
1km - 500m	-0.0206***	-0.0214***	0.0204**	-0.0122***	-0.0272***
500m - 250m	-0.0304***	-0.0381***	-0.0484***	-0.0214***	-0.0368**
250m - 100m	-0.00145	-0.0374**	-0.0690***	0.00423	0.0156
<100m	-0.0177	-0.00509	-0.133***	-0.00886	0.0158
Picture Variables					
Seaview breadth	0.0106***	0.00524***	0.0168***	0.00950***	0.0130***
Seaview (distant)	0.00363**	0.00519**	-0.00178***	0.00289*	0.00917**
Seaview depth	0.00512***	0.0198***	0.00589***	0.00701***	0.00254
Controls	YES	YES	YES	YES	YES
Observations	339,572	60,147	87,988	296,834	42,738
R-Squared	0.7942	0.7647	0.7713	0.7992	0.7941
RMSE	0.2074	0.1916	0.2103	0.2025	0.2219

Notes: Robust t-statistics in parentheses. Columns shows different samples, while controls include location, dwelling and time listed on the market, as discussed in the text. The results are largely robust to switching to clustering the error terms at the county level. A single asterisk (*) indicates significant at 10%, a double asterisk (**) indicates significant at 5% and a triple asterisk (***) indicates significant at 1%.

3. **Blue flag beach**: The price effect of proximity to a Blue Flag beach is, for sale properties, slightly less than beach and sand/shingle, but is still positive and significant for the <100m category (6% - 14.4%), besides the rural sample which is insignificant. In the full and straight-coast sample the coefficient for the 250-100m distance bin is slightly larger than the <100m distance category (8.9% compared to 6.8%, and 16% compared to 10.8%, respectively), potentially capturing the effect of traffic congestion at close proximity to Blue Flag bathing areas. In the rental cohort all but the rural models display a negative, or a statistically insignificant, coefficient for the <100m distance category.
4. **Cliffs:** In the countrywide sales sample, close proximity to cliffs displays a positive price effect (5.6%) and the 10% significance level. The rural sample has a coefficient of 10.5% which is significant at the 5% level. Straight coast and urban samples are insignificant, however the LiDAR sample estimates a very large statistically significant negative coefficient of -28.4%. The rental segment is largely insignificant for proximity to cliffs except for the LiDAR sample again which is -13.8%.

An overview of the coefficients from regressions using the full samples (all listings within 10km) samples is presented in Figure 3, for both sale and rental segments.

Figure 3. Graphical summary of results for distance-based coastal amenities (baseline sample)



In relation to the 'picture' variables, there is clear evidence that the proposed method for measuring view of the shore and the breadth and depth of sea views captures the underlying amenity.

1. **Seaview breadth**: In all ten 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 1.4% in the nationwide sales sample. Across the sale samples, the effect ranges from 1.3% in the urban sample to 1.7% in the rural sample. In the rental samples, the effect is similar in magnitude: ranging from 0.5% in the straight-coast sample to 1.7% in the LiDAR sample.
2. **Seaview (distant)**: Listings that have a middle score and no inner score (but also mention views) see a small positive and statistically significant price effect (0.9 - 1.2% based on calculations above for sea view breadth. In all but the LiDAR models the effect is positive and statistically significant. It is insignificant in the LiDAR sales model and negative and significant in the LiDAR rentals model.
3. **Seaview depth**: Lastly, the depth of a sea-view has a clear impact on housing prices. In all five sales samples, and in four of the five rental samples (excluding rural), the deeper the angle of the horizon that can be seen from a property, the higher the price. A one-degree increase in the angle is associated with a ~1.9% (except LiDAR: 0.94%) sale price effect, and a 0.5%-2% rental price effect (national sample to straight-coast).[9]

An overview of the results relating to coastal views is given in Figure 4. Given the potential for measurement error in relation to views, results are shown for both full and LiDAR samples. Particularly in the sales segment, LiDAR results largely confirm results from the broader sample, albeit with a slightly larger sign, suggesting mild measurement error.

[9] Elevation is not included as a control. When added, the coefficient for sea-view depth reduces by approximately 0.003 but it remains statistically significant at the 1% level.

Figure 4. Graphical summary of results for view-based coastal amenities (baseline sample)

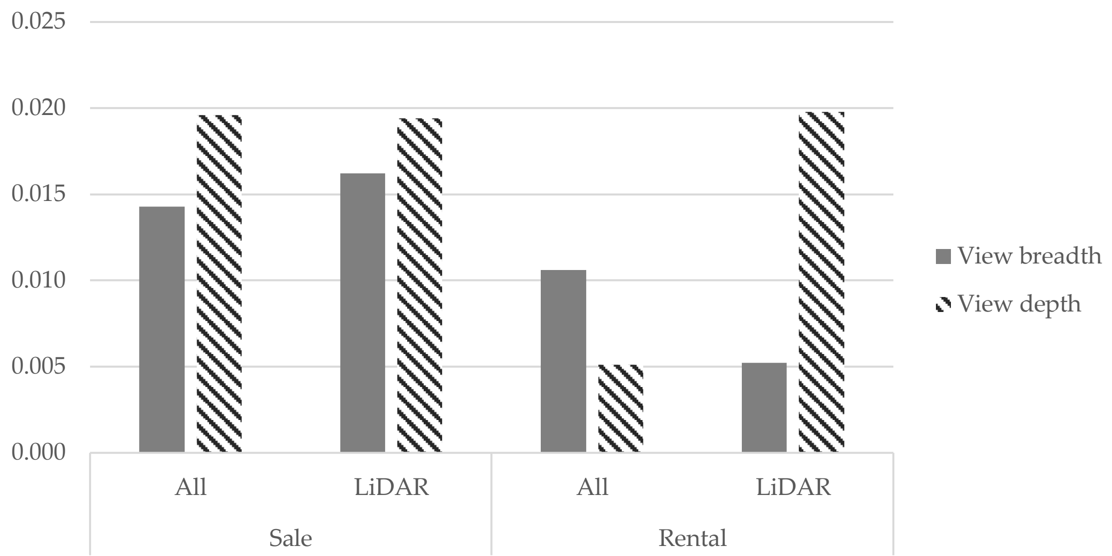


Table 4. Standardized monetary price effects of key regressors

	Sale price			Monthly rental price		
Variable	**1 SD Effect**	**Mean**	**Std. Dev**	**1 SD Effect**	**Mean**	**Std. Dev**
Seaview breadth	€17,259	81	71	€65	109	82
Seaview (distant)	€11,403	54	65	€18	46	61
Seaview depth	€12,822	2.11	1.68	€17	1.50	1.48
	Coeff * Av. Price	**N**		**Coeff * Av. Rent**	**N**	
Sand/Shingle <100m	€49,673	2,370		€63	4,729	
Beach <100m	€36,721	283		-€26	646	
Blue Flag <100m	€22,035	211		€10	312	
Cliffs <100m	€17,943	241		-€20	260	

