

House Prices and Neighbourhood amenities: Beyond the Norm?

Journal:	<i>International Journal of Housing Markets and Analysis</i>
Manuscript ID	IJHMA-04-2017-0043.R1
Manuscript Type:	Research Paper
Keywords:	Housing markets, quantile regression, hedonic pricing model, house prices, externalities, neighbourhood amenities

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Tables and Figures

Table 1 Variable Descriptives

Variable	Description	Type
Price	Sale Price in pounds sterling (£)	C
In Price	Natural logarithm of transaction Price	C
Area	Size of the property in m ²	C
Type	Type of property (Transformed to binary e.g. 1 if TER; 0 otherwise)	B
Class	Public or privately constructed (Transformed to binary e.g. 1 if PUB; 0 otherwise)	B
Bedrooms	Number of bedrooms (Transformed to binary e.g. 1 if 1BED; 0 otherwise)	B
Heating Type	Type of heating (Transformed to binary e.g. 1 if Gas; 0 otherwise)	B
Age	Age of the property (Transformed to binary e.g. 1 if PRE1919 ; 0 otherwise)	B
Garage	Transformed to binary e.g. 1 if GAR; 0 otherwise)	B
Time	Period of sale (Transformed to binary e.g, 1 if Q12014; 0 Otherwise)	B
Ward Location	Ward in which the property is located (Transformed to binary e.g. 1 if Ward1; 0 otherwise)	B
Multiple Deprivation	Level of multiple deprivation (deciles) (OA Level)	B
Crime Level	The number of recorded crime incidents (% per thousand) (Ward Level)	C
Unemployment	Unemployment rate (%) (Ward level)	C
CBD Distance	Distance to CBD [edge of CBD perimeter] (in bands) (metres)	B
Distance to Rail Halt	Distance to nearest rail halt (in bands) (metres)	B
Distance to Bus Stop	Distance to nearest bus stop (in bands) (metres)	B
Distance to Primary School	Distance to nearest primary school (in bands) (metres)	B
Distance to Secondary School	Distance to nearest secondary school (in bands) (metres)	B
Distance to GP	Distance to nearest GP Surgery (in bands) (metres)	B
Distance to Dentist	Distance to nearest Dentist (in bands) (metres)	B
Distance to Chemist	Distance to nearest Chemist (in bands) (metres)	B
Distance to Shopping centre	Distance to nearest Shopping Centre (in bands) (metres)	B
Distance to Open Space	Distance to nearest Area of public open space (in bands) (metres)	B

Notes: C – continuous; B – binary; OA – output area

Table 2 OLS and Quantile regression coefficient estimates

Parameter	OLS model		Quantile model													
	β	<i>t</i> -stat	5th		10th		25th		50th		75th		90th		95th	
	β	<i>t</i> -stat	β	<i>t</i> -stat	β	<i>t</i> -stat	β	<i>t</i> -stat	β	<i>t</i> -stat	β	<i>t</i> -stat	β	<i>t</i> -stat	β	<i>t</i> -stat
(Constant)	10.887	311.31**	10.16	187.78*	10.321	269.1*	10.464	420.66*	10.594	468.59*	10.631	401.83*	10.726	509.6*	10.747	396.21*
Size	0.007	48.60**	0.007	17.48*	0.007	36.97*	0.007	38.40*	0.007	59.49*	0.007	41.987*	0.0078	54.55*	0.008	48.88*
Apartment	0.216	14.71**	0.232	6.67*	0.221	9.13*	0.296	16.33*	0.277	19.41*	0.324	20.69*	0.327	22.15*	0.311	20.86*
Detached	0.324	21.72**	0.280	7.49*	0.248	13.07*	0.238	14.78*	0.259	16.48*	0.272	13.07*	0.301	17.05*	0.363	12.35*
Semi-detached	0.146	15.85**	0.089	5.03*	0.063	5.51*	0.077	8.16*	0.101	10.23*	0.127	15.597*	0.117	14.18*	0.1186	12.34*
Social Built	-0.13	-10.79**	-0.140	-6.40*	-0.155	-9.54*	-0.159	-9.16*	-0.112	-6.88*	-0.096	-5.078*	-0.05	-4.39*	-0.037	-2.28**
No-Garage	-0.018	-2.45*	-0.004	-0.22	-0.009	-0.72	-0.021	-2.50*	-0.024	-3.01*	0.002	0.258	0	0	0.0035	0.37
Electric heating	-0.016	-1.25	-0.063	-2.74*	-0.067	-3.72*	-0.032	-2.60*	0.001	0.090	-0.029	-2.963*	-0.006	-0.184	-0.013	-1.05
Gas heating	-0.011	-1.48	-0.019	-1.368	-0.016	-1.64	-0.003	-0.351	-0.001	-0.141	-0.008	-1.25	-0.012	-1.528	-0.0008	-0.08
Solid heating	0.008	0.02	-0.001	-0.036	0.004	0.24	-0.008	-0.857	-0.004	-0.344	0.009	0.908	0.0064	0.843	0.0116	1.283
Pre-1919	-0.058	-4.31**	-0.017	-0.516	-0.074	-3.34*	-0.052	-3.774*	-0.041	-3.092*	-0.027	-1.97**	-0.041	-3.554*	-0.033	-2.291**
Post-1980	0.075	4.70**	0.196	6.075*	0.126	5.16*	0.099	7.145*	0.0855	4.270*	0.080	4.387*	0.0721	6.135*	0.0548	2.945*
Inter-war	0.002	0.18	0.011	0.416	-0.048	-2.48**	-0.035	-3.210*	-0.034	-3.404*	-0.030	-2.624*	-0.042	-4.497*	-0.0403	-3.344*
Early modern	0.02	1.53	0.112	3.582*	0.066	3.04*	0.067	5.158*	0.053	3.701*	0.0761	4.268*	0.0520	4.457*	0.0611	3.483*
Rail<200	-0.054	-1.91	0.092	0.989	0.064	2.51*	0.101	4.160*	0.1468	4.196*	0.1456	3.950*	0.1302	4.223*	0.1288	3.611*
Rail<400	-0.011	-0.47	0.001	0.022	0.087	2.69*	0.107	6.447*	0.1369	5.525*	0.1488	7.179*	0.1449	8.933*	0.1718	2.531*
Rail<600	-0.002	-0.11	0.164	4.407*	0.123	7.61*	0.125	7.967*	0.1154	10.09*	0.1016	5.628*	0.1098	7.246*	0.1631	13.480*
Rail<800	-0.013	-0.75	0.082	3.173*	0.058	2.50**	0.091	4.051*	0.1043	7.230*	0.1301	13.081*	0.1364	10.720*	0.1433	7.753*
Rail<1000	0.018	1.26	0.101	4.366*	0.103	5.206	0.084	4.813*	0.1044	8.451*	0.1117	7.996*	0.1306	14.211*	0.1321	7.097*
Bus stop<200	-0.006	-0.77	-0.033	-1.67**	-0.026	-2.33*	-0.041	-4.65*	-0.026	-3.45*	-0.002	-0.236	0.012	1.398	0.015	1.72
Bus stop<400	-0.014	-1.64	-0.036	-1.755*	0.004	0.262	-0.012	-1.243	-0.011	-1.145	-0.018	-2.15**	-0.015	-1.748	-0.0250	-2.985*
Sec school<200	0.061	2.89**	0.249	5.737*	0.160	5.101*	0.104	4.901*	0.1080	4.457*	0.0526	3.882*	0.0519	2.398*	0.0496	1.692
Sec school<400	0.045	3.31**	0.159	4.810*	0.124	7.022*	0.077	5.991*	0.0518	3.506*	0.0470	3.073*	0.0671	4.301*	0.0581	4.342*

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Sec school<600	0.012	1.07	0.065	2.9503*	0.049	2.912*	0.013	1.123	-0.002	-0.175	-0.003	-0.238	0.0237	2.393*	0.0156	1.246
Sec school<800	-0.013	-1.42	0.026	1.087	0.011	0.893	-0.010	-0.946	0.0181	1.873	0.0071	0.66	0.0371	4.016*	0.0309	3.447*
Pri school<200	-0.02	-2.11*	-0.047	-2.442**	-0.036	-2.40**	-0.042	-3.787*	-0.0444	-4.1712*	-0.0434	-4.895*	-0.051	-5.732*	-0.0468	-4.282*
Pri school<600	0.008	0.98	0.011	0.536	0.006	0.557	0.011	1.183	0.0137	1.538	0.0060	0.658	0.0252	3.278*	0.0132	1.445
Pri school<800	0.028	2.17*	0.012	0.486	0.006	0.414	0.002	0.191	-0.004	-0.287	-0.004	-0.294	0.031	2.719*	0.020	1.696
Pri school<1000	0.049	2.33*	0.015	0.408	0.033	1.097	0.038	1.607	0.0835	4.2797*	0.0490	1.974**	0.0329	1.49	0.0049	0.131
Open<200	-0.001	-0.04	-0.101	-2.27**	-0.085	-1.202	-0.060	-1.260	-0.0043	-0.160	0.0050	0.331	0.0079	0.433	0.0321	1.048
Open<400	0.003	0.27	-0.078	-3.672*	-0.087	-5.699*	-0.035	-2.494*	-0.0363	-2.728*	-0.0494	-2.976*	-0.039	-3.029*	-0.0278	-1.996**
Open<600	-0.016	-1.70	-0.065	-2.500**	-0.074	-5.296*	-0.041	-2.929*	-0.0194	-1.746	-0.0254	-2.741*	-0.028	-3.524*	-0.0111	-1.145
Open<800	0.012	1.48	0.043	2.477**	0.023	2.08**	0.003	0.346	-0.013	-1.514	-0.0078	-0.99	-0.008	-1.017	0.0003	0.038
Open<1000	0.211	8.87**	0.033	0.489	0.044	1.035	0.074	2.765*	0.0215	1.235	0.0253	0.749	0.1027	1.87	0.1753	3.391*
<i>Adjusted R²</i>	0.818															
<i>F-Statistic/ AIC</i>	143.4*		2108		1260.9		1260.9		-660.96		-507.87		283.81		944.85	
<i>n</i>	3,780		3,780		3,780		3,780		3,780		3,780		3,780		3,780	

Dependent variable: Ln Sale Price; β = unstandardised beta; **Denotes significant at the 99% level; *95% level.
Model presented in its most parsimonious format for space requirement. Excludes: Wards (location) and time.

