The impact of social housing developments on nearby property prices: A Nelson Mandela Bay Case Study

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Abstract

Social housing projects often face substantial "Not-in-my-backyard" (NIMBY) sentiment and as a result are frequently plagued by local opposition from communities who argue that nearby property prices will be affected adversely by these developments. International hedonic pricing studies conducted have, however, produced mixed results with some concluding that social housing developments may in fact lead to an improvement in surrounding property values. There is, however, a paucity of South African evidence. This study considers the validity of the most pervasive NIMBY argument, the claim that social housing developments negatively affect nearby property values, by considering the property prices of 170 single-family homes in the Walmer neighbourhood, Nelson Mandela Bay, as a function of their proximity to an existing low-cost housing development. The results of this study indicate that in the case of one Nelson Mandela Bay low-cost housing development, a negative impact is exerted on the property values of nearby houses.

1 Introduction

Social housing is a relatively new concept in South Africa (A Toolkit for Social Housing Institutions, 2010). The two primary objectives of the social housing programme are to contribute to the restructuring of South African society in order to address structural, economic, social and spatial dysfunctionalities and to improve and contribute to the overall functioning of the housing sector in order to widen the range of housing options available to the poor (Social housing policy for South Africa, 2005).

The development of this form of housing has been plagued by "local opposition", who argue that these structures may lead to reductions in the property values of nearby houses (Iglesias, 2002). This is commonly referred to as the "Not-in-my-backyard" syndrome (NIMBY) (Iglesias, 2002). Negative preconceptions about social housing (as it is historically defined) form the basis of this argument (Cummings and Landis, 1993). However, the results of several international studies reveal that this is not always the case (Nguyen, 2005). Some studies have shown that social housing projects may actually have a positive influence on surrounding residential property prices (Lyons and Loveridge, 1993; Galster, Tatian and Smith, 1999). More specifically, a review of available literature by Nguyen (2005) reveals the following results (using hedonic price estimation): Cummings and Landis (1993)

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found no significant effect of a 42-unit condominium on surrounding property values in San Francisco County, California. Lyons and Loveridge (1993) found a significantly positive relationship between a public housing project and property values in Ramsey Country, Minnesota. Goetz, Lam and Heitlinger (1996) concluded that a privately owned and publicly subsidised housing project in Minneapolis, Minnesota had a negative effect on surrounding property values. Lee, Culhane and Wachter (1999) found that a public housing project in Philadelphia, Pennsylvania caused property prices in the surrounding area to decrease and Santiago, Galster and Tatian (2001) reached the conclusion that dispersed rehabilitated public housing in Denver, Colorado had a positive effect on property values.

There is, however, a paucity of South African studies that examine the impact of social housing developments on nearby property prices. The aim of this paper is to fill this gap. More specifically, this paper seeks to determine the effect (if any) of an existing housing establishment (the Walmer Township), catering for low-income earners, in Nelson Mandela Bay on property values in an adjacent residential area, by applying the hedonic pricing method. The reason for selecting this particular area is that the proposed social housing developments in Nelson Mandela Bay have received a great deal of negative publicity and community opposition in the local media (Vermeulen, 2008).

In what follows, Section 2 describes the current social housing landscape in South Africa, highlighting the characteristics of existing social housing developments. Section 3 discusses the hedonic pricing methodology. Section 4 presents the data and empirical results, including welfare estimates. Section 5 concludes this paper.

2 The South African Social Housing Programme

Social housing can be defined as "a rental or co-operative housing option for low-income persons at a level of scale and built form which requires institutionalised management and which is provided by accredited social housing institutions or in accredited social housing projects in designated restructuring zones" (Social Housing Policy for South Africa, 2005). Well-managed social housing projects have the ability to reconnect residents to resources within cities and are also able to assist with stabilising crime ridden environments (Part 3 of the National Housing Code, 2009). Current statistics indicate that the demand for this housing option will increase significantly (Social Housing Policy for South Africa, 2005). Approximately 1 million households were renting in metropolitan areas in South Africa in 2001. This figure has increased to approximately 2.2 million and the demand for social rental housing is predicted to rise by 7% per annum for the R19, 201 – R38,400 per annum income group (Social Housing Policy for South Africa, 2005).