Notes: The above table shows one-standard-deviation price effects, together with mean and standard deviation values, for 3 key continuous 'picture' regressors, using results from the nationwide samples, as shown in Tables 2 and 3. Seaview measures in inner- and middle-points, and angle in degrees, respectively. 'Playground' variables price effects are of the transformed coefficient for the closest distance category (<100m) multiplied by the average sale price and average monthly rent, respectively. Number of observations, N, for the closest distance category are also displayed.

Table 4 gives the one-standard deviation sale and rental price effects, at average prices, of each of the three key 'picture' regressors of interest, using the coefficients from the national sample. Price effects for the closest distance category to the 'playground' variables are also displayed. The largest sale price effects are for closest proximity to sand/shingle (€49,673) and for sea-view breadth (€17,259). Sea-view distant and sea-view depth have prices effects above €10, 000, while proximity to a beach, blue flag beach and cliffs are smaller than sand/shingle (€36,721 - €17,943, respectively). Sand/shingle and sea-view breadth have the largest effect on monthly rents (€63 & €65, respectively) followed by sea-view distant, sea-view depth and proximity to Blue Flag beaches. There is a large anomalous negative effect on rents of the closest proximity to beaches and cliffs.

4.2 Robustness checks

The methodological approach here develops a continuous measure of sea view without computing individual viewsheds for each dwelling, allowing different samples or additional listings to be added at no extra computational expense. The limit of such an approach, though, is the measure is simply a total and does not distinguish between the location of different visible points in the sea. Were individual points identifiable, it would be possible to compute the breadth angle of view. Similarly, the assumption underpinning the sea-view depth measure is that the maximum depth of view is related to the position of the nearest inner sea point (given that an inner sea point is visible), which isn't necessarily the nearest *visible* inner sea point.

The accuracy of sea view simulation is also highly dependent on the resolution of the digital surface model used. As noted in Section 2, the OSi's 10-meter DEM does not take into account trees, buildings and any other such obstructions of view, and therefore the sea views are likely to be over-estimated especially in urban settings (See appendix table 7 for Type 1 and Type 2 errors). Therefore, the principal robustness check is included above: the LiDAR sample reported is based on a much higher resolution digital surface model and, therefore, does not require the phrase 'views' to be in the text of the ad. As shown in Tables 2 and 3, this sample confirms that the novel measures of sea-view developed in this paper reflect a consistent and expected price effect. For all the key regressors, the results of the LiDAR specification have the same sign and statistical significance to the countrywide and straight-coast samples, although the coefficients are typically – but not always – larger in magnitude.[10]

[10] If the requirement for 'views' to be included in the text of the ad is left in, the results do not substantively change.

Nonetheless, the LiDAR specification is not without limitations. Specifically, the position of the address points, from where the view scores are extracted, can sometimes be located behind a house or on the roof and thus may not accurately represent the perspective of the view from a dwelling window. Improved address points and building outlines would help overcome this issue in future work.[11]

The results presented are from a specification including fixed effects for each of 229 micro- markets across the country and robust standard errors. Where standard errors are clustered at the county level, the sea-view breadth and depth variables remain strongly statistically significant, as do distance to shingle and blue-flag beaches. If a far more granular level of fixed effects is used – one for each of roughly 3,500 census divisions, again, sea-view breadth and depth are unaffected, while distance to shingle and beach also remain statistically significant.

Omitted variable bias is a frequently highlighted issue in the hedonic literature. We designed a simple proximity matching framework to test the if the view measure was successfully capturing the underlying amenity by creating a treatment/control group sample based on nearest neighbour matching. Observations that mentioned "views" in the text of the ad and also had an innerscore greater than zero were identified as a treated group. The, geographically, nearest neighbour distance was calculated and the control group were identified as the nearest neighbour which did not mention views nor had an inner score/middle score. If the nearest neighbour was not the opposite in terms of the above specification, or if they were greater than a distance of 100 meters from one another, the observations were dropped. This matched pairs of treated and control groups made up a sample of 11,292 observations (5,744 treated, 5,548 controlled, 7% of full sample). In theory these pairs would be otherwise exchangeable except for the view of the sea. Variations across pairs were capture by standard controls in the base model. When the base model was run on the proximity matched sample the coefficients for the 'picture' variables remained positive and highly statistically significant with the magnitudes reducing by approximately half, which is intuitive considering we are not comparing houses with a view to houses further away from the sea.

[11]OSi's PRIME 2 spatial dataset may contain much of the required precision in data. In addition, this dataset would also provide information on building square footage and garden size, which are not currently included in the daft.ie dataset.

Table 4. Regressions results for robustness checks (sales segment)

VARIABLES	Base Countrywide Model	Clustered error term by county	Proximity matched sample	Without 'views' interaction term in 'picture' variables	
Playground Variables					
Coastal Sand/Shingle <100m	0.149***	0.149***	0.0920***	0.173***	0.172***
	(15)	(8.29)	(3.82)	(17.2)	(8.96)
Beach <100m	0.112***	0.112**	0.117**	0.128***	0.121***
	(4.4)	(2.75)	(2.29)	(4.91)	(3)
Blue Flag <100m	0.0688**	0.0688	0.145**	0.0770***	0.0664
	(2.54)	(1.35)	(2.07)	(2.76)	(1.21)
Cliffs <100m	0.0564*	0.0564	0.0239	0.0748**	0.0994*
	(1.9)	(1.07)	(0.375)	(2.46)	(1.95)
Picture Variables					
Sea-view Breadth	0.0143***	0.0143***	0.00679***	-0.000261	0.00463***
	(14.9)	(10.2)	(3.56)	-(0.388)	(3.58)
Sea-view Distant	0.0110***	0.0110**	-0.00924	0.00283***	0.00192
	(4.85)	(2.42)	-(0.619)	(3.01)	(1.06)
Sea-view Depth	0.0196***	0.0196***	0.00777*	0.0148***	
	(12)	(6.11)	(1.95)	(12.7)	
Standard Controls	YES	YES	YES	YES	YES
Constant	12.52***	12.52***	12.57***	12.59***	12.59***
	(119)	(30.9)	(35.2)	(119)	(31.4)
Observations	159,472	159,472	11,277	159,472	159,472
R-squared	0.798	0.798	0.811	0.796	0.796
Root Mean Square Error	0.280	0.280	0.295	0.282	0.282

Notes: Robust t-statistics in parentheses. Columns shows different samples, while controls include location, dwelling and time listed on the market, as discussed in the text. A single asterisk (*) indicates significant at 10%, a double asterisk (**) indicates significant at 5% and a triple asterisk (***) indicates significant at 1%.

