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House Values and Proximity to a Landfill: A Quantile Regression Framework

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Abstract

This paper explores the quantile treatment effects of proximity to a landfill site on housing values in the Nelson Mandela Bay Metropole (NMBM), South Africa, extending the research by Du Preez and Lottering (2009) who found a negative relationship to exist between proximity to a landfill site and mean housing values. Quantile regression analysis is used to account for the different implicit price functions that 'wealthier' and 'poorer' representative agents face. The results corroborate the findings of Du Preez and Lottering (2009) and further identify the negative relationship to be most pronounced at the lowest and highest quantiles of the house values distribution. Specifically, house values increase by an average of ZAR19 or US$1.81 (0.2 percent) for every 100 meters further away from the landfill site. At the lowest quantile (5 percent) house values increase by only 0.11 percent with every 100 meters of distance from the landfill site while at the highest quantile (95 percent), house values increase by 0,21 percent. This clearly demonstrates that 'wealthier' representative agents stand to gain more by being situated further away from landfill sites than 'poorer' representative agents. The suitability of the quantile treatment approach is confirmed by way of the Koenker and Xiao (2002) Location-Scale-Shift test statistics.

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1 Introduction

That there are negative externalities associated with close proximity to a landfill site is a fact well documented (Nahman, 2011 and Ready, 2010). These disamenities include rampant pests, air, soil and water emissions as well as the spread of litter (Nahman, 2011 and du Preez & Lottering, 2009). It follows, therefore, that the prices of houses situated closer to landfill sites should be lower than those of houses situated further away, all else constant (Ready, 2010, Nelson, 1992, Hite, 2001 and Bouvier at al. 2000). The Hedonic Pricing Model (HPM) has been widely used to identify a direct empirical relationship between the characteristics of a house (distance from the landfill site being one such characteristic) and the price that an agent is willing to pay; where hedonic prices are the implicit prices of characteristics which are discovered by agents from observed prices and the associated levels of the attributes (Zietz et al. 2008; Quigly 1984; Parsons 1986; and Linneman 1981). This allows for estimation of the value of a commodity based on how people's willingness to pay for a house varies with changes in the characteristics of that house. Bouvier et al 2000; Nelson et al. 1992; du Preez and Lottering 2009 are some studies that use HPM to specifically identify the impact of a landfill on house prices.

International literature predominantly points to a negative correlation between house prices and proximity to a landfill site (du Preez and Lottering, 2009 and Ready 2010). Studies confirming a significant negative relationship between house values and proximity to a landfill show that house values increase by 5 to 7 percent for every 1,6 kilometers (1 mile) further a house is located from a landfill site (du Preez and Lottering, 2009). Ready (2010) cites a number of empirical studies - using data for different areas in North America - which corroborate the negative relationship between proximity to a landfill site and house prices. Havlicek et al. (1971) is the leading study, finding a significant increase in house prices with an increase in distance from a landfill site in Indiana. A hedonic study carried out by Baker (1982) on a landfill near Dryden, New York shows that there was a 21 percent reduction in property values at 0.25 miles, reducing to 0.55 percent at two miles from the landfill. Nelson et al. (1992) found that property values in Minnesota decreased by 6.2 percent per mile closer to the landfill site. Lim and Missios (2003); Hite et al. (2001) as well as Thayer et al. (1992) are some other studies - utilizing data for Toronto, Columbus and Baltimore respectively - which also find that house prices increase with distance from a landfill site. Bouvier et al (2000) looks at two active landfill sites in Massachusetts and identifies a negative co-efficient for one site and a positive co-efficient for the other, with both results being significant. As Ready (2010) concludes, it is evident that most studies have found a negative relationship and those that have found no statistically significant relationship have done so due to high sampling variability as a result of small sample sizes.

In the South African context, du Preez and Lottering (2009) is unique in examining the relationship between proximity to a landfill site and house prices; and identifies a negative relationship between house prices and proximity to a landfill site in the New Brighton township of the Nelson Mandela Bay Metropole (NMBM),Eastern Cape Province, South Africa. Their findings include; a mean ZAR36 or US$3.43 increment in house prices for every 100 meters further away from the landfill site a house is located and a ZAR1, 4 million or US$133 333 total disamenity effect for houses in the area (du Preez and Lottering, 2009). Specifically, a premium of 0.44 percent is found to be present for houses situated 100 meters away from the landfill site and 8.73 percent for houses situated 2 kilometers away.

While du Preez and Lottering (2009) have answered the question of whether landfills have a negative effect on house prices, the study only evaluated mean house prices and can be extended to a quantile regression framework. Zietz et al. (2008) proposes that because higher income representative agents live in higher valued houses and lower income representative agents live in lower valued houses, and because each cannot live in the other's house, the two groups have also developed differences in preferences to housing characteristics. There are, therefore, different implicit price functions (marginal willingness to pay) for 'wealthier' and 'poorer' agents (Zietz et al. 2008). This results in two sets of demand (buyers want different things) and supply (builders build accordingly) curves (Zietz et al. 2008). OLS only gives us the implicit prices that are specific to the mean house price of the sample, however, if there are two different representative agents as there are in this case, then quantile regression is more appropriate to account for the different implicit price functions.

Research in this area is relevant to buyers and sellers, who need to price the economic impact of these disamenities into their decisions. Bouvier et al. (2000) emphasises the importance of residents' perceptions regarding landfill sites to the extent that perceptions affect house prices, even if perceptions are incorrect. Specifically, Hite (1998) finds that house prices only decline when buyers are aware of the presence of a landfill. However, these perceptions cannot be input as an explanatory variable into the model, therefore by quantifying the actual effect of proximity to a landfill site on property values, it makes it easier for buyers and sellers to arrive at a realistic market value for the properties in question (Bouvier et al. 2000). The downside of a negative perception of the effect leads to a depreciation in the housing price market of an area, lower tax base and lower levels of services. Empirical research is crucial to identifying the welfare effect of proximity to a landfill emerges by comparing house with similar characteristics which are only disparate in their proximity to the landfill (du Preez and Lottering, 2009). This will also provide the relevant information to individuals applying for landfill permits, the authorities in charge of granting these permits as well as the local residents (Ready, 2010).

This paper contributes to the existing body of knowledge by using the same GIS dataset of du Preez and Lottering (2009) and extending their OLS Hedonic Pricing Model to include the quantile regression analysis framework. The aim is to break down the negative effect of proximity to a landfill site along the distribution of house prices in New Brighton, which is a township in the Nelson Mandela Bay Metropole (NMBM) in the Eastern Cape Province of South Africa.