Plans to provide affordable accommodation options for low-income earners in South Africa officially commenced in 1996, with the establishment of the National Housing Finance Corporation (NHFC) (A Toolkit for Social Housing Institutions, 2010). The primary goal of the NHFC was to ensure the development and appropriate funding of institutions offering a variety of tenure options for residential purposes. Over the next 12 years, various policy and legislative procedures were developed, which resulted in the Social Housing Act (No. 16 of 2008), which seeks to establish and promote a sustainable housing environment. Examples of completed social housing projects in South Africa include BG Alexander (Hillbrow, Johannesburg), Botlhabela Village (Alexandra Far East Bank, Sandton), Candella Road (Durban), Elangeni (Inner City, Johannesburg), Hope City (Mpumalanga), Skyview (East London) and Haven Hills South (East London) (Project Review Series, 2011).

A closer examination of the Haven Hills South project in East London, for example, reveals the following: the vision of the project was to "provide social housing in a township environment", and was identified by the Buffalo City Municipality (BCM) as a pilot initiative to develop an integrated urban living environment, aimed at individuals who would qualify for social housing (Project Review Series, 2009). The complex is situated 7 kilometers from the East London CBD. This project commenced in July 2002 and was completed and occupied in June 2003. In accordance with the Social Housing Policy for South Africa, low-income earners[1] qualified on a rental basis. The project consists of 258 units ranging from one to three bedroom units. The sizes of the one, two and three bedroom units, respectively, are $25m^2$, $35m^2$ and $45m^2$. Each unit comes standard with an open plan living area and kitchenette, which includes a sink and preparation area. Aluminum window frames and a stable front door were fitted to each unit. Tenants are charged a monthly rental of R950, R1451 or R1551, respectively, for a one, two or three bedroom unit. The average maintenance cost per unit is approximately R96 per month. Facilities and amenities include play areas for children, pre-paid water and electricity and one parking bay per unit.

Current estimates of the price per social housing unit vary. Total development costs of the Haven Hills South project in East London, for example, amounted to R29 000 000, resulting in an average cost per unit of roughly R112 403 (Project Review Series, 2011). The Nelson Mandela Metropolitan Municipality is due to commence construction of 269 semi-detached houses for the residents of Silverton, New Brighton. The estimated cost of this project is in the region of R18 000 000, implying a cost per unit of R66 914 (Housing Project Launched in New Brighton, 2010).

In Nelson Mandela Bay, the focal area of this study, certain sites have been approved for social housing developments by the National and Provincial Departments of Human Townships (Social Housing Boost for Nelson Mandela Bay, 2009). These sites include the Inner City, Lower Baakens, Walmer, Mount Croix, Despatch CBD, Uitenhage CBD and William Moffet (Social Housing Boost for Nelson Mandela Bay, 2009). To date, none of these approved sites has been developed. These proposed social housing developments in Nelson Mandela Bay have been met with severe resistance from residents, who argue that "property values will be substantially affected in a negative manner" (Vermeulen, 2008). Despite the fact that these proposed developments have not been completed, there is another low-income housing development which can be used instead to determine its effect on surrounding property prices. Given Nelson Mandela Bay residents' concern that housing prices will be affected, hedonic pricing is the natural method to use.

3 Analytical Framework

3.1 The hedonic pricing method (HPM)

Houses are differentiated goods which are made up of bundles of attributes (Epple, 1987). Most of the attributes that make up a house are market-induced (i.e. erf size, number of rooms, etc.) (Haab and McConnell, 2002). A few attributes such as air pollution or proximity to an airport are non-market induced (Haab and McConnell, 2002). There are a number of techniques that can be used to determine the locational effect of air pollution, for example, on house prices, namely the contingent valuation method, travel cost method, the direct monetary damages technique or the averting costs technique (Cameron, 1992). Many studies have used the hedonic pricing method (HPM) to estimate the effect of air pollution on house prices (Kiel and McClain, 1995; Chattopadyay, 1999; Beron, Murdoch and Thayer, 2001). Other non-market applications of this method include estimating the relationship between house prices and hazardous waste sites (Kohlhase, 1991; Hite, Chern, Hitzhusen and Randall, 2001; Nelson, Generoux and Generoux, 1992), and water pollution (Hoehn, Berger and Blomquist, 1987). The theory and application of hedonic models were first rationalised by Rosen (1974). The HPM relies on the systematic variation in house prices due to differing attribute combinations to impute the willingness to pay for the attributes (Epple, 1987; Haab and McConnell, 2002; Sirmans, Macpherson and Zietz, 2005). Typically, the estimation of a

[1] Low-income persons are broadly defined as those whose household income is below R7,500 per month. The target market for social housing projects includes persons opting for the mobility and flexibility that rental housing allows, those who simply cannot afford inner city residential property prices, singles with dependents who tend to opt for affordable rental options and persons currently living in informal settlements because it is the only affordable option available to them.