Table 3 Summary of variables which depart from the OLS

Variable	OLS β	Quantile β	Δ coefficient	Δ in Sig.	Trend in pricing (increase/decrease)
Apartments	.216	75 th = .324 90 th = .327	+.108 +.111	Yes	Positive toward (HQs)
Detached	.324	10 th = .248 90 th = .363	-.076 +.039	No	Negative toward (LQs) Positive toward (HQs)
Social built	-.130	95 th = -.037 90 th = -.050	-.093 -.080	No	Negative toward (HQs)
Post-1980	.075	5 th = .196 10 th = .126	+.121 +.051	No	Positive toward (LQs)
Inter-war	.002	10 th = -.048 95 th = -.040	-.048 -.040	Yes	Negative toward (All Qs except 5 th)
Early modern	.02	5 th = .112	+.092	Yes	Positive toward (All Qs)
Rail <200	-0.054	50 th = .146	+.200	Yes	Positive toward (All Qs)
Rail <400	-0.011	95 th = .178	+.189	Yes	Positive toward (All Qs)
Rail <600	-0.002	5 th = .164 95 th = .163	+.162 +.161	Yes	Positive toward (All Qs)
Rail <800	-0.013	95 th = .143	+.142	Yes	Positive toward (All Qs)
Rail <1000	0.018	5 th = .101 95 th = .132	+.100 +.131	Yes	Positive toward (All Qs)
Bus Stops<200	-0.006	25 th = .041	-.040	Yes (LQ's)	Negative toward (All Q's except 90 th , 95 th)
Bus Stops<400	-0.014	5 th = -.036 95 th = -.025	-.022 -.011	Yes (LQs; HQs)	Negative toward (All Q's except 10 th)
Sec School <200	0.061	5 th = .249	+.18.8	No	Positive toward (LQs)
Sec School <400	0.045	5 th = .159	+.114	No	Positive toward (LQs)
Sec School <600	0.012	5 th = .065	+.053	Yes	Positive toward (LQs)
Sec School <800	-0.013	90 th = .037 95 th = .031	+.050 +.044	Yes	Positive toward (HQs)
Open space <200	-0.001	5 th = .101	+.101	Yes	Positive 5 th Q only
Open space <400	0.003	5 th = -.078 10 th = -.087	-.078 -.087	Yes	Negative toward (LQs)
Open space <600	-0.016	5 th = -.065 10 th = -.074	+.049 +.068	Yes	Positive toward (LQs)
Open space <800	0.012	5 th = .043	+.031	Yes (LQs)	Positive toward (5 th , 10 th Qs)
Open space <1000	0.211	95 th = .173	+.152	No	Positive (95 th Q only)

NB: The most extreme deviations are presented. LQs depicts Lower Quartiles; HQs depicts Higher Quartiles.