2 Methodology

The methodology adopts and extends that of du Preez and Lottering (2009); first the hedonic price function is derived, then the compensated demand function and consumer surplus is calculated. However, the methodology is extended to include quantile regression and the location shift and location-scale shift tests of Koenker and Xiao (2002).

2.1 Specifying the hedonic pricing function

Rosen (1974) is the theoretical starting point when estimating a Hedonic Pricing Model, where hedonic prices are the implicit prices of characteristics, which are discovered by agents from observed prices and the associated levels of the attributes. Simply put, the hedonic pricing method links utility to the characteristics of the good consumed (du Preez and Lottering, 2009).

When applied in the context of house prices, it illustrates the decisions faced both buyers and sellers (Rosen, 1974). The price of a house is determined by the physical, locational and environmental characteristics of the house. The physical characteristics include house size, number of bedrooms, number of bathrooms, etc.; locational characteristics include proximity to amenities and environmental characteristics which include air pollution, noise pollution and proximity to a landfill. Following du Preez and Lottering (2009), the empirical relationship between the price of a house and the levels of its attributes can be expressed in the following non-linear hedonic pricing function:

$$P_h = P(C_i, L_j, E_k)[i = 1..f,\ j = 1..g,\ k = 1..h] \quad (1)$$

where:

P represents the house prices in an urban area of interest

C represents the physical characteristics

L represents the location characteristics

E represents the environmental characteristics

However, consumers are unable to mutually exclusively choose from each category of attributes those which maximize their utility, and combine them into the perfect home, therefore the function is non-linear and the implicit price (marginal willingness to pay) for each characteristic becomes quite important (Rosen, 1974 and du Preez and Lottering, 2009). The implicit price function for a characteristic is obtained by differentiating house price in equation (1) with respect to that characteristic and can be represented as follows:

$$\frac{\partial P_h}{\partial E_k} = \partial P(C_i, L_j, E_k)/\partial E_k \quad (2)$$

where if E is considered to represent only distance from a landfill site, then $\frac{\partial P_h}{\partial E_k}$ is the marginal increase (assuming a positive relationship) in the house price for a 1 unit increase in the distance from the landfill site (du Preez and Lottering, 2009).

3 Data and Estimation

3.1 Data

In keeping with du Preez and Lottering (2009) this study makes use of a dataset of 40 000 houses for the New Brighton area within the NMBM. The Ibhayi landfill site is the relevant landfill site which was untilised between 1981 and 2001 with a representative sample of 134 houses within a 2 kilometer radius of the landfill site. The 2 kilometer radius was dictated by the extent of the eastern section formal housing which extends this far. Only the formal housing situated on the Northern and Eastern borders are included in the survey. The property market in the area, which is essentially a township, is underdeveloped, therefore municipal and private property valuations were used in lieu of market determined house prices. This GIS database is routinely used by estate agents to value house prices in the township. (Du Preez and Lottering, 2009)

Data on the following variables were collected:

Table 1: Description of the Variables

Variables	Basic Description
Value	Continuous dependent variable for the Rand value of housing (divided by 1000)
Erfsize	Continuous variable for size of the Erf in square meters
Sizebuild	Continuous variable for size of the main building in square meters
Outbuild	1 if house has an outbuilding
Distance	Continuous variable for distance from the landfill site in meters

Table 2 contains some descriptive statistics, the first of which gives the mean house values in the area are ZAR9991 with a minimum house value of ZAR4330 and a maximum house value of ZAR36530. These figures reveal that the area is mostly low cost housing. The Skewness, Kurtosis and Jacque-Bera normality tests all point to the data not being normally distributed which makes a case for quantile regression over mean OLS regression.

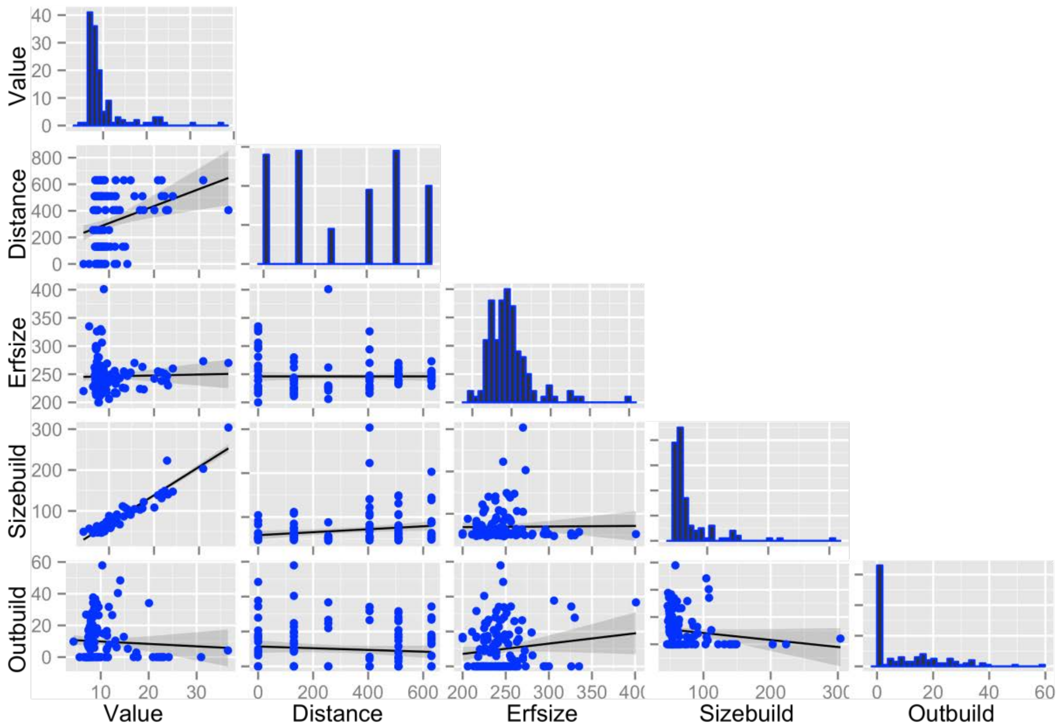
Table 2: Descriptive Statistics

	Value	Distance	Erfsize	Sizebuild	Outbuild
N	134	134	134	134	134
Mean	9.991	307.090	246.187	69.047	9.869
S.D.	5.011	230.004	27.979	36.292	12.581
Min	4.33	0.000	200.000	45.900	0.000
Max	36.53	630.000	401.000	303.800	57.900
Skewness	2.654	-0.024	2.084	3.408	1.205
Kurtosis	7.815	-1.544	7.207	14.865	0.907
JB	516.300^{***}	12.951^{***}	401.686^{***}	1544.235^{***}	38.393^{***}