HPM entails two distinct stages. During the first stage, a hedonic pricing function is estimated by means of regression analysis. The hedonic pricing function can be specified as:

$$P = f(S, L, M) \tag{1}$$

where: P represents the sales price of a property, S represents the on-site characteristics of the property, L represents the location and surrounding neighbourhood characteristics, and M represents the market characteristics. The first-stage HPM estimates can be used to calculate the implicit prices of housing attributes. For example, the implicit price of attribute L in Equation (1) can be estimated by the following equation:

$$\partial P/\partial L = \partial P(S, L, M)/\partial L \tag{2}$$

During the second stage of analysis, the implicit prices calculated during the first stage are used to estimate a demand function for the attribute of interest (Rosen, 1974). Consumer surplus estimates can then be derived from this function.

One of the main shortcomings of the HPM is the estimation of the demand function. This is because the second stage may not reveal any new information and, thus, the estimated demand equation simply mirrors the results of the first-stage regression (Brown and Rosen, 1982). This is often referred to as the identification problem (Brasington and Hite, 2005). Chattopadhyay (1999) overcomes this obstacle by applying the hedonic two-stage estimation technique on household level data. The literature, however, reveals that the most widely accepted solution is the use of segmented markets (Brown and Rosen, 1982; Palmquist, 1984; Brasington, 2000; Zabel and Kiel, 2003). In this case, a separate hedonic function is estimated for each metropolitan area assumed to be affected by the environmental disamenity. This will (theoretically) generate a number of different parameter estimates for the relationship between house prices and the environmental quality, thus revealing different implicit prices, from which the demand function can be estimated. From this, total welfare effects can be estimated (Brasington and Hite, 2005).

It is generally accepted that market segmentation occurs between metropolitan areas, but one cannot segment areas within the same metropolitan region (Palmquist, 1984). One possible reason for this segmentation between different metropolitan areas, and not within the same metropolitan area, is due to potentially different construction costs and job opportunities (Brasington and Hite, 2005). Of course, in order to estimate implicit prices for environmental quality in segmented markets, the environmental quality in question would have to extend to all of these markets. However, when one is dealing with a localised amenity/disamenity (for example, social housing developments) one may encounter difficulties when segmenting the market (as different metropolitan areas are not likely to be affected by the amenity/disamenity in question).

Due to these difficulties, most studies only estimate the first-stage hedonic model (Haab and McConnell, 2002). The estimation of a first-stage hedonic pricing function normally requires the analyst to make certain strategic decisions. These include decisions about the extent of the market, the selection of explanatory variables, how to address the issues of spatial autocorrelation and omitted variables, and the selection of an appropriate functional form.

3.2 Choice of independent variables

As can be seen from Equation 1, the price of a house is typically determined by its characteristics. These normally include structural, environmental and neighbourhood characteristics. Ideally, all housing attributes that matter to home buyers should be included in the hedonic model. Unfortunately, it is practically impossible to include all attributes that are relevant to homebuyers' decisions. Table 1 contains the top twenty characteristics used to specify hedonic pricing equations in previous studies, the number of times the characteristic has been used and the number of times its estimated coefficient has been positive, negative or insignificant (Sirmans et al., 2005).

House attributes tend to be correlated (Haab and McConnell, 2002). This may pose a problem for the selection of explanatory variables (Leggett and Bockstael, 1999), as it is preferable to include as many housing attributes as possible in order to reduce omitted-variable bias (Tu, 2005). Inclusion of highly correlated variables may result in spurious regression results and in this study multicollinearity is thus tested in order to prevent bias of standard errors for parameter estimates.

3.3 Spatial autocorrelation

The transaction price of a house is determined not only by its structural and neighbourhood characteristics, but also by transaction prices of prior sales within its vicinity (Can and Megbolugbe, 1997; Brasington and Hite, 2005). This spatial relationship is appropriate because an individual will often base his/her offer bid after having researched the prior transaction prices in the surrounding area (Brasington and Hite, 2005). This practice, known as "comparable sales", is often employed by real estate experts when trying to estimate the market value of a specific property (Can and Megbolugbe, 1997).

In order to capture this spatial interplay, a spatial autoregressive term can be included in the hedonic regression (Can and Megbolugbe, 1997). This term can be formally defined as:

$$\sum jWijPj, t - m \tag{3}$$

where: Wij = (1/dij)/$\sum$(1/dij) (inverse function of the distance, d, between the subject property, i, and a prior transaction, j.)

Pj,t-m = price of a transaction, j, occurring within the prior 6 months of the subject property, i.