Figure 1 OLS and Quantile estimates for property type

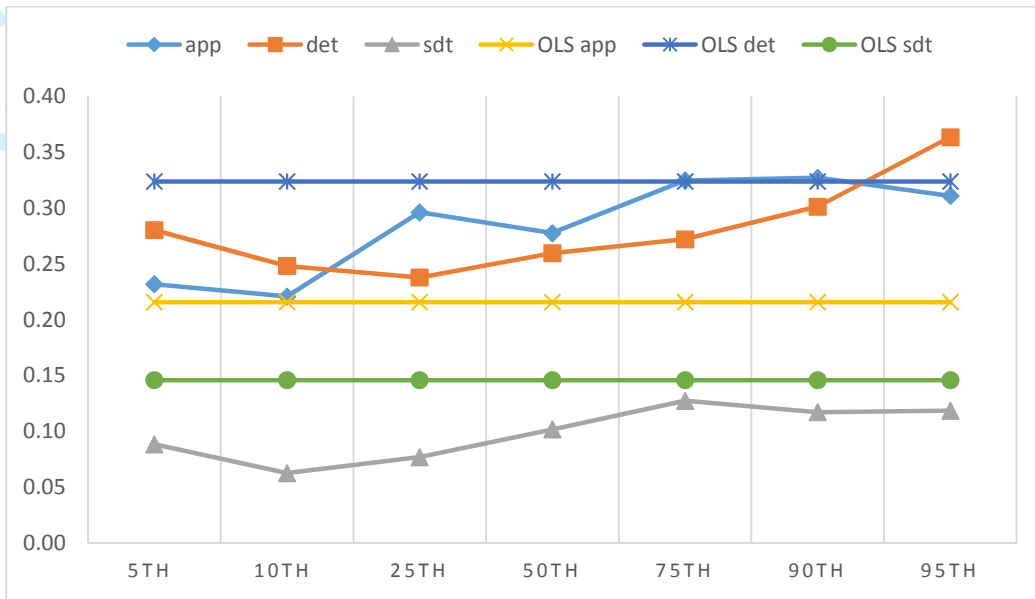


Figure 2 OLS and Quantile estimates for property Age

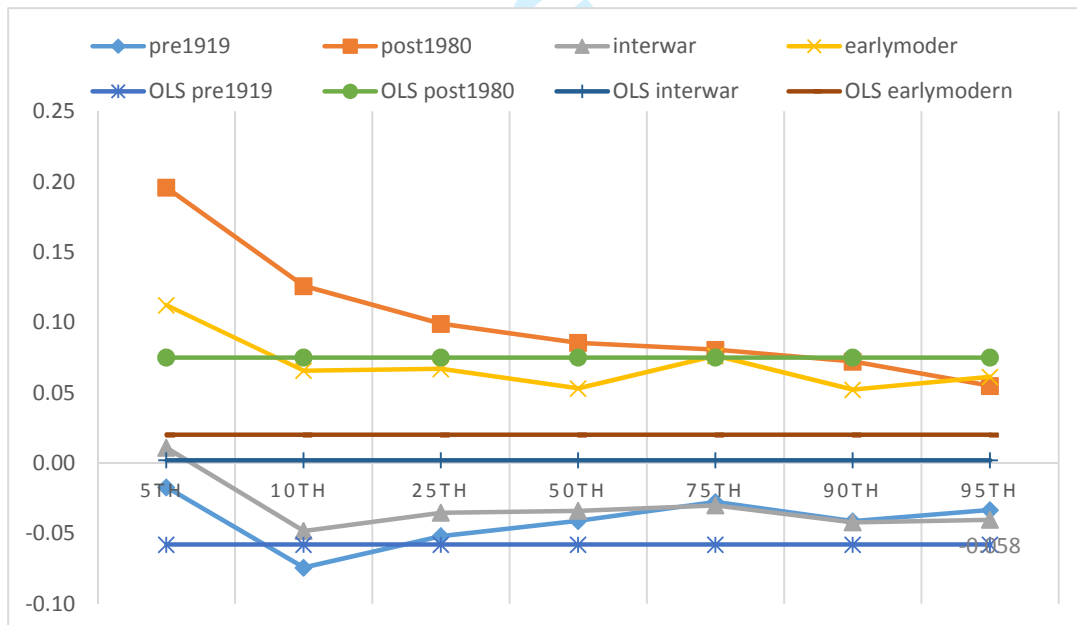


Figure 3 Distance to Rail Halts OLS and Quantile coefficients

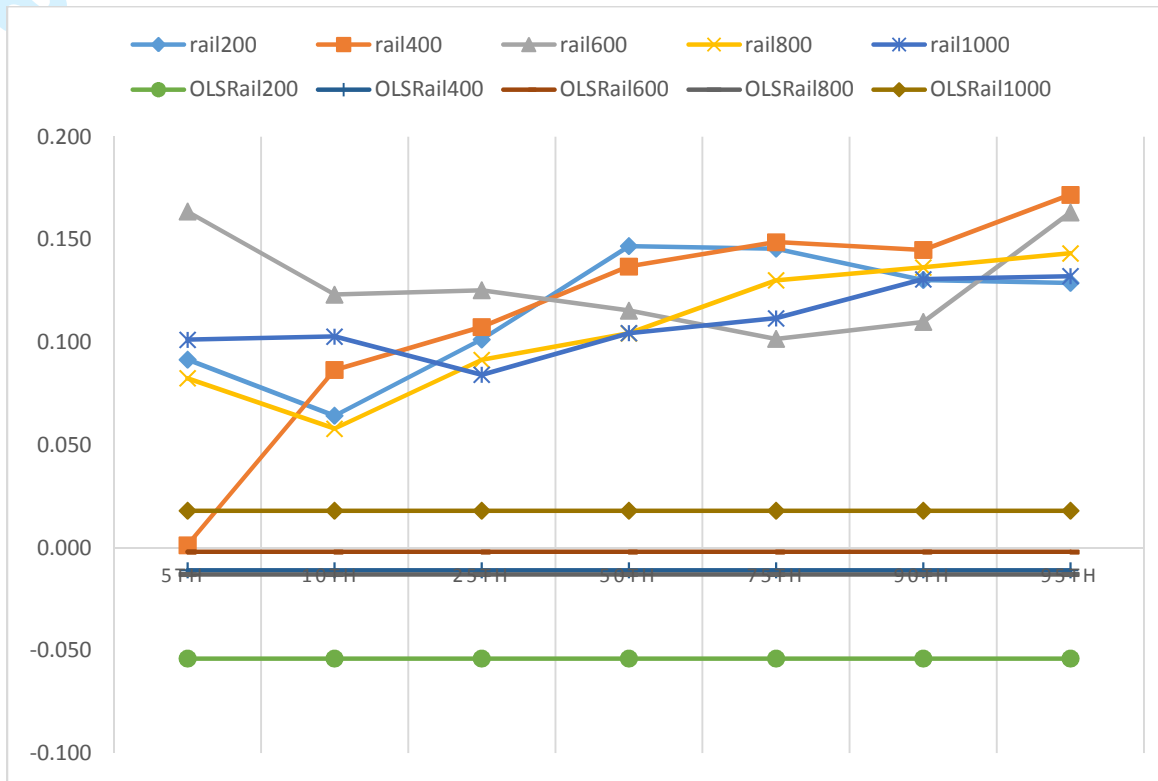


Figure 4 Distance to Secondary schools OLS and Quantile coefficients

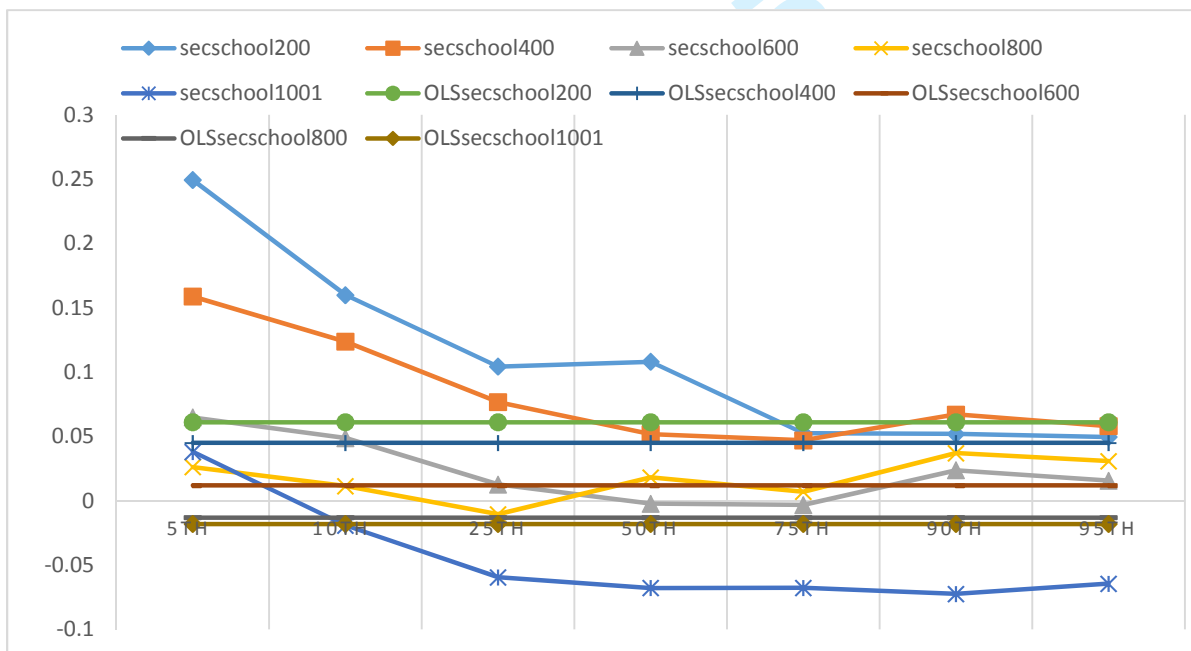


Figure 5 Distance to Primary schools OLS and Quantile coefficients

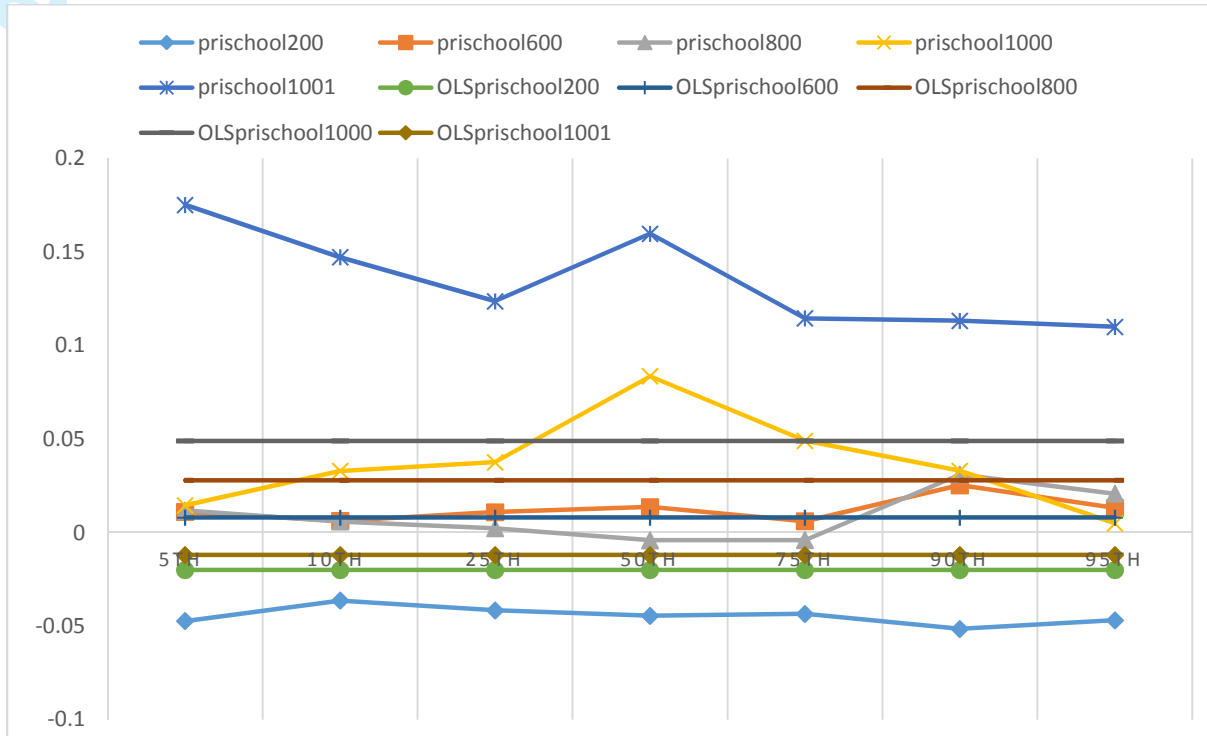
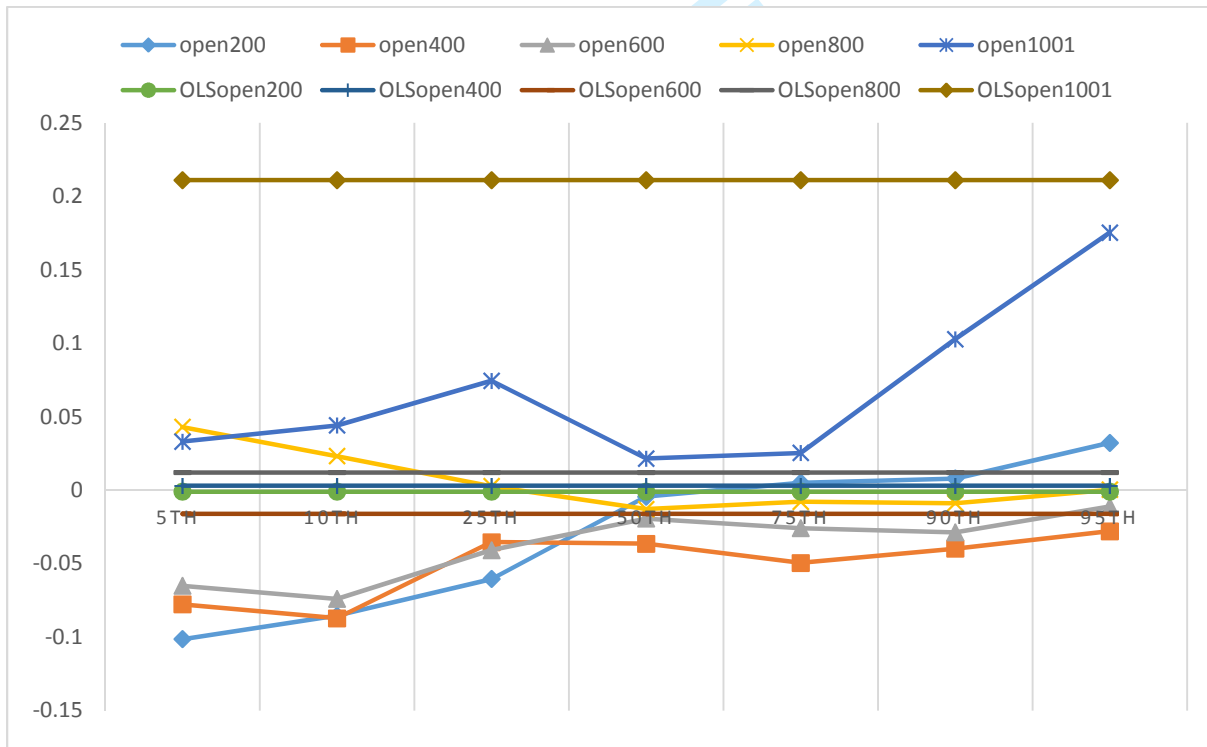


Figure 6 Distance to Public Open Space OLS and Quantile coefficients



House Prices and Neighbourhood amenities: Beyond the Norm?