Note: The table reports the descriptive statistics for the house price in 1000 South African Rands (Value), distance of the property from the landfill (Distance), size of the erf in square meter (Erfsize), size of the main building in square meter (Sizebuild), and outbuilding size in square meter. All values are in levels. The sample includes *n*=134 observations. In addition to the mean, standard deviation (S.D.), minimum (Min), maximum (Max), Skewness, and Kurtosis statistics, the table reports the Jarque-Bera normality test (JB). ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

The histograms, scatterplots and regression lines in Figure 1, below, provides additional information that the data is not normally distributed.

Figure 1: Histograms and Scatterplots of the Variables



Note: Figure presents univariate histograms and bivariate scatterplots for the house price in 1000 South African Rands (Value), distance of the property from the landfill (Distance), size of the erf in square meter (Erfsize), size of the main building in square meter (Sizebuild), and outbuilding size in square meter. All values are in levels. The sample includes *n*=134 observations. Solid lines in the scatterplots represent linear regression fits with their 95% confidence intervals (gray shaded regions).

3.2 Estimation

The hedonic price model is specified to be a function of a number of control variables, X_i, all of which are expected to increase the observed price or value, V_i. The first of these is the size of the plot, which is referred to as an *erf*; thus, $Erfsize_i$ denotes the erfsize associated with the house. The second of these is the size of the domicile or building, $Sizebuild_i$. In addition to the various sizes, we include a control for whether or not the *erf* contains outbuildings, $Outbuild_i$. The final variable included is the primary variable of interest in the analysis, the distance from the landfill, $Distance_i$.

$$V_i = f(Erfsize_i, Sizebuild_i, Outbuild_i, Distance_i) \quad (3)$$

Under OLS, (3) can be specified in the normal fashion, below. However, modeling the conditional mean, as is done with OLS, could obscure other features in the data. Quantile regression, which instead, models the conditional quantile of the outcome variable, could be more useful than OLS. Specifically, it allows for variation in the effects of an explanatory variable (on the dependent variable) at different quantiles of the distribution (Zietz et al., 2008).

Quantile hedonic price regressions, following the methods of Koenker and Basset (1978) and Buchinsky (1998), are estimated to account for the reality that housing markets are likely to be segregated. For example, low-income families are often found in the same neighborhoods, and these tend to be separated from higher income family neighborhoods. If buyer income were known, it would be possible to control for this segregation via clustering. However, such information is not available. A quantile model, on the other hand, is based on data that is sorted from low to high, according to the observed outcome value. Thus, segregation is implicit in a quantile model. Clearly, if the coefficients are constant across quantiles, the normal linear representation is appropriate, which suggests that the available housing market data is not segregated by value.

To formalize the structure, we specify a random sample described by (V_i, X_i). $Q_\theta(V_i, X_i)$ is the θ^{th}quantile of the conditional distribution of house values, given the regressors. From the preceding information, both the standard linear form – see (4) – and the quantile form – see (5) – can be specified.

$$V_i = X_i'\beta + u_i \tag{4}$$

$$Q_\theta(V_i|X_i) = X_i'\beta_\theta \tag{5}$$

In (5), β_θ is the estimated vector of quantile regression coefficients and is interpreted as the marginal change in the conditional quantile θ, due to a marginal change in the corresponding element of the vector coefficients on V_i. In the quantile regression, the conditional quantile of the unobserved error is assumed to vanish. Thus, $Q_\theta(u_{\theta i}|X_i) = 0$; however, the distribution of the error terms is not specified.

In order to estimate, Koenker and Basset (1978) suggest minimizing the asymmetrically weighted absolute sum of the errors. Therefore, the θ_{th} $(0 < \theta < 1)$ regression quantile solves:

$$\min_{\beta \in R^k}\left\{\sum_{i:\, y_i \geq x_i\beta} \theta\, |y_i - x_i\beta| + \sum_{i:\, y_i < x_i\beta} (1-\theta)|y_i - x_i\beta|\right\} \tag{6}$$

However, the estimated standard errors are potentially heteroskedastic; therefore, bootstrapping is undertaken to avoid understating the standard errors (Bouvier et al., 2000).

As suggested above, it is possible that the estimated parameters are constant across the distribution, although it is not expected. More reasonably, they will differ. The way in which they differ, though, has implications for the interpretation of the results. For example, under the location-scale-shift hypothesis, the estimated quantile parameters are constant up to an affine transformation related to the inverse of the underlying distribution of the error terms. As noted in Under the location-scale hypothesis, the shape of the conditional distribution is also not affected, although the covariate effects should vary randomly about a constant; in other words, the location-scale model would correspond to an ordinary linear model. Quantile regression based tests for these to hypotheses, location-shift and location-scale-shift, as outlined by Koenker and

Xiao (2002) are employed. The analysis is undertaken in R (R Core Team, 2014), using the ‘quantreg’ package (Koenker, 2013).

4 Results

The primary empirical results are presented in Table 3, while tests of the location-shift and location-scale-shift hypotheses are presented in Table 4. Furthermore, much of the information contained in Table 3 is illustrated Figure 2. The starting point for much of the hedonic price literature is an OLS regression, and those results begin Table 3. As expected, the estimates are all significant (at the 1% level), except for Erfsize. We confirm the findings from a number of other studies (Ready (2010); Havlicek et al. (1971); Nelson et al. (1992); Lim and Missios (2003); Hite et al. (2001); Thayer et al. (1992) and Bouvier et al (2000)) finding that house prices are generally increasing in the distance to a disamenity. In this case, that disamenity is the landfill. There is a positive relationship between the value of the house and the distance from the landfill. The overall effect at the mean, see du Preez and Lottering (2009), is outlined in (7).

$$V_i = 9,479 + 0.19\, Distance_i \qquad (7)$$

Thus, the value of a property situated right next to the landfill site would have a value of ZAR9,479; the value of a property located 2000 meters away would have a value of ZAR9,859. Therefore, the maximum amount by which a landfill site can reduce the value of a house is ZAR380. Succinctly, house values increase by 0.2 percent if they are situated 100 meters away from the landfill site and 4 percent if they are 2 kilometers away, but the effect is assumed to be constant.