A summary of the results from these robustness checks is given in Figures 5 and 6. Figure 5 shows the coefficient and 95% confidence interval for the distance-to-coast variables. In general, the results are very similar to the baseline model, although for blue-flag beaches and for cliffs, clustering by county means that conventional thresholds for statistical significance are no longer exceeded. The matching method is likely to be more relevant for views, than for distance to the coast, given the nature of treatment. Figure 6 shows that using a nearest-neighbour matched sample roughly halves the magnitude of the coefficients, compared to the baseline. While the baseline may be thought of as an upper bound for the effect of views, given the potential for omitted variables (despite the wide set of controls), the matched sample is more likely to show the lower bound.

Figure 5. Graphical summary of results for distance variables, by robustness check

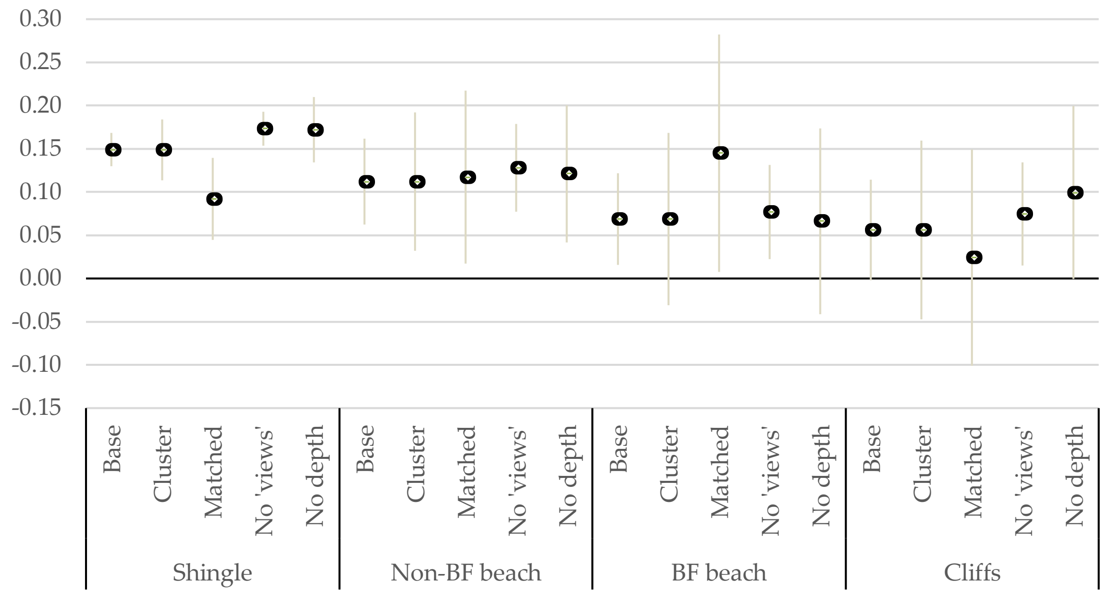
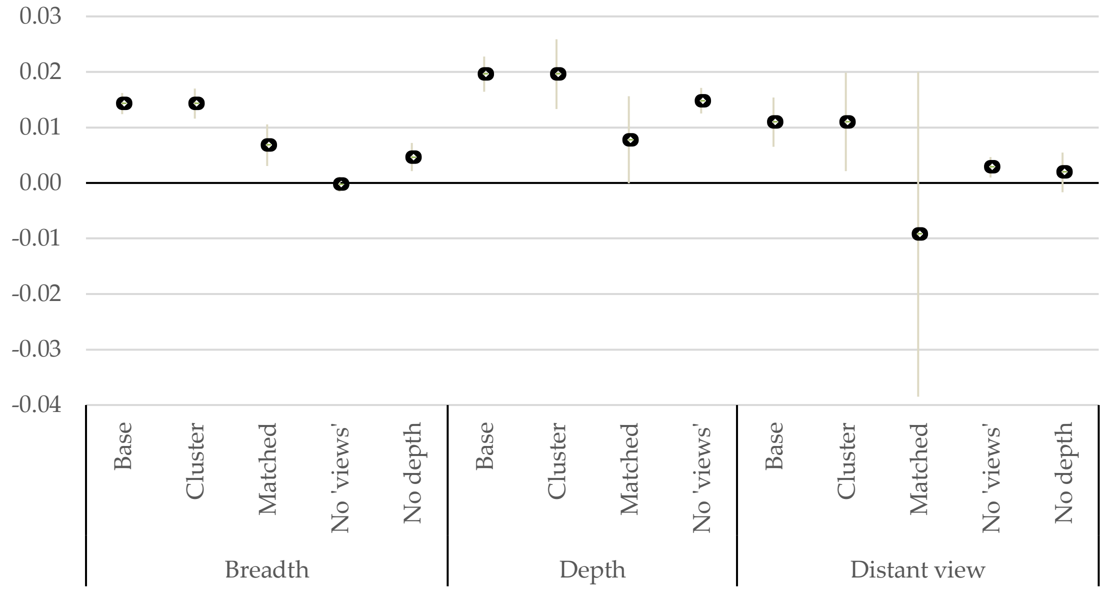


Figure 6. Graphical summary of results for view variables, by robustness check



Lastly, to further test the reliability of the methodology for capturing sea-view breadth, the sea-view breadth variable was split by quartile and upper vintile and distance from the coast. Table 5 displays, for the country-wide sales sample, the matrix of coefficients for categorical sea-view breadth variables by quartile, upper vintile, and distance to the coastline. The results clearly indicate that, with greater distance from the coast, views have a diminishing effect on prices. The premium for a property with a second-quartile sea-view breadth (23-68 inner points visible) is larger for properties closest to the shore (19.4%) than other properties, such as those 0.5km-1km away (9.4%), and that all enjoy a statistically significant sale price premium relative to those more than 1km from the coast. For properties with the broadest view and closest to the coast, the premium is 28.9% (converting the 0.254 coefficient in log terms into percentages). These findings are in line with previous literature, for example those in Benson et. al (2000) and Samarasinghe and Sharp (2008).