ABSTRACT

Purpose: Understanding the key locational and neighbourhood determinants and their accessibility is a topic of great interest to policy makers, planners and property valuers. In Northern Ireland, the high level of market segregation means it is problematic to understand the nature of the relationship between house prices and the accessibility to services and prominent neighbourhood landmarks and amenities. Therefore, this paper attempts to quantify and measure the (dis)amenity effects on house pricing levels within particular geographic housing sub-markets.

Design: Most hedonic models are estimated using regression techniques which produce one coefficient for the entirety of the pricing distribution, culminating in a single marginal implicit price. This paper employs a quantile regression approach which provides a 'more complete' depiction of the marginal impacts for different quantiles of the price distribution using sales data obtained from 3,780 house sales transactions within the Belfast Housing market over 2014.

Findings: The findings emerging from this research demonstrate that housing and market characteristics are valued differently across the quantile values and that conditional quantiles are asymmetrical. Pertinently, the findings demonstrate that OLS coefficient estimates have a tendency to over or under specify the marginal mean conditional pricing effects due to their inability to adequately capture and comprehend the complex spatial relationships which exist across the pricing distribution.

Originality: Numerous studies have used OLS regression to measure the impact of key housing market externalities on house prices, providing a single estimate. This paper uses a quantile regression approach to examine the impact of local amenities on house prices across the house price distribution.

KEY WORDS: housing markets, quantile regression, hedonic pricing model, house prices.

Introduction

Housing can be considered as a bundle of utility-bearing characteristics. As such; the implicit price of property attributes can be revealed from the observed prices of differentiated products and the quantities of characteristics associated with them. These characteristics are often decomposed into vector implicit structural attributes, neighbourhood and environmental traits and accessibility estimates (Kim *et al.*, 2015). This approach observes the unbundling of the housing product to assess the (implicit) value that individuals are revealing by their (explicit) choices in the housing market (Sheppard, 1999). Price modelling in housing markets traditionally applies hedonic ordinary least squares (OLS) regression modelling

originally pioneered by Lancaster (1966) and Rosen (1974). However, Koeneker and Hallock (2001) suggest that simple OLS assumes a constant marginal impact across the entire distribution of the dependent variable – such assumption is not always prevalent in housing markets. Indeed, research conducted by Sirmans et al. (2005) demonstrates high variability in magnitude and direction of coefficient estimates between housing characteristics and house prices. This heterogeneity and diverseness within results, whilst illuminating the idiosyncratic nature of ‘specific’ markets and behaviour/preference choices (Malpezzi, 2003), also points towards ‘quantile effects’ which occur when housing characteristics are valued differently across the conditional distribution of house prices (Liao and Wang, 2012; Zhang and Leonard, 2014). Essentially, pricing effect varies across the price spectrum.

To address this, a viable approach for understanding the price relationship is the application of quantile regression. This method dissects the pricing into quantiles to explore the effect of the explanatory variables across the pricing distribution, by estimating the changes in a specific quantile. This permits a more comprehensive understanding of the effect of explanatory variables on house prices as well as modeling the difference in the level of the effect. At the same time it reflects changes in the magnitude of the coefficients (Kim *et al.*, 2015). As highlighted by Newsome and Zietz (1992), this eliminates the biased estimation issues when applying the OLS estimation to house price sub-samples and is particularly valuable for the examination of segmented markets, as it reduces statistical issues related to truncated data based on the mean value (Heckman, 1979).

House price analysis within the Northern Ireland, and specifically, the Belfast housing market is limited, with existing studies tending to employ the standardised hedonic framework. Whilst the results of these extant studies have demonstrated robust findings as to the marginal effects on house prices, arguably they have failed to account for the variability across the price spectrum and the associated impacts of housing choice. This is an important issue pertinent to the Belfast housing market, as it is unique (asymmetrical) in its market characteristics which has a tendency to distort normal market behaviour and activity. Belfast has emerged unevenly from conflict and remains a bifurcated city (Murtagh and Keaveney, 2006). Whilst the last decade observed a stabilisation in ethno-religious segregation due to peace, political stability, growth in the macro economy, housing market and in business confidence; Belfast’s post-conflict renaissance remains somewhat questionable as issues such as multiple deprivation (the spatial distribution of deprivation or disadvantage), ethno-

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3 religious segregation and a sense of residential fatalism (unalterable housing choices) remain.
4 Indeed, Murtagh (2011) observes that new mixed housing spaces have developed in the high-
5 value end of the housing market, manifesting in “class restructuring” and socio-spatial
6 segregation, or clustering. McCord et al. (2013) highlight that this has changed the
7 topographical composition across the housing market. Indeed, the existing bifurcated market
8 impacts upon the pricing structure across the market and importantly upon access to services
9 and amenities. The result of these processes has manifested in a complex mosaic of price
10 patterns distinguished by enclaves of gentrification and deprivation as a result of extant
11 barriers such as peace walls which scar the Belfast housing market landscape. The continued
12 access to contested space and the associated policy remedies has resulted in market based
13 (both economic and social) implications which have undoubtedly further impacted upon
14 access to services and neighbourhood amenities.
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24 In response to these issues, this paper empirically estimates the effect of housing
25 characteristics across the Belfast housing market, specifically examining key neighbourhood
26 amenities, in order to determine whether any differences exist in the hedonic effects between
27 the quantile house price levels. This provides further understanding of the effects of specific
28 property and locational features when estimating pricing within the Belfast housing market
29 and is important for illustrating the potential variability in attribute and locational effect
30 across the price spectrum elsewhere.
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36 The paper proceeds as follows. Section 2 reviews the relevant literature related to house
37 prices and the role of externalities within housing markets, detailing the considered value
38 proposition of quantile hedonic analysis relative to more conventional OLS modelling
39 techniques. This is followed by the data and methodology in section 3, with the results
40 presented and discussed in Section 4. Finally, some conclusions are offered in Section 5.
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48 Literature Review

49 In the context of housing literature, amenities and environment effects are key considerations
50 and hedonic methods with spatial analyses have gained popularity to provide estimates of the
51 proximity “effect” of a variety of positive and negative environment-specific externalities on
52 property prices (Des Rosiers *et al.*, 1999; Irwin, 2002; McConnell and Walls, 2005). Indeed,
53 over the past four decades, a plethora of studies have reported significant positive and
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3 negative effects on house price from a variety of proximate locational externalities (Quang
4 and Grudnitski, 1994; Kauko, 2003) inferring that the value of a specified (dis)amenity is, at
5 least, partially captured in the price of residential properties proximate to it (Crompton,
6 2001). This includes an extensive volume of research devoted to estimating amenity values
7 for land use diversity and landscape structure (Patterson and Boyle, 2002; Des Rosiers *et al.*,
8 2002). A large and growing literature estimates the effects of neighbourhood open space on
9 residential property values (Bolitzer and Netusil, 2000; Tyrväinen and Miettinen, 2000;
10 Lutzenhiser and Netusil, 2001, Smith *et al.*, 2002). There is a burgeoning body of work
11 relating to the property value impacts of home location proximate to neighbourhood style and
12 distance and accessibility to amenities (Hendon, 1972; Espey and Owusu-Edusei, 2001;
13 Morancho, 2003; Song and Knaap 2004; Van den Berg and Ter Heijne, 2005; Jorgensen *et*
14 *al.*, 2007; Kong *et al.*, 2007; Zhang *et al.*, 2012; Brunauer *et al.*, 2013; Dziauddin *et al.*, 2013;
15 Liao and Chen; 2013; Reed, 2013; Dubé *et al.*, 2014).

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26 Nonetheless, this extensive volume of existing research show differing and mixed pricing
27 effects of proximity to neighbourhood amenities and house prices, and perhaps more
28 pertinently, this research has tended to consider the mean effects only - assuming that, on a
29 percentage basis, conditional house prices are all equally affected by neighbourhood
30 characteristics and amenities. Indeed, studies such as Bayer *et al.* (2004), who examined
31 equilibrium residential sorting, provide empirical evidence that confirms these differences
32 with their estimates precisely characterising these preferences. Their study found that
33 marginal willingness-to-pay for desirable housing characteristics and location attributes,
34 including neighbourhood socio-demographic compositions, accessibility to workplace and
35 proximity to amenities, increases with income.