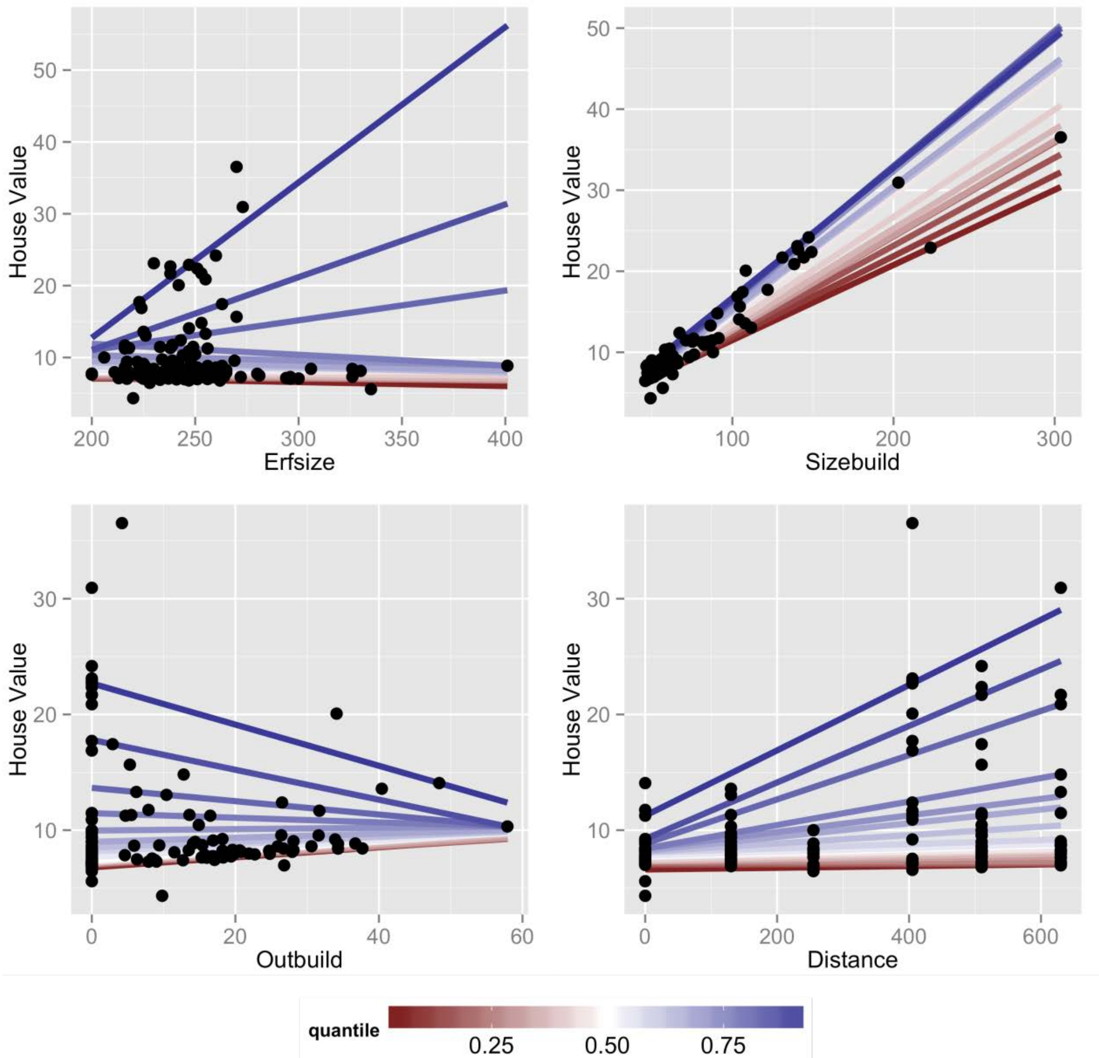
In the quantile regression model (also reported in Table 3 and illustrated in Figure 2 for different percentiles of the price distribution), the results show the average effect is far from constant. Instead, it is located in the lowest and the highest quantiles of the house value distribution. The *distance* coefficients in all other quantiles are small in magnitude and largely insignificant. Putting the estimates in Table 3 into perspective, we consider the two ends of the distribution. At the lowest quantile (5 percent), house prices are ZAR8541 adjacent to the landfill but ZAR8721 furthest from the landfill site. At the 90^{th} and 95^{th} percentiles, prices adjacent to the landfill are ZAR10638 and ZAR10659, respectively; these increase to a maximum of ZAR10998 and ZAR11099 2 kilometers away from the landfill. In other words, the lowest 5 percent of house values are 0.11 percent higher, if they are situated 100 meters away from the landfill, and 2.11 percent higher, if they are situated 2 kilometers away. For house values in the 90^{th} percentile, 100 meters means a 0.16 percentage point increase in house values, while 2 kilometers translates into 3.38 percentage points. At the 95^{th} percentile, house value increases are 0.21 percent and 4.13 percentage points, respectively, if located 100 meters or 2 kilometers away from the landfill. In short, the magnitude of house price differentials at the top and the bottom of the distribution are not inconsequential. Thus, these results suggest that our expectation of non-constant effects were borne out, thus justifying the choice of quantile regression over OLS. However, there are no statistical bounds to the price differentials reported above; thus, it is necessary to confirm that the differentials are statistically significant.