Table 6: Coefficients for sea-view breadth, by quartile and distance to coast bins

Sea-view Quartiles (Inner points visible)	**0m-100m**	**100m-250m**	**250m-500m**	**500m-1km**
1st quartile (1-22 points)	0.159***	0.132***	0.0835***	0.0537***
2nd quartile (23-68 points)	0.194***	0.166***	0.143***	0.0937***
3rd quartile (69-118 points)	0.200***	0.141***	0.0866***	0.0822***
4th quartile (119-227 points)	0.206***	0.121***	0.1000***	0.0977***
95th Percentile (>227 points)	0.254***	0.192***	0.110***	0.139***

Notes: The coefficients given are for categorical sea-view breadth variables, by quartile and distance to the coastline. A base of 0 was specified for properties > 1 km from the sea with no sea view score. A single asterisk (*) indicates statistical significance at 10%, a double asterisk (**) at 5% and a triple asterisk (***) at 1%.

4.3 Results by Tenure and Cycle

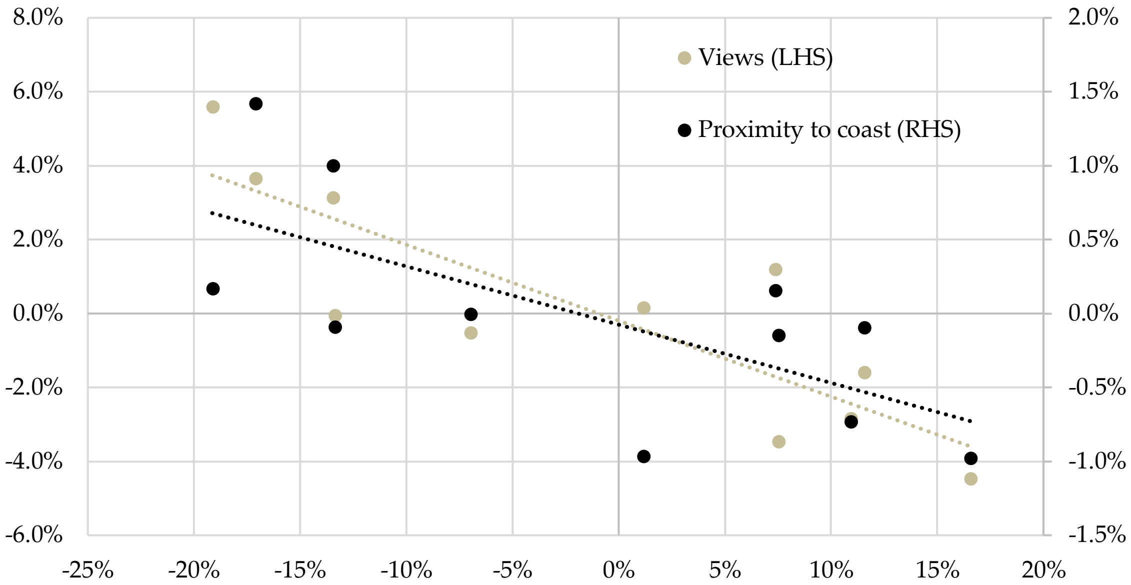
The substantial size of the dataset allows an investigation of whether the premium for coastal amenities differs by tenure and by market conditions. The almost-identical empirical specifications employed for both sales and rental samples allows a direct comparison of the effects in the two markets, while interacting the key regressors with indicator variables for specific years allows an analysis of the evolution of the effects over time.

Revisiting the results in Tables 2 and 3, there are seven principal coastal amenities: proximity to shingle, beach, Blue-Flag and cliffs, and seaview breadth, distant, and depth. For the country-wide sample, for all seven variables, the magnitude of the sale price effect is larger than the rental price effect. For the four distance variables, the within-100m coefficients are as follows: 15% vs. 5% for regular coast, 11% vs. -2% for beach, 7% vs. insignificant for Blue Flag beach, and 6% vs. insignificant for cliffs. For view breadth and depth, again, the sale coefficients are larger: 1.4% and 2.0% compared to 1% and 0.5%. These results are mirrored in the LiDAR sample.

This means that the market yield on coastal assets is low. Taking the figures from Table 4, and expressing the average annual rental effect as a fraction of the sale price effect, the average yield ranges from close to 1% for Blue Flag beaches and view depth, to 6% for view breadth. The overall finding that the rental coefficients are on average lower in magnitude is consistent with Lyons (2013), who proposed that this discrepancy could be due either to buyers' desire to 'lock in' access to amenities in fixed supply or, more likely, to thresholds in search costs limiting the ability of renters to value secondary amenities.

The size of the dataset also allows an analysis of amenity premiums over time, with the period 2006-2017 seeing very different market conditions in Ireland. Figure 7 shows on the horizontal axis annual percentage changes in sale prices, as measured by the official CSO residential property price index, and amenity coefficients by year. The vertical axes of the scatter plot show changes in coefficients, by year, for simplified regressors of sea views and proximity to coast. It is clear from the figure firstly that there is movement in the amenity prices over time and secondly that the changes in amenity prices are strongly inversely correlated with the housing market cycle. When sale prices were falling sharply – by 10% or more each year from 2009 to 2012 – the premium for proximity to coast and for sea views grew dramatically. Conversely, when sale prices were rising by double-digit rates (2014, 2015 and 2017), these premiums fell. As the trend lines in Figure 3 suggest, the correlation coefficients between changes in the overall price index and in amenity prices are strongly negative: -70% for proximity to coast, and -85% for sea view. This supports the "property ladder" hypothesis in Lyons (2013), that in tight housing markets, relative demand shifts out for low-amenity properties.

Figure 3: Scatterplot of changes in sale prices and changes in amenity valuations, 2006-2017



Note: Figure shows, for sale listings, a scatterplot of changes in sale prices (horizontal axis) and changes in coefficients of proximity to coast and sea views, interacted by year.