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45 In this regard, literature on house prices had not examined this diffuse dimension until recent
46 applications of quantile regression (Mueller and Loomis, 2014). Quantile regression is
47 particularly useful when examining segmented markets (such as what occurs in most urban
48 residential housing markets). The full characterisation of the conditional distribution, rather
49 than the conditional mean, of house prices is examined in several studies (Gyourko and
50 Tracy, 1999; Coulson and Mcmillen, 2007; McMillen, 2008; Zietz *et al.*, 2008; Mak *et al.*,
51 2010; Ebru and Eban, 2011). Indeed, the seminal investigation by Gyourko and Tracy (1999)
52 demonstrated that quantile analysis estimated quality improvements in high-end housing
53 much higher than the original OLS specification. Coulson and McMillen (2007) and
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3 McMillen (2008), who construct quantile house price indexes and reflect on house price
4 appreciation, identify significant variations in the values of physical attributes across
5 conditional quantiles. In a similar vein, other studies employing quantile regression find
6 strong evidence that marginal implicit prices vary across the conditional distribution of house
7 prices. Liao and Xizhu (2012) present evidence of ‘substantial variation’ of the implicit prices
8 of housing characteristics within a quantile regression framework in the Chinese context.
9 Other studies conducted by Mak *et al.* (2010), and Ebru and Eban (2011) employed quantile
10 regression techniques to analyse Hong Kong and Istanbul real estate prices respectively,
11 revealing that housing attributes were valued differently across the conditional price
12 distribution. Significantly, the findings of Mak *et al.* (2010) showed that quantile effects exist
13 even for single condominiums. Zietz *et al.* (2008) applying a novel spatial quantile regression
14 for Orem-Provo, Utah, discovered that housing attributes are valued quite differently across
15 the conditional price distribution, however, they observe negligible spatial dependence and
16 conclude that quantile effects are of greater importance. In a different context, a study
17 conducted by Xuming and Yicheng (2009) applied the quantile regression methodology to
18 examine the accuracy of mass appraisal for the purpose of real estate taxation and mortgages.
19 Their findings illustrated that property characteristics impact differently to real estate prices
20 within different value ranges.
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33 The corpus of the existing research presents persuasive evidence that the relationship between
34 house prices and neighbourhood amenities and characteristics is complex and not all forms of
35 neighbourhood externalities are valued equally by households. This is enshrined in the
36 seminal hedonic theoretical construct as furnished by Rosen (1974) who proposed that
37 identical houses in similar neighbourhoods will have different prices if the houses have
38 different levels of environmental amenity or disamenity. Ultimately this implies that potential
39 buyers may be willing-to-pay more (less) for (dis) amenity proximity preference thus
40 resulting in house price differentials between houses with varying levels of environmental
41 (dis)amenity is buyers’ marginal willingness-to-pay.
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50 The value of going beyond the conditional mean model has been demonstrated in rapidly
51 expanding literatures in econometrics, social sciences, and more latterly in property studies.
52 Quantile regression has arguably emerged as a useful supplement to ordinary mean-based
53 regression. As existing literature findings illustrate, the upper or lower quantiles of the
54 response variable depend on the covariates very differently from the mean. Therefore,
55 quantile regression can provide a more complete description of functional changes than
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3 focusing solely on the mean. This makes very minimal assumptions on the form of error
4 distribution and thus is able to accommodate non-normal errors, which are common in many
5 applications (Koenker, 2005; Reich et al., 2010). Despite this emerging corpus of literature,
6 some recent studies have illustrated challenges pertaining to the quantile approach. Reich et
7 al. (2010) note that although theory for quantile regression is well versed, the development of
8 convenient inference procedures has been challenging, as the asymptotic covariance matrix of
9 quantile estimates involves the unknown error density function, which cannot be estimated
10 reliably.
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18 Moreover, Beyerlein (2014) indicates that the quantile regression approach is based on
19 'samples' meaning that assessing the 'quantiles' or percentiles can be difficult. Nonetheless
20 the author does indicate that this problem may be solved by assessing the percentage of
21 observations at or below the respective threshold and then modeling the associated quantile.
22 This is also acknowledged by Reich et al. (2010) who highlight that inference for quantile
23 models is challenging, particularly for clustered or censored data, as limited options exist for
24 inferential analysis. This has been subject to various research studies amongst others (Jung,
25 1996; Lipsitz, 1997; Yin and Cai, 2005 and Wang and Fygenson, 2009).
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33 Another challenge corresponds to the wider applicability of 'intuitive interpretation'
34 (Koenker, 2005). The interpretation of a single measure obtained from linear regression
35 appears more straightforward than the interpretation of a number of quantile regression
36 coefficients, which may not combine to form a simple picture. As quantile regression
37 coefficients quantify how much a specific quantile of the outcome distribution is shifted by a
38 one-unit increase in the predictor variable, this interpretation is consonant to that of linear
39 regression. Indeed, the only tangible difference is that of an average difference for standard
40 linear regression - whereas there is no appropriate terms in common language to easily
41 describe results from quantile regression (Reich et al., 2010). Despite this lack of clarity (in
42 some instances), as existing studies have tended to highlight, the pattern of regression
43 coefficients over the whole range of quantiles reveal the true nature of the underlying
44 associations. Whilst simplicity of interpretation is an important criterion for the choice of a
45 statistical approach, the quantile regression method is not considerably inferior to linear
46 regression. In contrast, it offers much more information and is less sensitive with respect to
47 the distribution of the outcome variable (Beyerlein, 2014).
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Data and Methodological framework

Data

The sales information is drawn from the Belfast housing market comprising 3,780 sales transacted during 2014. The initial dataset comprising 3,853 observations was examined for outliers and other data anomalies and subjected to statistical procedures¹ for outlier removal (resulting in 73 cases being removed). In addition, missing observations were purged along with those incorrect as a consequence of erroneous data entry. Where appropriate, variables were transformed into a binary state as illustrated in **Table 1**. To capture accessibility, services and important amenities, distance calculations were ascertained using X , Y coordinates for each sales observation. Census tract data was sourced from the Northern Ireland Neighbourhood Information Statistics (NINIS) and Northern Ireland Statistical Research Agency (NISRA). At the census geography, where feasible, Output Areas (OAs)² [the lowest level geographic information], were utilised to account for and provide specific demographic, socio-economic characteristics (for example; level of employment, population demographics and the Multiple Deprivation Measure (MDM))³. Where appropriate, the Euclidian distance measures were transformed into distance band dummy variables. This was a necessary step in order to band each respective property attribute and distance to nearest market amenity and service. This step also served to ensure sampling adequacy for the hedonic modelling stage. The variables utilised in the statistical analysis are evidenced in **Table 1**.

<<<Insert Table 1 Variable Descriptives>>>

Hedonic modelling

Hedonic modelling is the traditional technique applied within property analysis to ascertain the marginal effects of property attributes to capture the relationship between house prices and housing/spatial attributes. Typically, as identified in the seminal writings of Rosen (1974) the

¹ This research employed Cook's distance procedure to remove problematic outlier cases using the criteria formula: $4/(n - k - 1)$, where n is the number of cases in the analysis and k is the number of independent variables.

² OA's are computer-generated and intended to be of uniform population size, take account of postcode and ward B boundaries and to be as socially homogeneous as possible. The 5,022 Northern Ireland OAs contain an average of 336 persons and 125 households. The minimum threshold for publication of census data was 100 persons and 40 households.

³ The Multiple Deprivation Measure provides information on seven types or 'domains' of deprivation and an overall multiple deprivation measure comprising a weighted combination of the seven domains presented at the Output Area and Super Output Area geography. The MDM was further dissected into deciles and transformed into binary state

basic form of the house price model is the functional relationship between the price P of a heterogeneous good i and its quality characteristics represented by a vector x_i :

$$P_i = f(x_i; \beta) + u_i \quad (1)$$

Where P_i is a property with a price P , x_i is the structural attributes of size and quality, and also attributes of the neighbourhood in which the property is located (indicators of the adjacent environment and accessibility), β relates to the vector of coefficients which are estimated for the characteristics, with u_i representing the error term.

The hedonic approach is however open to critique as the price function is an envelope function signifying that there is no 'exact' theoretical guidance for its specification which can give rise to mis-specification challenges, particularly for any given sample data. In the absence of clear guidance, it is appropriate to test several functional forms such as the semi-logarithmic or logarithmic-logarithmic (multiplicative) hedonic equation in order to determine the optimal approach. In this regard, the semi-log hedonic specification can be applied where:

$$\ln(P_i) = \alpha + \sum_{j=1}^J \beta_j z_{ji} + e_i \quad (2)$$

where the natural log of the i^{th} house is a function of the J characteristics assumed to influence price, α and β the coefficients estimated, and e the normally distributed error term.

When employing the semi-log specification, the functional form facilitates the evaluation of the percentage effect. As highlighted by Halvorsen and Palmquist (1980) for the semi-log model specification capturing the true percentage change of a dummy variable is:

$$g = 100[\exp([\alpha]) - 1] \quad (3)$$

Where; the relative effect on the dependent variable of the presence of the factor represented by the dummy variable bn .

In order to identify the influence of different factors on real estate value, this paper introduces a quantile regression model to analyse the factors. For assessment value functions, quantile regression makes it possible to statistically examine the extent to which housing

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3 characteristics are valued differently across the distribution of housing values. In line with
4 Koenker and Hallock (2001) and Kim *et al.* (2015) methodologies, quantile regression is
5 based on the minimization of weighted absolute deviations to estimate conditional quantile
6 (percentile) functions (Koenker & Bassett, 1978), where the quantile hedonic specification
7 generalizes the concept of unconditional quantile to a quantile of conditioned on one or more
8 covariates. For the median (quantile=0.5), symmetric weights are used, and for all other
9 quantiles asymmetric weights are employed⁴. In contrast, where classical OLS estimates
10 conditional mean functions, quantile regression employs the full data set, a sample selection
11 problem does not arise (Xuming and Yicheng, 2009), as this avoids the problem of
12 truncation. Least squares minimizes the sum of the squared residuals, therefore, the symmetry
13 of the piecewise linear absolute value function implies that the minimisation of the sum of
14 absolute residuals must equate with the number of positive and negative residuals, ensuring
15 the same observations above and below the median.⁵
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27 *Model Parsimony*

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29 Initial model inspection of the standardised residuals for both the linear and semi-log forms
30 was undertaken to establish the relative ‘goodness of fit’ and account for any potential
31 neglected nonlinearities within the OLS specification. Given the importance of the
32 relationship between price and building size (floor size in m²), this was initially inspected in
33 order to establish whether any non-linearity exists for optimal model structure. As evidenced
34 in **Appendix 1**, the log-Price and area relationship explains 39.3%, whereas the Log-Price
35 and Log-Area explains 34.5%, illustrating that the Area (Size) variable requires no further
36 transformation. Nonetheless, preliminary analysis highlighted issues pertaining to model
37 structure given the inclusion of neighbourhood characteristics, which have a tendency to
38 demonstrate spatial autocorrelation. Whilst spatial autocorrelation within spatial econometric
39 analysis remains a significant and emerging field of study, considerable debate still concerns
40 which is the most apposite approach for addressing it and how the variation in the methods
41 impact upon spatial dependence (For a full discussion see Koschinsky et al., 2012). Setting
42 that aside, the model developed within the confines of this research does not employ a
43 ‘spatial econometric’ model, rather, the OLS specification encapsulates locational (fixed
44 spatial effects) dummies employing sub-markets (OA level using electoral market
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57 ⁴ see endnotes for a full methodological overview

58 ⁵ See Endnotes for a full discussion
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delineation) to control for the spatial component when testing the quantile regression approach. Therefore, the models developed compare the traditional global OLS with a Quantile OLS which both employ spatial dummies to permit robust comparison.