Table 3: Ordinary and Quantile Regression Estimate

Quantile	Intercept (β_0)	Erfsize (β_1)	Sizebuild (β_2)	Outbuild (β_3)	Distance (β_4)	AIC
OLS	-0.3274	0.0014	0.1313^{***}	0.0345^{***}	0.0019^{***}	470.21
	(1.2386)	(0.0035)	(0.0125)	(0.0092)	(0.0004)	
0.05	3.1040^{***}	-0.0057	0.0935^{***}	0.0389^{***}	0.0009^{**}	467.95
	(1.0844)	(0.0052)	(0.0048)	(0.0072)	(0.0004)	
0.10	1.9778^{***}	0.0008	0.0926^{***}	0.0465^{***}	0.0002	414.46
	(0.3880)	(0.0009)	(0.0043)	(0.0013)	(0.0001)	
0.15	2.1672^{***}	0.0004	0.0924^{***}	0.0460^{***}	0.0001	390.70
	(0.3321)	(0.0003)	(0.0058)	(0.0007)	(0.0000)	
0.20	1.4900^{***}	0.0000	0.1081^{***}	0.0477^{***}	0.0000	371.41
	(0.3887)	(0.0003)	(0.0059)	(0.0006)	(0.0000)	
0.25	1.4857^{***}	0.0000	0.1082^{***}	0.0478^{***}	0.0000	360.28
	(0.3922)	(0.0003)	(0.0059)	(0.0006)	(0.0000)	
0.30	0.8558^{*}	0.0007	0.1160^{***}	0.0459^{***}	0.0001	357.25
	(0.5066)	(0.0006)	(0.0067)	(0.0015)	(0.0001)	
0.35	0.8690^{*}	0.0006	0.1160^{***}	0.0462^{***}	0.0001	356.96
	(0.4682)	(0.0006)	(0.0062)	(0.0014)	(0.0001)	
0.40	0.9315^{**}	0.0005	0.1159^{***}	0.0468^{***}	0.0001	361.73
	(0.4474)	(0.0005)	(0.0067)	(0.0011)	(0.0001)	
0.45	0.6153	0.0006	0.1214^{***}	0.0466^{***}	0.0001	369.85
	(0.6106)	(0.0006)	(0.0096)	(0.0015)	(0.0001)	
0.50	-0.0937	0.0008	0.1339^{***}	0.0466^{***}	0.0002	375.90
	(1.0367)	(0.0008)	(0.0173)	(0.0018)	(0.0001)	
0.55	-1.2356^{***}	0.0008	0.1560^{***}	0.0478^{***}	0.0002	371.42
	(0.4543)	(0.0012)	(0.0078)	(0.0036)	(0.0001)	
0.60	-1.2560^{***}	0.0008	0.1564^{***}	0.0491^{***}	0.0002^{*}	368.21
	(0.4402)	(0.0011)	(0.0075)	(0.0036)	(0.0001)	
0.65	-1.1713^{***}	0.0005	0.1571^{***}	0.0507^{***}	0.0001	369.04
	(0.3618)	(0.0009)	(0.0064)	(0.0032)	(0.0001)	
0.70	-1.1056^{***}	0.0003	0.1571^{***}	0.0513^{***}	0.0001	375.13
	(0.3426)	(0.0009)	(0.0062)	(0.0032)	(0.0001)	
0.75	-1.4998^{***}	0.0004	0.1646^{***}	0.0510^{***}	0.0002	385.41
	(0.5576)	(0.0011)	(0.0101)	(0.0042)	(0.0002)	
0.80	-1.9546^{***}	0.0001	0.1753^{***}	0.0528^{***}	0.0003	392.31
	(0.5090)	(0.0013)	(0.0084)	(0.0048)	(0.0002)	
0.85	-1.9418^{***}	-0.0004	0.1771^{***}	0.0553^{***}	0.0008	402.20
	(0.5290)	(0.0018)	(0.0071)	(0.0067)	(0.0005)	
0.90	-1.7915^{***}	-0.0001	0.1725^{***}	0.0551^{***}	0.0018^{***}	415.87
	(0.5402)	(0.0019)	(0.0067)	(0.0087)	(0.0006)	
0.95	-1.5966^{***}	-0.0007	0.1721^{***}	0.0552^{***}	0.0022^{***}	442.49
	(0.4691)	(0.0017)	(0.0043)	(0.0086)	(0.0005)	

Note: Table reports the estimates of the ordinary least squares and quantile regression estimates of the model $\text{Value}_i = \beta_0 + \beta_1\text{Erfsize}_i + \beta_2\text{Sizebuild}_i + \beta_3\text{Outbuild}_i + \beta_4\text{Distance}_i + \varepsilon_i$ given in Equation (3). OLS is the ordinary least squares estimator with identically and independently distributed (*iid*) error term assumption. The numbers in the Quantile column refer to the τth quantile. Standard errors of the estimates are given in the parentheses. Standard errors of the OLS estimates are computed using the heteroscedasticity consistent estimator suggested by Long and Ervin (2000). Standard errors of the quantile regression estimators are computed using the wild bootstrap method of Feng *et al.* (2011) with 1000 bootstrap draws. AIC denotes the Akaike information criterion. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Figure 2: Bivariate Linear Quantile Regression Fits



Note: Figure presents bivariate scatter plot of the House Value against the covariates Erfsize, Sizebuil, Outbuild, and Distance as well as the bivariate linear quantile regression lines for quantiles $\tau \in [0.05, (0.10), 0.95]$, which results in 19 quantile regression lines at quantiles τ=0.05, 0.15, …, 0.95. The bivariate quantile regression lines corresponds to model $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$, where y_i is the House Value and x_i is one of the covariate variables Erfsize, Sizebuild, Outbuild, and Distance. The quintile regression lines are superimposed on the plot and indicated by solid lines.

We consider the statistical significance of the previously reported percentile-based price differentials by testing the location-shift and location-scale-shift hypotheses. Under the location-shift hypothesis, an ordinary linear model with heteroskedasticity is the null hypothesis, i.e., that quantile regression slopes are independent of the quantile (Koenker and Hallock, 2000). Under the location-scale-shift hypothesis, the estimated covariate effects are expected to be affine transformations of the error distribution (Koenker and Xiao, 2002). The formal statistical results are reported in Table 4, below, although Figure 3 illustrates compelling evidence that these null hypotheses are not supported in the house price data used for this analysis. In terms of the figure, we would expect, under the location-shift hypothesis, to see constant estimates; generally, that is not the case. Under the location-scale-shift hypothesis, we would expect to see the shape of the quantile estimates for all of the covariates to be similar; however, we do not see that, either. Formally, both null hypotheses are rejected, and are, separately, for all covariates in the model. Therefore, covariates alter the shape of the conditional distribution, as well as its location and its scale (Koenker and Hallock, 2000).