5. Concluding remarks

Housing is a composite good with each dwelling comprising a bundle of attributes and amenities that can affect its value. This paper examined in detail whether coastal amenities, both aesthetic and recreational are reflected in the value of housing. It did this using both an unusually large dataset, which covered a national sample over a number of market phases for both sales and rental segments, and novel measures of the breadth and depth of sea views. It found clear evidence of willingness to pay for both aesthetic ("picture") and recreational ("playground") amenities, in particular proximity to shingle and beaches (especially Blue Flag beaches) and the breadth and depth of a sea-view.

Properties within 100m of the coast exhibit a sale price premium of 15% in the baseline (5% for rental properties), compared to properties more than 1km away. Based on the LiDAR sample, a 2% premium is attached to a one-degree increase in sea-view depth and a 1.5% premium in sales (0.5% in rentals) to a one-point increase in the measure of view breadth developed here. Despite the very rich set of dwelling and location controls, omitted variable bias cannot be ruled out. A treatment-control matched sample gave what we interpret to be lower bounds for the causal effect of views: 0.7% and 0.8% for breadth and depth, respectively. Analysis by quantile also strengthened the evidence for causal interpretation of the results, with an increase in view breadth having a bigger impact on property values (a) the closer to the coast, and (b) at higher view breadths: for the top vintile closest to the coast, the coefficient is five times larger than for the bottom quartile more than 500m from the coast.

The large size of the dataset allows both a comparison across sale and rental segments and over very different market conditions. There is clear evidence both that sale price effects are larger than rental ones, and that amenity prices are greater in a down-market (when sale prices are falling) than in an up-market (when prices are rising). While amenity valuations being larger in the sale segment than in rentals is consistent with "lock-in" effects, the clear signs of counter-cyclical amenity pricing suggest instead "property ladder" effects - with the sale/rent difference potentially being driven instead by limits to renter search effort.

The results presented here are limited by the quality of the data used. While there is strong theoretical and empirical support for the use of list prices, it remains for future analysis to confirm that the relationships shown here also hold for ultimate transaction prices. Similarly, the calculation of the view relies on accurate data on the physical environment: while the LiDAR subsample showed similar results, again, as data improve, the results found here can be further tested and extended.

There are two main sets of policy implications. The first relates to the maintenance of coastal amenities. The price effects documented here give a lower bound to the minimum value of the services provided by coastal amenities – in addition to services enjoyed by local residents, and thus captured in the housing market, these amenities may offer additional services not reflected in housing values. Where the value of services provided is captured, even indirectly, for example through an annual property tax, this provides a link between the benefits of amenities and their cost of maintenance. The costs range from maintaining Blue Flag beaches[12] to efforts to stem coastal erosion. In this context, a practical application of the sea-view depth measure, developed in this paper, would be useful in the decision of whether to build a sea wall which would inhibit sea views but at the same time offset future coastal erosion costs. The second set of policy implications relates to accommodating urbanization and city growth. The existence of large distance- and view-based amenities implies that land-use restrictions should, subject to other considerations such as flood risk, reflect underlying preferences and allow high-density

[12]In 2007 *An Taisce* estimated that each Blue Flag beach costs the management authority an average of c.€40K per season to maintain. This figure excludes the larger elements of visitor infrastructure such as walkways, car parks and fencing all of which generate additional costs (McKenna et al. (2011).

development closer to coastlines, in order to maximise the supply of a valuable set of "blue space" amenities.

This paper is the first to directly measure the relative values of aesthetic and recreational amenities associated with coastline and also the first to compare sale and rental price premiums. Nonetheless, numerous strands for future research remain. These include, for example, examining the impact of coastal amenities on time-to-sell and other housing market outcomes and the impact of changes in accredited water or beach status. Also, the methodology described here can be used not only in other markets or with better data, but in other settings, including mountains, urban green space and city skylines.

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Appendix

Table 1. Summary Statistics: Countrywide sample within 10km of coast.

Variable	Observations	Mean	Std. Dev.	Min	Max
Price (€)	159, 537	309, 100	219, 402	317	2, 000, 000
Distance to Sand/Shingle (Meters)	159, 537	3, 622	2, 992	2	16, 171
Distance to Beach (Meters)	159, 537	5, 976	4, 268	2	37, 656
Distance to Blue Flag Site (Meters)	159, 537	10, 643	7, 595	4	53, 443
Distance to Cliffs (Meters)	159, 537	8, 007	4, 618	3	29, 638
Inner Score	159, 537	10	37	0	431
Middle Score	159, 537	21	76	0	973
Horizon Angle (degrees)	159, 537	0.263	0.915	0	20.93
Inner Score if > 0	20, 317	82	71	1	431
Middle Score if > 0	19, 566	170	149	1	973
Horizon Angle if > 0	19, 848	2.12	1.68	0.06	20.93

Table 2. Summary Statistics: Straight Coast Sample.

Variable	Observations	Mean	Std. Dev.	Min	Max
Price (€)	37, 105	299, 436	201, 488	1, 000	2, 000, 000
Distance to Sand/Shingle (Meters)	37, 105	1, 955	1, 938	6	14, 048
Distance to Beach (Meters)	37, 105	3, 392	3, 164	6	15, 393
Distance to Blue Flag Site (Meters)	37, 105	7, 843	5, 631	4	52, 252
Distance to Cliffs (Meters)	37, 105	5, 457	4, 293	33	18, 325
Inner Score	37, 105	10	31	0	288
Middle Score	37, 105	37	105	0	955
Horizon Angle (degrees)	37, 105	0.27	0.83	0	20.93
Inner Score if > 0	5, 774	63	52	1	288
Middle Score if > 0	6, 165	225	155	1	955
Horizon Angle if > 0	5, 656	1.80	1.33	0.06	20.93

Table 3. Summary Statistics: LiDAR Sample

Variable	Observations	Mean	Std. Dev.	Min	Max
Price (€)	23, 783	328, 167	241, 267	1, 300	2, 000, 000
Distance to Sand/Shingle (Meters)	23, 783	1, 411	1, 468	2	8, 148
Distance to Beach (Meters)	23, 783	4, 143	3, 008	6	14, 477
Distance to Blue Flag Site (Meters)	23, 783	7, 263	4, 709	16	26, 310
Distance to Cliffs (Meters)	23, 783	7, 614	3, 655	18	15, 914
Inner Score	23, 783	5	17	0	199
Middle Score	23, 783	23	66	0	536
Horizon Angle (measured in degrees)	23, 783	0.10	0.52	0	7.09
Inner Score if > 0	5, 007	24	29	1	199
Middle Score if > 0	6, 033	92	105	1	536
Horizon Angle if > 0	1, 166	2.13	1.07	0.30	7.09