To address any issues pertaining to multicollinearity within the OLS and QR approach, a model selection procedure was employed to increase model robustness, stability and to handle detrimental variables. As discussed by deSmith *et al.* (2007), whilst the inclusion of additional estimators can enhance model performance, this can contrive and distil the explanatory relationships between parameters and culminate in an excessively complicated model structure which is often difficult to interpret (particularly when examining neighbourhood (spatial) characteristics). In this regard, this paper employs the most parsimonious model format, whilst maximising model performance. To select the optimal model structure, model development was tested using a regression procedure in order to classify any detrimental variables. Diagnostic analysis employing the Variance Inflation Factor (VIF) and Tolerance limits were also scrutinised to measure any influential variables (For full model see Appendix 1). This approach was further complimented using an information theoretic statistic, the Akaike Information Criterion (AIC). This statistic is premised on the maximum likelihood estimates of the model parameters where the probability of the observed data would be as large as possible. The estimates are based on maximum likelihood estimates of the model parameters which provide an approximate AIC value:

$$AIC = n + n \ln(2\pi) + n \log \left(\frac{RSS}{n} \right) + 2K \quad (6)$$

This multi-model inference procedure was applied to ensure the most appropriate explanatory variables were included in the final modelling phase⁶ with the selection procedure filtered by the AIC. The model inference was conditioned on fixed explanatory variables containing all spatial and neighbourhood characteristics, with the predictor floating variables comprising the structural variables. This permitted the minimum AIC value and most parsimonious model for analysis⁷ to be deployed. The initial iterative modelling results revealed that the

⁶According to Burham and Anderson (2002, 2004) if the value of δAIC is higher than 7 the model has a relatively poor fit relative to the best model, whereas a value less than 2 indicates that a model is equivalent to the minimum AIC model.

⁷The RSS is the sample residual sum of squares and K is the number of estimable parameters in the model including the intercept and the residual variance $\hat{\sigma}^2$. This balances error with model complexity (increasing K), with the optimal model comprising the minimum AIC score. This equation gives the small sample

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3 most parsimonious model form excluded crime and unemployment neighbourhood variables
4 – perhaps as they are already captured within the indicators which constitute the measure of
5 Multiple Deprivation and a number of the neighbourhood convenience amenities, such as
6 distance to the CBD, doctor surgeries, dental practices, pharmacists and shopping centres.
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8 Interestingly, the bedroom coefficients and distance to CBD displayed no statistical
9 significant effects or additive value to the explainability within the model framework.
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11 Furthermore, the bedroom coefficients also exhibited severe levels of Variance Inflation⁸,
12 likely demonstrating a collinear relationship with property size (Appendix 1). As a
13 consequence these structural and neighbourhood predictors were removed from further
14 analysis.
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23 Empirical Results and findings

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26 The empirical analysis is conducted on the OLS regression and subsequent quantile
27 regression employing seven quantiles across the house price distribution, as evidenced in
28 **Table 2**.
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31 <<<Insert Table 2 OLS and Quantile regression coefficient estimates>>>

32 *Property (structural) attributes*

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35 In terms of comparison, the OLS and quantile coefficients show a general trend in terms of
36 the estimates sign and statistical significance for the structural characteristics of the
37 properties. Examination of the size (m²) parameter within the OLS and quantile estimates
38 shows that they are all statistically significant, with marginal effects only increasing above
39 the 50th percentile of the price distribution - which incrementally increase as per each quantile
40 (95th quantile; $\beta = .008$, $p < .05$). This suggests that size is valued differently across the
41 quantiles and that conditional quantiles are not identical. Indeed, the results show this effect
42 when considering the nature of the property type (**Figure 1**). The analysis exhibits OLS
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52 approximation (AIC_C), that converges to standard AIC for large samples. The value of σ^2 is used as a proxy for
53 the likelihood of the model given the data. The AIC values for the various models are transformed to ΔAIC ,
54 which is the difference between AIC of each model and the minimum AIC found for the set of models compared
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56 ⁸ VIF signifies the magnitude of inflation within the standard errors associated with the beta weight. Various acceptable
57 levels of VIF have been used in extant research (Pan and Jackson, 2008 = 4; Rogerson, 2001 = 5; Hair and Anderson, 1995 =
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coefficients to generally over or under specify the marginal mean conditional pricing effects. Scrutiny of the type of property reveals a number of (relatively) high disparate pricing effects. For apartments, estimates shows the OLS coefficient effect of 0.216 ($t = 14.717$, $p < .01$) is more relative to the coefficient estimates for both the 5th and 10th quantiles ($\beta = .232$; $\beta = .221$), whereas above the 25th quantile the OLS underestimates the positive pricing effect by circa 10%. Alternatively, for detached properties the mean conditional OLS coefficient generally over specifies the effect when comparing against the quantiles. Below the 90th quantile estimate, the results show a high variability of around 7-8% (at the 10th and 25th quantile) demonstrating that the OLS mean conditional estimate is tending to over value and is more reflective of the higher priced properties. This is a similar picture for the semi-detached properties as evidence in **Figure 1**.

<<< **Insert Figure 1 OLS and Quantile estimates for property type**>>>

Interestingly, the construction of publically built housing (social built) shows a different relationship illustrating the OLS estimate to be relatively concomitant up to the 50th quantile which diminishes significantly up the 95th quantile. Significantly, this shows a marginal decrease in the level of the pricing effect the higher up the quantile distribution, and that higher valued socially built housing has a diminished effect than lower valued socially constructed housing (**Table 2**). Scrutiny of the garage coefficient (no garage) also reveals that the OLS, and quantile coefficients - up to the 50th quantile, bear the same sign with marginal fluctuation in coefficient values. Pertinently, above the 50th quantile the estimates turn positive and are not statistically significant. This infers that the effect or value of having no garage is only a contributory factor at the lower and mean value range of housing in the sample.

Analysis of property age reveals a mixed picture across the sample. Pre-1919 built properties demonstrate relatively marginal movement across the pricing distribution. This is undoubtedly due to pre-1919 housing generally being homogenous housing stock (characteristically small terrace housing or large Edwardian houses). The findings do however reveal some marked differences across the distributional quantile values in terms of effect and statistical significance across the age profile of housing. Post-1980s properties reveal that across the quantiles there is a higher pricing effect in comparison to the OLS coefficient, which diminishes the further up the quantiles towards the higher priced properties. The differential is relatively large (5th Quantile: $\beta = .196$, $p < .05$; OLS: $\beta = .075$,

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3 $p < .00$). For inter-war⁹ period properties, the OLS coefficient is statistically insignificant (β
4 $= .002$; $t = .181$, $p > .05$). However there is a more complex relationship which emerges when
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6 analysing the quantiles (**Table 2**). At the 5th Quantile level of the pricing distribution $\beta =$
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8 $.011$, however is statistically insignificant. From the 10th quantile to the 95th quantile the
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10 findings show a statistically significant negative pricing effects of circa 3% to 4% (**Figure 2**),
11 revealing a completely different finding to the conditional mean OLS coefficient. A similar
12 depiction is observed when investigating the early modern property age coefficient. The OLS
13 variable displays a statistically insignificant β of $.02$, whereas the quantile analysis shows a
14 higher value at the 5th quantile ($\beta = .112$, $p < .05$) which also marginally varies between $.052$
15 and $.076$ across the remaining quantiles, which are all statistically significant at the 95%
16 level. The results therefore show that when analysing the pricing distribution, the OLS
17 coefficient appears to not capture a 'truer' depiction of the age characteristics of the
18 properties, and indeed clearly shows that these effects are complex and idiosyncratic across
19 each type and price level, undoubtedly due to the heterogeneity between housing price, size,
20 age and type.
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29 <<<Insert Figure 2 OLS and Quantile estimates for property Age>>>

30 31 32 *Public Transportation*

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35 Turning to the external neighbourhood amenities and services, proximity to public
36 transportation shows a very disparate pricing effect across each of the coefficients price
37 distribution. Proximity to rail halts/stations reveals a negative OLS estimates across all the
38 distance bands, with the exception of >1000 metres which is slightly positive. All OLS
39 estimates are statistically insignificant. Conversely, at the 200 metre threshold the quantile
40 results show a statistically significant ($p < .01$) increasing pricing effect between the 10th and
41 95th quantiles – peaking at the 50th quantile coefficient ($\beta = .1468$; $t = 4.1963$, $p < .01$). This is
42 a similar interpretation for properties located within 400 metres of a rail halts, however the
43 level of the pricing effect incrementally increases for the higher quantiles (at a low level),
44 illustrating that higher priced properties price the amenity of proximity to the rail halts
45 (17.1%) more so than lower priced properties. This is also the case across the pricing
46 distribution for proximal distances from rail hubs at the 600 metre band. At this distance the
47 5th and 95th quantile prices show the same statistically significant positive effect (16.4%) with
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⁹ Inter war period (1919-1939)