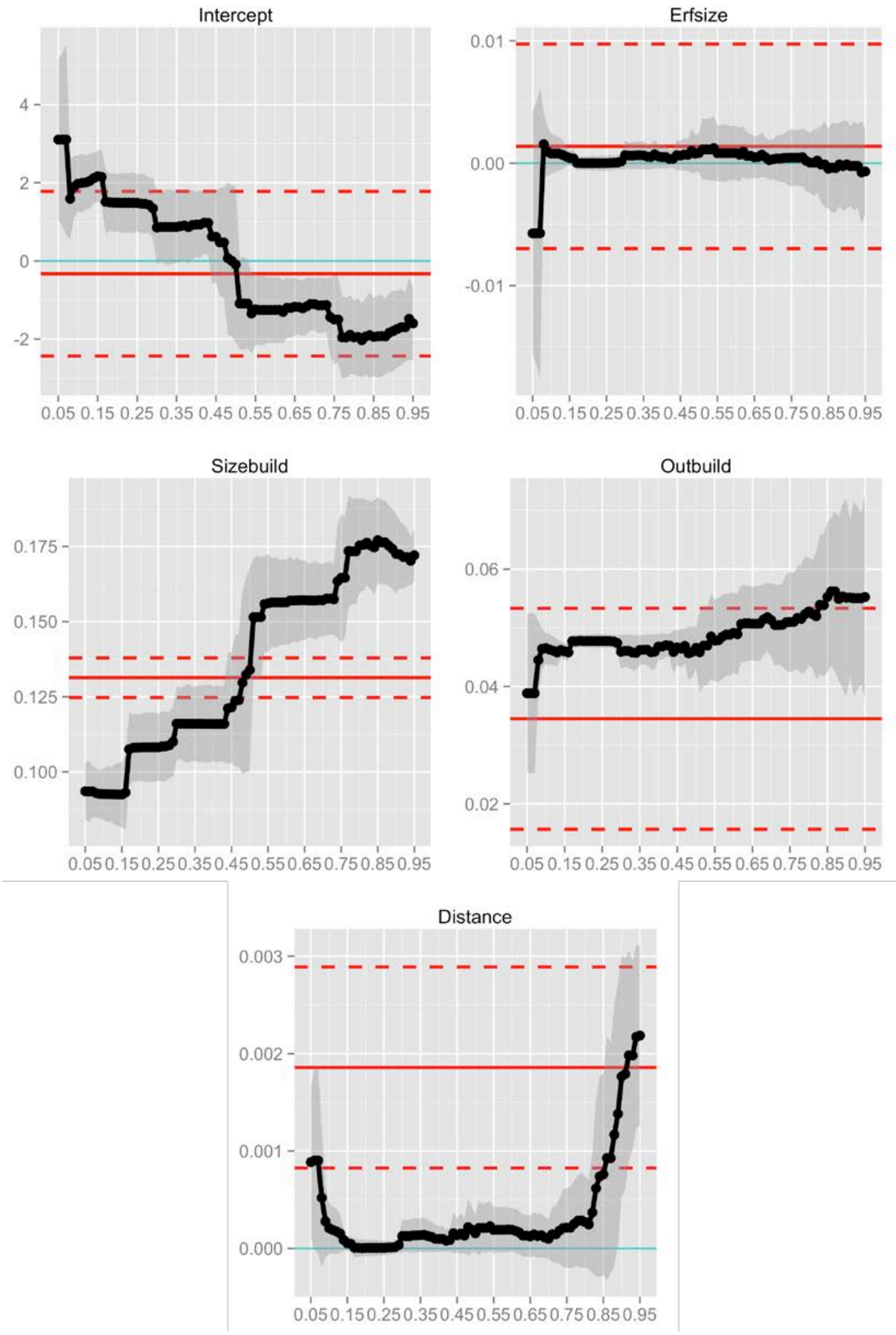
Table 4: Tests of the Location–Scale-Shift Hypothesis

	Location Shift		Location-Scale Shift	
Variable	$\tau \in [0.10, (0.02), 0.90]$	$\tau \in [0.20, (0.02), 0.80]$	$\tau \in [0.10, (0.02), 0.90]$	$\tau \in [0.20, (0.02), 0.80]$
Erfsize	20.326***	17.538***	20.608***	12.316***
Sizebuild	1662.712***	1200.055***	27.604***	16.767***
Outbuild	22.549***	8.038***	29.465***	23.285***
Distance	78.397***	35.649***	14.517***	14.140***
Joint Effect	1868.978***	1319.516***	119.322***	83.323***

Note: Table reports the location shift and location-scale shift tests of Koenker and Xiao (2002), which generalize the Khamaladze (1981) test to quantile regression. These tests are based on the Kolmogorov-Simirnov-type statistic and have non-standard distributions. The tests reported are based on the general quantile regression model $\text{Value}_i = \beta_0 + \beta_1\text{Erfsize}_i + \beta_2\text{Sizebuild}_i + \beta_3\text{Outbuild}_i + \beta_4\text{Distance}_i + \varepsilon_i$ given in Equation (3). Tests for joint significance as well for the significance of each component are reported. The tests are reported for quantiles $\tau \in [\tau_1, (\Delta\tau), 1\text{-}\tau_1]$, where $\Delta\tau$ is the increment step from τ_1 to 1-τ_1. Tests are reported for τ_1=0.10 and τ_1=0.20. Critical values for the univariate tests are 2.640 at 1% for τ_1=0.10 and 2.483 at 1% for τ_1=0.20. For the joint tests 1% critical values are 6.340 and 6.023 for τ_1=0.10 and τ_1=0.20, respectively. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

In addition to providing information about the likely validity of the location-shift and location-scale-shift hypotheses, Figure 3, below, provides additional information. The figure includes the estimated conditional quantile function of the house value distribution, separately, for each variable. Following Koenker and Hallock (2000), with the exception of Erfsize, all other quantile regression estimates lie outside of the mean regression confidence interval. In other words, and in agreement with what we have outlined above, it is not suitable to employ a linear regression, i.e., assume that the location-shift model is appropriate.

Figure 3: Multivariate Linear Quantile Regression Estimates



Note: The figure plots the intercept and slope estimates at the 91 equally spaced quantiles from the 0.05th quantile to 0.95th quantile. Estimates are based on the general quantile regression model Value$_i$ = β_0 + β_1Erfsize$_i$ + β_2Sizebuild$_i$ + β_3Outbuild$_i$ +

β_4Distance$_i$ + ε_i given in Equation (3). The parameter estimates are plotted against the quantiles with a dotted bold line. A point-wise 95% confidence interval is indicated (gray shaded regions) around the quantile regression parameter estimates. The confidence intervals are obtained using the wild bootstrap method of Feng *et al*. (2011) with 1000 bootstrap draws. Superimposed on the graphs are the OLS parameter estimates (solid horizontal line) and their 95% confidence intervals (two dashed horizontal lines). A horizontal line is drawn at zero (thin light line) to indicate $\beta_j = 0$, the null effect.