Table 4. Summary Statistics: Urban Sample

Variable	Observations	Mean	Std. Dev.	Min	Max
Price (€)	131, 162	317, 322	223, 937	317	2, 000, 000
Distance to Sand/Shingle (Meters)	131, 162	3, 672	2, 961	2	12, 851
Distance to Beach (Meters)	131, 162	5, 965	4, 038	6	31, 923
Distance to Blue Flag Site (Meters)	131, 162	10, 456	7, 328	4	50, 996
Distance to Cliffs (Meters)	131, 162	8, 274	4, 590	7	19, 041
Inner Score	131, 162	9	35	0	431
Middle Score	131, 162	17	69	0	916
Horizon Angle (measured in degrees)	131, 162	0.19	0.75	0	16.74
Inner Score if > 0	12, 728	89	75	1	431
Middle Score if > 0	12, 146	182	148	1	916
Horizon Angle if > 0	12, 459	1.97	1.56	0.15	16.74

Table 5. Summary Statistics: Rural Sample

Variable	Observations	Mean	Std. Dev.	Min	Max
Price (€)	37, 105	299, 436	201, 488	1, 000	2, 000, 000
Distance to Sand/Shingle (Meters)	37, 105	1, 955	1, 938	6	14, 048
Distance to Beach (Meters)	37, 105	3, 392	3, 164	6	15, 393
Distance to Blue Flag Site (Meters)	37, 105	7, 843	5, 631	4	52, 252
Distance to Cliffs (Meters)	37, 105	5, 457	4, 293	33	18, 325
Inner Score	37, 105	10	31	0	288
Middle Score	37, 105	37	105	0	955
Horizon Angle (measured in degrees)	37, 105	0.27	0.83	0	20.93
Inner Score if > 0	5, 774	63	52	1	288
Middle Score if > 0	6, 165	225	155	1	955
Horizon Angle if > 0	5, 656	1.80	1.33	0.06	20.93

Table 6. Summary Statistics of Relevant Coastal Variables. Rental Sample

Variable	Observations	Mean	Std. Dev.	Min	Max
Monthly Rent (€)	339, 774	1, 129	674	195	10, 000
Distance to Sand/Shingle (Meters)	339, 774	3, 358	2, 676	2	15, 374
Distance to Beach (Meters)	339, 774	5, 761	3, 668	3	37, 752
Distance to Blue Flag Site (Meters)	339, 774	9, 878	6, 772	2	53, 518
Distance to Cliffs (Meters)	339, 774	9, 049	4, 079	2	30, 170
Inner Score	339, 774	9	38	0	430
Middle Score	339, 774	13	60	0	966
Horizon Angle (measured in degrees)	339, 774	0.12	0.59	0	14.70
Inner Score if > 0	28, 051	109	82	1	430
Middle Score if > 0	26, 341	169	141	1	966
Horizon Angle if > 0	27, 616	1.50	1.48	0.05	14.70

Table 7. Type 1 and Type 2 errors for test "views" and viewshed model scores

	Viewshed score>0 Dummy		
"Views"	0	1	Total
0	26,815 (16.8%)	106,251 (66.6%)	133,066
1	4,505 (2.8%)	22,020 (13.8%)	26,525
Total	31,320	128,271	159,591

Viewscore dummy given a value of 1 if inner score>0 or middle score >0. 0 for all else. "Views" =1 if the term "Views" is mentioned in the text of the ad. 0 if not

Table 8. Regression output, sale segment, with t-statistics

	Country-wide	Straight Coast	LiDAR	Urban	Rural
Dependent Variable: natural log of the listed sale price					
Playground Variables					
Sand/Shingle					
1km - 500m	0.0374***	0.0378***	0.0255***	0.0399***	0.0219**
	(11.1)	(7.14)	(3.53)	(11.2)	(2.54)
500m - 250m	0.0550***	0.0547***	0.0277***	0.0544***	0.0554***
	(12.1)	(7.43)	(3.01)	(11.1)	(5.12)
250m - 100m	0.0597***	0.0539***	0.0636***	0.0499***	0.0727***
	(9.71)	(5.11)	(5.69)	(7.44)	(5.29)
<100m	0.149***	0.119***	0.174***	0.127***	0.174***
	(15)	(6.28)	(10.6)	(11.5)	(9.13)
Non-Blue Flag Beach					
1km - 500m	0.0063	0.00553	0.0374***	-0.00634	0.0409***
	(1.3)	(0.892)	(3.94)	-(1.21)	(3.22)
500m - 250m	-0.0229***	-0.0338***	0.0452***	-0.0388***	0.0425**
	-(3.03)	-(3.69)	(3.81)	-(5.03)	(1.97)
250m - 100m	0.0337***	0.00278	0.0595***	0.0173	0.0651**
	(2.73)	(0.178)	(3.83)	(1.39)	(1.99)
<100m	0.112***	0.0678*	0.103***	0.0975***	0.151***
	(4.4)	(1.79)	(3.24)	(3.69)	(2.59)
Blue Flag Beach					
1km - 500m	0.0110*	0.0281***	0.0411***	0.0122*	-0.0111
	(1.72)	(2.88)	(2.72)	(1.84)	-(0.534)
500m - 250m	0.0564***	0.0799***	0.0719***	0.0397***	0.0415
	(5.32)	(4.92)	(3.31)	(3.57)	(1.3)
250m - 100m	0.0892***	0.149***	0.105***	0.0685***	0.106**
	(4.73)	(5.71)	(2.84)	(3.45)	(2.16)
<100m	0.0688**	0.103**	0.135***	0.0998***	0.065
	(2.54)	(2.57)	(3.1)	(3.23)	(1.4)
Cliffs					
1km - 500m	-0.0258***	-0.0178**	0.0106	-0.0468***	0.0237*
	-(4.84)	-(2.58)	(0.506)	-(8.19)	(1.9)
500m - 250m	-0.0254***	-0.0609***	-0.143***	-0.0496***	0.0355**
	-(3.17)	-(5.62)	-(3.16)	-(5.61)	(2.14)
250m - 100m	0.0238*	0.0137	-0.153***	0.017	0.019
	(1.74)	(0.55)	-(3.25)	(1.11)	(0.698)