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3 a less pronounced, albeit more uniform spread across the remaining quantiles. Interestingly,
4 this concave parabola effect evident at the 600 metre distance from rail halts/stations
5 illustrates that both lower and higher priced properties value proximity to rail halts, similarly,
6 arguably due to an amenity effect resulting from urban renaissance and gentrification
7 processes. The findings suggest that this notable disparity between higher and lower priced
8 properties (the extremes) at specific distances clearly indicate how the market prices the
9 economics of rail stations/halts. The economic reality at proximity to access nodes is an
10 economic and social enabler.
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17 Generally the results demonstrate both a vertical inverse parabola effect with distance from
18 rail halts, and a horizontal varied effect across the price distribution at various distances. The
19 findings exhibit the truncation effect for valuing proximity to a rail halt. Overall, examination
20 of the distance effects across each quantile shows a noteworthy trend, whereby up to the 50th
21 quantile the distance bands increase, peaking at the 600 metre distance range, whereas above
22 the 50th quantile they peak at the 400 metre range (**Figure 3**), inferring that slightly higher
23 priced properties are located slightly closer to the rail halts, perhaps explained by closer
24 walking distance without excessive noise pollution. Pertinently, the results show that
25 employing quantile analysis beyond the conditional mean estimates illuminates some
26 important (statistically significant) insights across the price distribution when examining
27 distance to this key public transportation amenity.
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36 <<<Insert Figure 3 Distance to Rail Halts OLS and Quantile coefficients>>>

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39 Examination of proximity to bus stops displays some interesting relationships 'beyond' the
40 OLS estimate. The OLS reveals a diminutive and statistically insignificant effect at both the
41 <200 and <400 metre distance bands. When considering the quantiles, two distinctive
42 relationships can be observed. Firstly, at the <200 metre distance, the 5th quantile up to the
43 50th quantile all show a statistically significant negative relationship between 2.6% and 4.2%,
44 illustrating that lower priced properties are arguably affected by their adjacency to bus stops
45 on main arterial routes. Secondly, at the <400 metre threshold, only the 5th quantile and 95th
46 quantile demonstrate a statistically significant pricing effect of -3.6% and -2.5%, indicating
47 that only the lowest and highest valued properties are impacted by the adjacency to bus stops
48 as a result of an inaccessibility (walking distance). This infers that the economics of
49 transportation friction costs are superseded by the disamenity effect of possible the noise and
50 air pollution implications and distance effects.
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Access to Education

Scrutiny of the effect of proximity to both primary and secondary schools further serves to highlight the differential value effects between the mean conditional price distribution and the quantile estimates. The OLS coefficients show the distance effect for proximity to secondary schools to be initially positive (6.1%) and statistically significant with a decay pricing effect evident across the distance bands which become negative at the 800 metre distance band and statistically insignificant. This signifies that adjacency to secondary schools for houses located up to 600 metres has an amenity effect – illustrating the price effect of a good school. In turn, the quantile estimates show differing pricing effects which are considerable at the lower pricing level against higher valued properties both across the price distribution and within each quantile over distance (**Figure 4**). Within a 200 metre radius, properties at the 5th quantile display a 24.9% pricing effect which decreases linearly towards the 90th quantile ($\beta = .0519$). This is also generally reflective of the findings evident at the 400 metre distance range, albeit it the pricing effect is not as high (**Table 2**). Indeed, the results show the OLS mean conditional value completely ignore the differential effects clearly impacting on the price distribution. Moreover, at the 600 metre radius, whilst the OLS is insignificant, the quantile results exhibit the lower (5th and 10th) quantiles to still comprise a 6.5% and 4.9% price effect respectively, with the 90th quantile also showing a 2.3% effect. This suggests that particular elements of the market still demonstrate an amenity effect at this distance which suggests that the market rationalises the economics of the ‘catchment effect’ for both the higher and lower valued properties. Interestingly, at the 800 metre range, only the 90th and 95th quantiles show a pricing effect of circa 3-3.7%, inferring that higher priced properties still value secondary schools as a proximal amenity.

<<<Insert Figure 4 Distance to Secondary schools OLS and Quantile coefficients>>>

With regards to primary schools, the OLS coefficients signify an initial negative relationship ($p < .01$) of circa 2% at a distance band of up to 200 metres which diminishes and turns positive up to a distance threshold of 1000 metres ($\beta = .049$; $t = 2.334$, $p < .01$). This shows that proximal distance to primary schools has a preliminary marginal negative pricing effect – perhaps a result of congestion and noise pollution, nonetheless this turns into a positive pricing effect up to a 1 kilometre radius of primary schools (**Table 2**) This is generally consistent with the quantile estimates, however a few noticeable differences exist. Within the

200 metre benchmark, the quantiles all illustrate a marginally higher negative pricing effect (4-5%) compared to the OLS. (Figure 5). Moreover, whilst the OLS coefficients are statistically significant for both the 800 metre and 1000 metre distance bands, the quantile analysis only exhibits higher priced properties to show any significance.

<<<Insert Figure 5 Distance to Primary schools OLS and Quantile coefficients>>>

Access to Open Space

When considering the proximity to an area of open space, the OLS and quantile estimates display relatively similar insights as the direction of the pricing effects, commonly negative at the 200 to 600 metre distance band and then becoming positive at the 800 metre or 1 kilometre distance. Nevertheless, the quantile coefficients achieve more statistical significance across particular elements of the price distribution at particular distances. Within 200 metres, the 5th quantile is the only coefficient which shows a negative statistically significant effect ($\beta = -.101$, $p < .001$). This infers that lower priced properties in close adjacency to areas of open space observe a disamenity effect, perhaps due to issues pertaining to anti-social behaviour. Indeed, there appears to be a similar picture at the 400 metre distance band. The OLS coefficient is marginally positive and statistically insignificant (Table 2), whereas all the quantiles reveal a negative statically significant relationship which is higher at the lower end of the pricing distribution (5th = $-.078$, $p < .05$). At the one kilometre mark, the OLS shows a statistically significant positive pricing effect of 21.12% ($t = 8.875$, $p < .01$), alternatively the quantile estimates reveal only the 25th and 95th quantile to be statistically significant indicating a 7.4% and 17.5% positive pricing effect respectively (Figure 6). This suggests that at this distance band the OLS is only capturing the effect of higher priced properties which benefit from a 'green' area without suffering proximity disamenity effects whilst being more likely to have private gardens which preclude a reliance on public open space. Generally, the findings clearly show the conditional mean does not capture the more subtle relationships between property pricing and access to open space.

Insert Figure 6 Distance to Public Open Space OLS and Quantile coefficients

Overall, the analysis has illustrated the quantile approach provides some more granular insights as to the specific effects of both structural characteristics of housing and the (dis)amenity effects of proximity to key neighbourhood services. Pertinently, these insights

clearly reveal that the nature of the price distribution can have significant effects as to how particular attributes impact on value and equally as important that the OLS conditional mean has a tendency to mis-specify the extent of these effects for certain characteristics. Moreover, the findings highlight that the economic realities of choice selection for higher and lower priced properties for specific neighbourhood characteristics. The deviation of these estimate differentials can be observed in **Table 3**.

<<<Insert Table 3 Summary of variables which depart from the OLS>>>

Conclusions

This paper has applied a quantile regression approach in order to empirically estimate how quantiles of house prices respond differently to a one-unit change in the proximal effects of structural property and neighbourhood characteristics across the conditional distribution of house prices. Utilising quantile regression has permitted the differentiation of the distance effect of particular amenities impacts upon both lower and higher priced properties. The estimates clearly show that the implicit pricing of certain neighbourhood amenities and services varies considerably across the response distribution. This illustrates the existence of quantile effects and that heterogeneous households value neighbourhood characteristics differently, and secondly, it highlights the usefulness of estimating the conditional quantile functions supplementary to the conditional mean. Pertinently, the findings emerging from this research demonstrate that housing and market characteristics are valued differently across the quantile values and that conditional quantiles are asymmetrical. This infers that buyer preferences for locational and specific housing attributes vary significantly for particular determinants which prices the economics of choice selection.

The findings also demonstrate that OLS coefficient estimates have a tendency to over or under specify the marginal mean conditional pricing effects. The findings illustrate that lower priced properties and higher priced properties show different pricing effects which both diminish and proliferate with relation to externalities. This is evident for rail halts which clearly illustrate this effect and moreover highlight this effect changes across the intervening quantiles and with proximity. Indeed, this suggests that at particular quantile levels the proximity to a metro is factored into the economic decision making of a purchaser or not. Moreover, the results present the complex rather than uniform pricing effects across a suite of neighbourhood characteristics. This serves to highlight the varying effects of proximal

distances across the pricing distribution. Indeed, the analysis serves to highlight the varying effects of proximal distance upon the quantile coefficients, which reveal negative and positive effects within the distance bands across the price distribution, and pertinently against the mean conditional price estimates generated by the OLS. This is significant for valuers and others concerned with the urban environment in understanding the pricing structure of the housing market in terms of how external neighbourhood characteristics are valued across the entirety of the pricing spectrum.

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EndNotes:

As the symmetry of the absolute residuals yield the quantiles as observed in equation 4;

$$\min_{\xi \in R} \sum p\tau(y_i - \xi)$$

where the function $p\tau(\cdot)$ is the tilted absolute value function that yields the sample quantile as its solution. Least squares regression offers a model for how to define conditional quantiles in an equivalent fashion, whereby if the sample $\{y_1, y_2, \dots, y_n\}$ it may be solved;

$$\min_{\mu \in R} \sum_{i=1}^n (y_i - \mu)^2$$

The sample mean and the estimate of the unconditional population mean, EY , can be obtained. If the scalar μ is replaced with a parametric function $\mu(x_i, \beta)$ and solved;

$$\min_{\beta \in R^p} \sum_{i=1}^n (y_i - \mu(x_i, \beta))^2$$

with an estimate of the conditional expectation function $E(Y|x)$ can be obtained.