5 Conclusion

This study extended the research by du Preez and Lottering (2009) to include quantile regression analysis to account for the different implicit price functions that 'wealthier' and 'poorer' representative agents face. The results corroborate the findings of Du Preez and Lottering (2009) who found a negative relationship to exist between proximity to a landfill site and mean housing values, and further identifies the negative relationship to be most pronounced at the lowest and highest quantiles of the housing price distribution. Specifically, house values increase by an average of ZAR19 (0.2 percent) for every 100 meters further away from the landfill site. At the lowest quantile (5 percent) house values increase by only 0.11 percent with every 100 meters of distance from the landfill site while at the highest quantile (95 percent), house values increase by 0,21 percent. This clearly demonstrates that 'wealthier' representative agents stand to gain more by situated further away from landfill sites than 'poorer' representative agents. The suitability of the quantile treatment approach is confirmed by way of the Koenker and Xiao (2002) Location-Scale-Shift test statistics where covariates are found to alter the shape of the conditional distribution as well as its location and scale (Koenker and Hallock, 2000).

The resulting negative impact of the landfill site on house prices in the New Brighton township of the Nelson Mandela Bay Metropole, Eastern Cape, South Africa, has ramifications for individuals applying for landfill permits, the authorities in charge of granting these permits as well as the local residents (Ready, 2010). It highlights the importance of empirical research in identifying the welfare effect of proximity to a landfill site if landfills are going to be a sustainable long term solution to waste management. For house prices to be preserved, houses must be situated far from landfill sites, especially houses in the highest quantiles of the house price distribution. The finding that at the lowest quantile, house prices are not substantially affected by close proximity to a landfill site is not surprising, but must be treated with caution to avoid a situation where the poorest communities in South Africa all find themselves residing near landfill sites. This is already a reality in the form of unofficial landfills, however, policy makers need to avoid exacerbating a situation already strained by lack of service delivery and income inequality.

Further research could extend to evaluating what effect the volume of waste has on the housing values. Considering that this study looks at just one landfill site, it was not necessary to include volume as an explanatory variable, however, there is rationale for future studies to do such a comparison. Ready (2010) finds that all landfills accepting a high volume of waste have a negative effect on house prices while 20-28 percent of low value landfills had no effect on house prices. This is corroborated by Lim and Missios (2003) who compared a high volume landfill with a low volume landfill in Toronto and found the same result. If there is a negative relationship between waste volumes and house prices, then the municipality may find it best to accept lower volumes of waste at the site to improve the welfare effect of the landfill site. This may have far reaching consequences such that policy makers may choose to have a larger number of low volume landfill sites rather than a small number of high volume sites.

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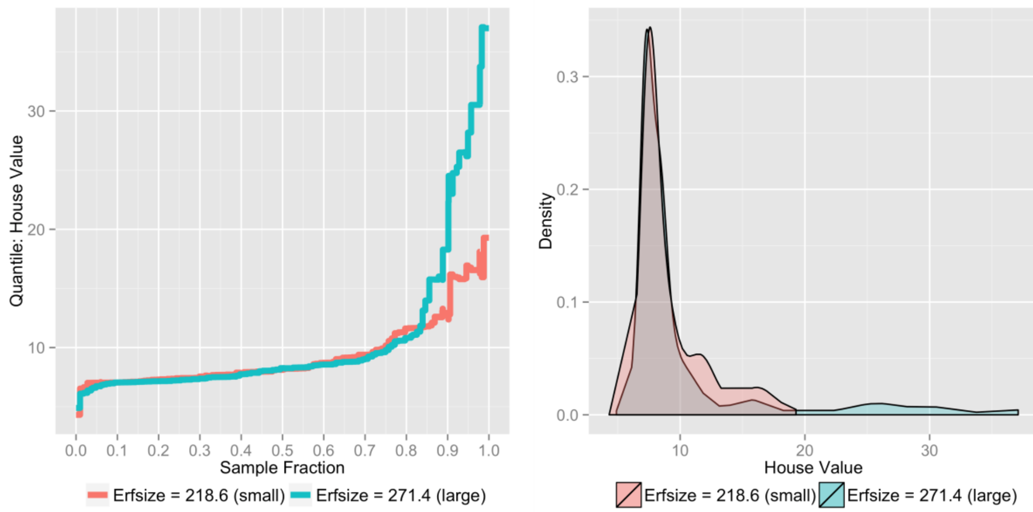
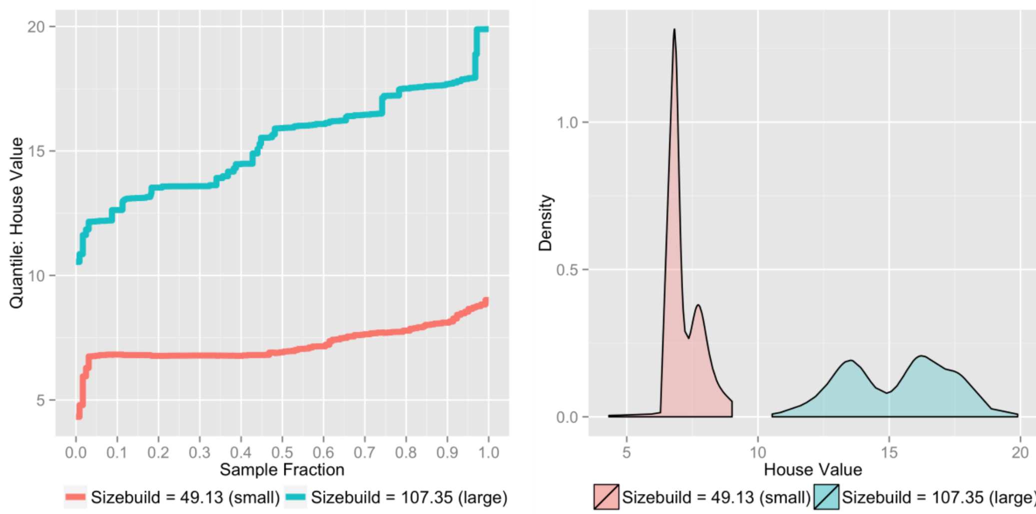
Appendix