<100m	0.0564*	-0.0327	-0.250***	0.0267	0.100**
	(1.9)	-(0.597)	-(3.51)	(0.739)	(2.05)
Picture Variables					
Seaview breadth	0.0143***	0.0162***	0.0142***	0.0126***	0.0166***
	(14.9)	(8)	(4.94)	(11.9)	(8.25)
Seaview (distant)	0.0110***	0.0120***	-0.000491	0.00938***	0.0122***
	(4.85)	(3.33)	-(0.385)	(3.83)	(3.18)
Seaview depth	0.0196***	0.0194***	0.00944***	0.0185***	0.0182***
	(12)	(5.18)	(2.92)	(9.38)	(6.51)
Controls	YES	YES	YES	YES	YES
Observations	159,472	37,056	23,777	131,066	28,406
R-Squared	0.798	0.797	0.831	0.83	0.668
RMSE	0.28	0.267	0.259	0.258	0.35

Notes: Robust t-statistics in parentheses. Columns shows different samples, while controls include location, dwelling and time listed on the market, as discussed in the text. The results are largely robust to switching to clustering the error terms at the county level. A single asterisk (*) indicates significant at 10%, a double asterisk (**) indicates significant at 5% and a triple asterisk (***) indicates significant at 1%.

Table 9. Regression output, rental segment, with t-statistics

	Country-wide	Straight Coast	LiDAR	Urban	Rural
Dependent Variable: natural log of the listed monthly rental price					
Playground Variables					
Sand/Shingle					
1km - 500m	0.0228***	0.0202***	0.00771**	0.0186***	-0.000589
	(13.1)	(6.47)	(2.28)	(9.93)	-(0.11)
500m - 250m	0.0205***	0.0277***	-0.000131	0.0154***	0.0216***
	(8.9)	(6.63)	-(0.03)	(6.29)	(3.06)
250m - 100m	0.0342***	0.0575***	0.0143***	0.0406***	-0.0150*
	(11)	(10)	(2.6)	(11.9)	-(1.77)
<100m	0.0540***	0.0570***	0.0573***	0.0624***	0.00853
	(12.6)	(7.56)	(8.29)	(13.9)	(0.658)
Non-Blue Flag Beach					
1km - 500m	0.00543**	-0.00256	0.0224***	0.00971***	0.0207*
	(2.07)	-(0.776)	(5.16)	(3.59)	(1.94)
500m - 250m	-0.00770**	-0.0156***	0.00749	-0.00652*	0.0501***
	-(2.07)	-(3.31)	(1.24)	-(1.71)	(2.67)
250m - 100m	0.000362	-0.0168***	0.0184**	-0.00517	0.0623***
	(0.0647)	-(2.79)	(2.37)	-(0.91)	(2.65)

<100m	-0.0229**	0.00893	-0.0357***	-0.0320***	0.0504**
	-(2.27)	(0.7)	-(3.05)	-(2.91)	(2.04)
Blue Flag Beach					
1km - 500m	-0.0112***	0.0209***	0.0333***	-0.0171***	0.0204**
	-(3.03)	(3.93)	(5.43)	-(4.28)	(2)
500m - 250m	0.0127**	0.0387***	-0.00348	0.00948	0.0399**
	(1.98)	(3.38)	-(0.355)	(1.38)	(2.17)
250m - 100m	0.0192*	0.0575***	0.0387**	0.0102	0.0846**
	(1.8)	(3.82)	(2.53)	(0.953)	(2.36)
<100m	0.0084	0.105***	-0.00454	-0.00294	0.144**
	(0.48)	(3.97)	-(0.213)	-(0.16)	(2.3)
Cliffs					
1km - 500m	-0.0206***	-0.0214***	0.0204**	-0.0122***	-0.0272***
	-(6.24)	-(5.34)	(2.01)	-(3.43)	-(3)
500m - 250m	-0.0304***	-0.0381***	-0.0484***	-0.0214***	-0.0368**
	-(5.57)	-(6.39)	-(3.07)	-(3.72)	-(2.49)
250m - 100m	-0.00145	-0.0374**	-0.0690***	0.00423	0.0156
	-(0.133)	-(2.45)	-(3.72)	(0.337)	(0.713)
<100m	-0.0177	-0.00509	-0.133***	-0.00886	0.0158
	-(0.891)	-(0.0809)	-(3.69)	-(0.384)	(0.436)
Picture Variables					
Seaview breadth	0.0106***	0.00524***	0.0168***	0.00950***	0.0130***
	(21.6)	(4.37)	(12.6)	(18)	(10.3)
Seaview (distant)	0.00363**	0.00519**	-0.00178***	0.00289*	0.00917**
	(2.17)	(2.12)	-(3.11)	(1.65)	(2.25)
Seaview depth	0.00512***	0.0198***	0.00589***	0.00701***	0.00254
	(4.69)	(7.46)	(5.34)	(5.84)	(1.08)
Controls	YES	YES	YES	YES	YES
Observations	339, 572	60, 147	87, 988	296, 834	42, 738
R-Squared	0.7942	0.7647	0.7713	0.7992	0.7941
RMSE	0.2074	0.1916	0.2103	0.2025	0.2219

Notes: Robust t-statistics in parentheses. Columns shows different samples, while controls include location, dwelling and time listed on the market, as discussed in the text. The results are largely robust to switching to clustering the error terms at the county level. A single asterisk (*) indicates significant at 10%, a double asterisk (**) indicates significant at 5% and a triple asterisk (***) indicates significant at 1%.