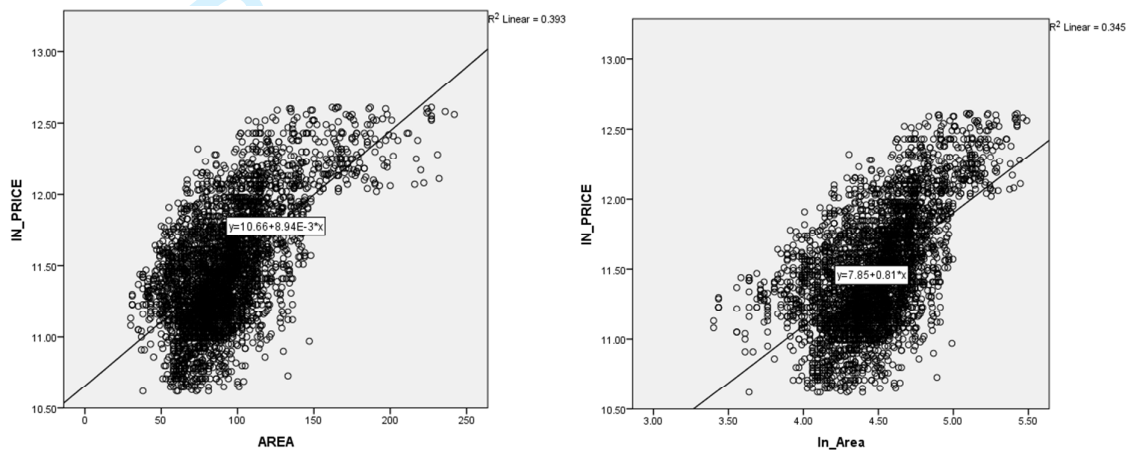
For quantile regression, an estimate of the conditional median function may be obtained by replacing the scalar ξ in Equation (4) with the parametric function $\xi(x_i, \beta)$ and setting τ to $1/2$. To obtain estimates of the other conditional quantile functions, the absolute values with $p\tau(\cdot)$ may be replaced and solved:

$$\min_{\beta \in R^p} \sum \rho_{\tau}(y_i - \xi(x_i, \beta))$$

when $\xi(x_i, \beta)$ is formulated as a linear function of parameters, the resulting minimisation problem solved by linear programming methods. Following the approach of Kim et al. (2015) the bootstrap method as furnished by Buchinsky (1995) is utilised to obtain the standard errors for the coefficients.

Appendix 1

Functional Form



Full OLS Model Description

	<i>B</i>	<i>t</i> -stat	Tolerance	VIF
(Constant)	10.906	315.786**		
Size	.007	48.412**	.482	2.074
Apartment	.244	16.852**	.346	2.892
Detached	.327	21.920**	.517	1.933
Semi-detached	.148	16.105**	.455	2.197
Social Built	-.128	-10.546**	.685	1.460
No Garage	-.021	-2.704**	.810	1.235
WARD1	-.091	-2.552*	.603	1.657
WARD2	-.347	-6.643**	.686	1.457
WARD3	-.322	-12.699**	.320	3.121
WARD4	-.287	-7.386**	.508	1.970
WARD5	-.170	-6.820**	.327	3.055
WARD6	-.703	-22.101**	.416	2.402
WARD7	-.226	-6.960**	.360	2.778
WARD8	-.557	-16.277**	.540	1.852
WARD9	-.318	-11.127**	.319	3.134
WARD10	-.462	-14.391**	.523	1.913
WARD11	-.389	-13.960**	.289	3.455

WARD12	.068	2.863**	.470	2.129
WARD13	-.416	-12.842**	.514	1.945
WARD14	-.514	-16.294**	.466	2.146
WARD15	-.335	-10.818**	.350	2.854
WARD16	-.368	-9.895**	.432	2.317
WARD17	-.364	-9.328**	.431	2.322
WARD18	-.227	-6.276**	.386	2.589
WARD19	-.639	-4.883**	.929	1.076
WARD20	-.399	-7.430**	.739	1.352
WARD21	-.161	-3.017**	.749	1.334
WARD22	-.213	-6.705**	.413	2.422
WARD23	-.352	-11.930**	.555	1.800
WARD24	-.466	-14.684**	.467	2.142
WARD25	-.107	-2.775**	.495	2.021
WARD26	-.459	-9.051**	.730	1.369
WARD27	-.250	-7.047**	.415	2.411
WARD28	-.440	-10.426**	.488	2.050
WARD29	-.325	-10.183**	.287	3.479
WARD30	-.396	-12.675**	.437	2.289
WARD31	-.301	-8.016**	.615	1.627
WARD32	-.538	-14.315**	.556	1.798
WARD33	-.127	-4.215**	.462	2.166
WARD34	-.410	-6.899**	.820	1.219
WARD35	-.374	-14.225**	.321	3.118
WARD36	-.290	-12.055**	.296	3.376
WARD37	-.153	-5.187**	.454	2.201
WARD38	-.031	-.967	.317	3.153
WARD39	-.839	-9.793**	.867	1.153
WARD41	-.271	-8.980**	.380	2.630
WARD42	-.020	-.672	.232	4.319
WARD43	-.365	-14.551**	.474	2.110
WARD44	-.411	-10.690**	.445	2.247
WARD45	-.225	-7.739**	.431	2.318
WARD46	-.187	-3.242**	.684	1.462
WARD47	-.371	-9.193**	.493	2.027
WARD48	-.189	-3.676**	.668	1.497
WARD50	-.323	-11.001**	.369	2.710
WARD51	-.591	-11.251**	.680	1.470
WARD53	-.180	-7.044**	.558	1.793
Electric heating	-.023	-1.844	.910	1.098
Gas heating	-.012	-1.628	.909	1.100
Solid heating	.000	.027	.920	1.087
Pre-1919	-.058	-4.377**	.302	3.315
Post-1980	.071	4.447**	.644	1.552
Inter War	.007	.676	.335	2.983

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3	Early Modern	.023	1.749	.637	1.571
4	MDM Decile2	.004	.215	.263	3.805
5	MDM Decile3	.079	3.306**	.301	3.321
6	MDM Decile4	.018	.876	.220	4.542
7	MDM Decile5	.029	.834	.551	1.816
8	MDM Decile6	.179	8.418**	.213	4.686
9	MDM Decile7	.161	7.179**	.265	6.068
10	MDM Decile8	.202	7.791**	.289	3.462
11	MDM Decile9	.225	9.550**	.319	4.384
12	MDM Decile10	.310	11.971**	.310	6.100
13	Rail<200	-.079	-2.861**	.558	1.792
14	Rail<400	-.024	-1.030	.468	2.138
15	Rail<600	-.010	-.514	.467	2.142
16	Rail<800	-.014	-.813	.423	2.363
17	Rail<1000	.019	1.401	.432	2.315
18	CBD<600	.011	.174	.872	1.147
19	CBD<1000	.269	8.125**	.492	2.034
20	CBD<2000	-.013	-.936	.744	1.343
21	CBD<4000	.001	.075	.763	1.311
22	CBD<5000	-.012	-.608	.794	1.259
23	Q12014	-.004	-.493	.700	1.428
24	Q22014	.001	.175	.709	1.410
25	Q32014	-.009	-1.109	.705	1.419
26	Sec school<200	.046	2.259*	.771	1.296
27	Sec school<400	.034	2.632**	.659	1.518
28	Sec school<600	-.001	-.051	.597	1.675
29	Sec school<800	-.018	-2.002*	.564	1.773
30	Sec school>1000	-.019	-1.791	.386	2.593
31	Pri School<200	-.021	-2.225*	.676	1.478
32	Pri School<600	.011	1.373	.610	1.638
33	Pri School<800	.043	3.629**	.529	1.892
34	Pri School<1000	.071	3.561**	.703	1.423
35	Pri School>1000	.038	1.439	.478	2.092

Dependent variable: Ln Sale Price; β = unstandardised beta;

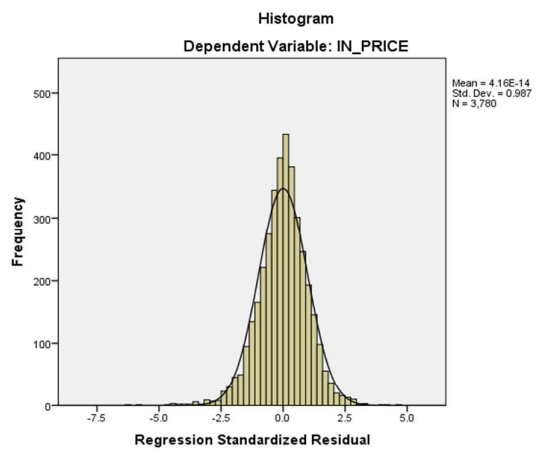
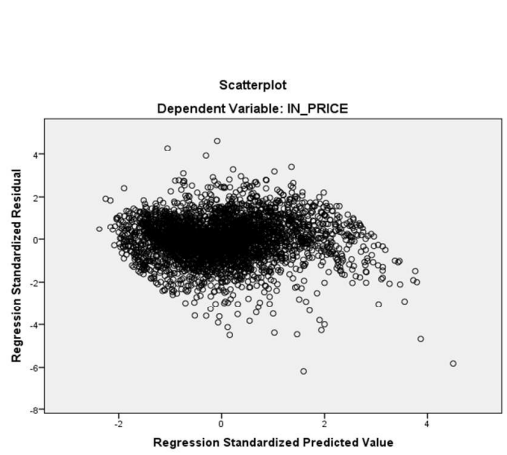
**Denotes significant at the 99% level; *95% level.

Collinearity Diagnostics

	Unstandardized Coefficients			Collinearity Statistics		
	<i>B</i>	<i>t-stat</i>	<i>Sig.</i>	Tolerance	VIF	
53	(Constant)	10.906	315.786	0.000		
54	beds1	.030	.214	.831	.023	44.402
55	beds2	.172	1.256	.209	.002	503.586
56	beds3	.176	1.310	.190	.002	542.132
57	beds4	.172	1.318	.188	.005	184.922

beds5	.082	.634	.526	.041	24.599
beds6	-.188	-1.344	.179	.177	5.641

Residual diagnostics



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