Conditional Quantile and Density Functions for House Value

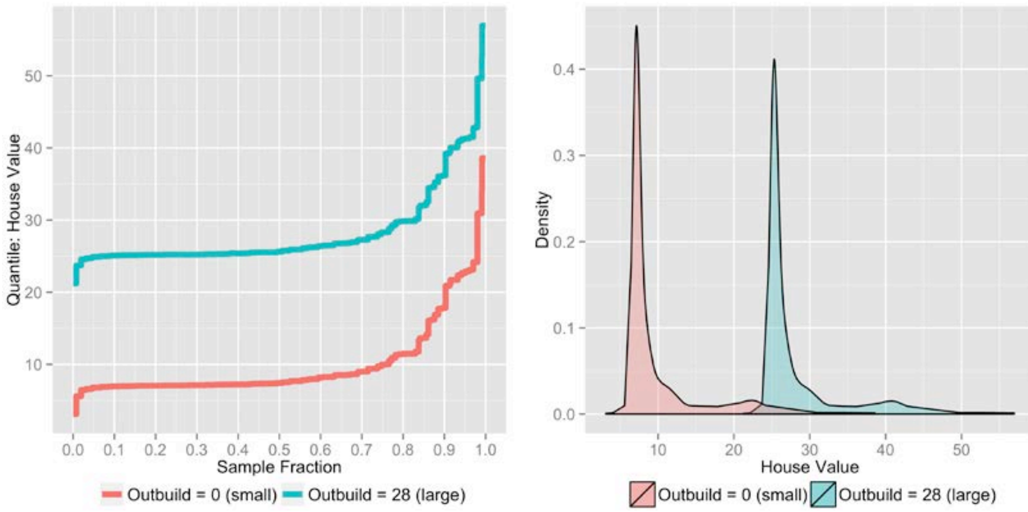
Panel A: Bivariate quantile regression with covariate Erfsize



Panel B: Bivariate quantile regression with covariate Sizebuild



Panel C: Bivariate quantile regression with covariate Outbuild



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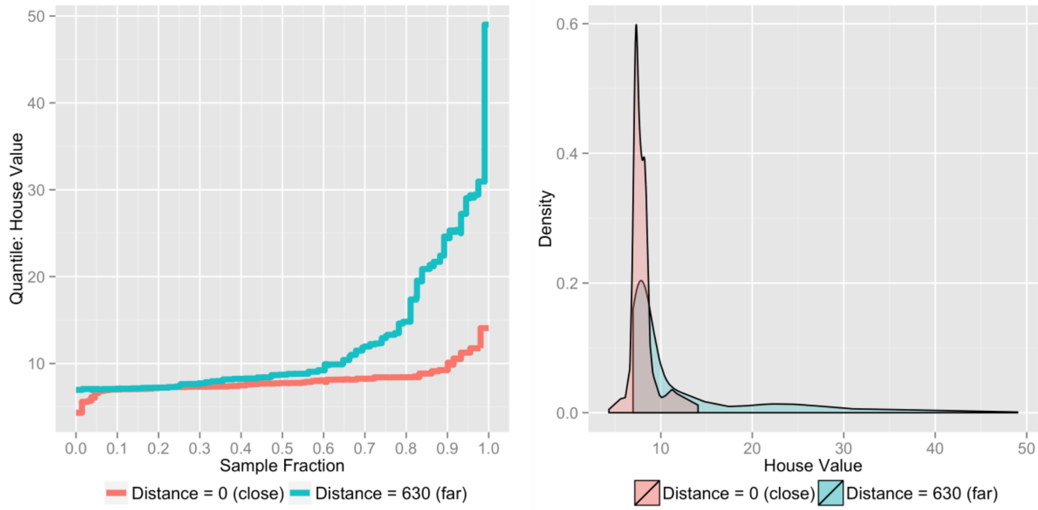
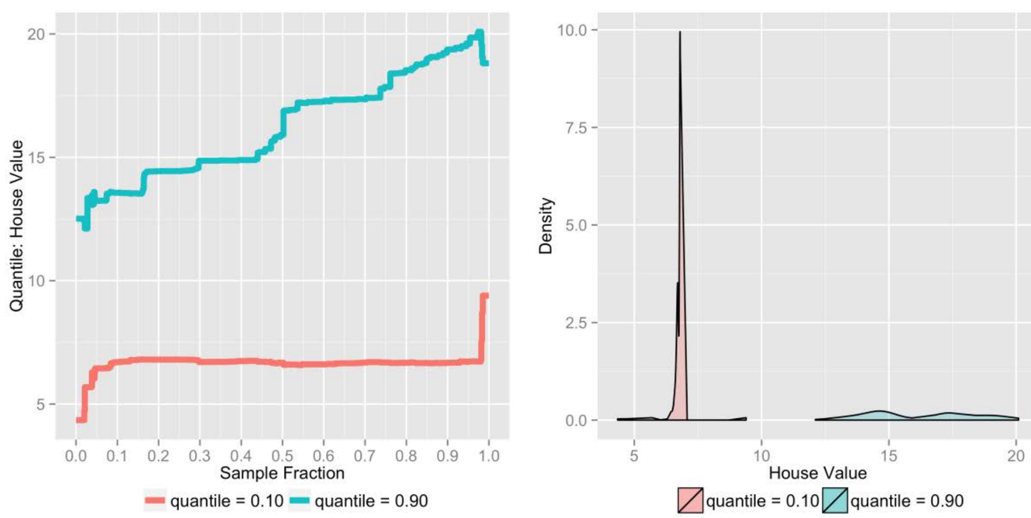
Panel D: Bivariate quantile regression with covariate Distance



Panel E: General multivariate quantile regression with covariates Erfsize, Sizebuild, Outbuild, and Distance



Note: Each panel of the figure plots conditional quantile (left) and density (right) functions for the House Value variable based on a bivariate quantile regressions model (Panel A-D) and a multivariate quantile regression model (Panel E). Two estimates are presented, one for the 0.10th (relatively low) quantile and another for the 0.90th (relatively high) quantile. The low quantile values are 218.6, 49.13, 0, and 0, while the relatively high quantile values are 0, 271.4, 107.35, 28, and 630, respectively for the variables Erfsize, Sizebuild, Outbuild, and Distance. Conditional quantiles and densities are evaluated at the low and high quantile values. The densities are estimated using the univariate adaptive kernel density estimation method of Silverman (1986) as used by Portnoy and Koenker (1989).