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

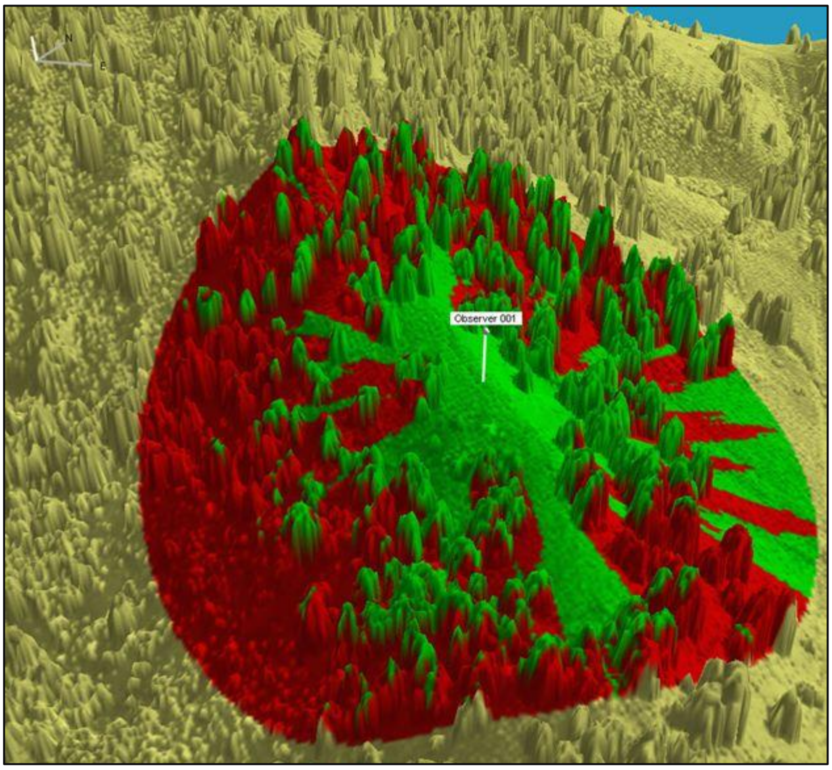

Figure 2: LiDAR Sample Areas (shaded area in Galway represents OPW's inland flood risk sub-sample)

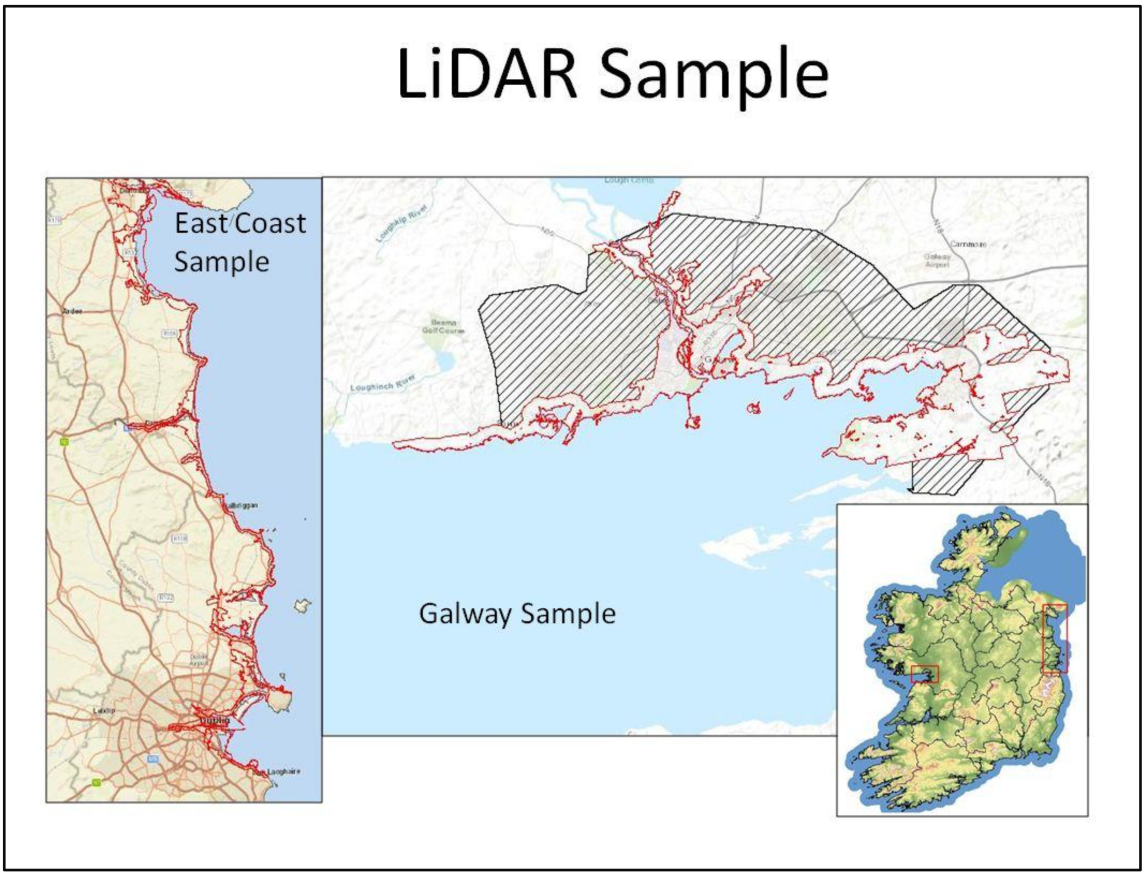

Figure 3: Straight coast geographical samples

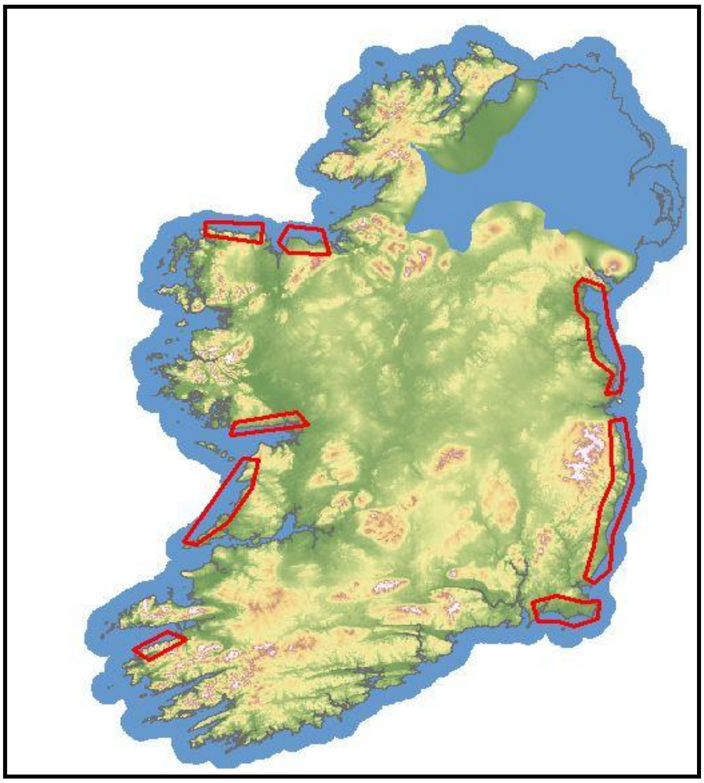

Figure 4: Example of LiDAR detail in inner point viewshed projection on Galway city coastline