Of critical importance is how Wij is defined (Can and Megbolugbe, 1997). This is due to the fact that the value of Wij will determine which houses should be considered neighbouring and the extent to which these houses influence the price of the specific house in question (Tu, 2005). It is assumed that the further away a neighbouring house is located from the specific house in question, the less of an influence it would have on the house in question. It is thus hypothesised that W is an inverse function of the distance, d, between the subject property, i, and a prior transaction, j. Wij can be specified as:

$$Wij = (1/dij)/\sum(1/dij) \tag{4}$$

In practice, it is recommended that all transactions concluded within the prior 6 months of the subject property transaction be included in the compilation of the spatial autoregressive term (Can and Megbolugbe, 1997). Exploratory work on spatial structure conducted by Can and Megbolugbe (1997) also indicated that spatial dependencies were located within a radius of 3.2 km of the subject property.

An added benefit of including the spatial autoregressive term in the hedonic model is that it captures the influence of omitted variables[2] (Brasington and Hite, 2005). Examples of such variables include air pollution, presence of shopping centres, highways, etc. Unmeasured influences help to determine the value of neighbouring houses, which, in turn, are related to the subject house. These unmeasured influences on neighbouring houses are similar to the unmeasured influences on the subject house. Thus, by including the spatial autoregressive term, the influence of omitted variables is incorporated into the hedonic equation. The omitted-variable issue is not addressed by traditional hedonic estimation, which leads to biased coefficients of the variables in the estimated hedonic equation.

3.4 Functional form selection and the Box-Cox transformation

Hedonic pricing theory provides very little guidance on the selection of an appropriate functional form for the hedonic model (Bender, Gronberg and Hwang, 1980; Cropper, Deck and McConnell, 1988;

[2]Other attempts to overcome omitted variable bias include "focusing on narrow geographic areas where many influences are already controlled for" and vast data collection procedures which attempt to capture all explanatory variables (Brasington, 2003; Brasington and Hite, 2005).

Haab and McConnell, 2002). Generally, a goodness-of-fit criterion has been used when selecting an appropriate form for a specific hedonic function (Cropper et al., 1988). If the primary objective of the research is to value a good's attributes, a functional form should be selected that most accurately estimates the marginal implicit prices of the attributes (Cropper et al., 1988). In terms of goodness-of-fit and accuracy of marginal price estimates, the application of a linear Box-Cox function has proven to be the functional form of choice (Cropper et al., 1988; Haab and McConnell, 2002).

For $Y^{(\lambda)}$, a basic Box–Cox transformation on a single variable (Y), the transformation[3] can be defined as

$$Y^{(\lambda)} = \frac{y^{\lambda} - 1}{\lambda} \; for \; \lambda \neq 0 \quad \text{or} \tag{5}$$

$$Y^{(\lambda)} = ln \; Y \; for \; \lambda = 0 \; (Haab \; and \; McConnell, \; 2002)$$

For transformation of both sides of the equation with different parameters[4], a more complex version is used. This transformation can be represented as

$$\frac{y^{\lambda} - 1}{\lambda} = \alpha + \textstyle\sum_{i=1}^{k} \beta_i \frac{x_i^{\theta} - 1}{\theta} + \sum_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \lambda \text{ and } \theta \neq 0 \tag{6}$$

For the purposes of this study, Equation 6 is referred to as an unrestricted Box–Cox model (uBC). For a restricted Box–Cox model (rBC), both sides of the equation are transformed by the same parameter. Thus, the rBC is equal to the UBC, with the restriction that $\lambda = \theta$:

$$\frac{y^{\lambda} - 1}{\lambda} = \alpha + \sum_{i=1}^{k} \beta_i \frac{x^{\lambda} - 1}{\lambda} + \sum_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \lambda \neq 0 \quad \text{or} \tag{7}$$

$$\ln Y = \alpha + \sum_{i=1}^{k} \beta_i \ln X_i + \sum_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \lambda = 0$$

The Box–Cox model that transforms only the dependent variable (leaving the independent variables unchanged) is known as the left-hand Box-Cox model (lhBC):

$$\frac{y^{\lambda} - 1}{\lambda} = \alpha + \sum_{i=1}^{k} \beta_i X_i + \sum_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \lambda \neq 0 \quad \text{or} \tag{8}$$

$$\ln Y = \alpha + \sum_{i=1}^{k} \beta_i X_i + \sum_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \lambda = 0$$

The right–hand Box–Cox model (rhBC) transforms only the continuous independent variables, leaving the dependent variable unaltered:

$$Y = \alpha + \textstyle\sum_{i=1}^{k} \beta_i \frac{x_i^{\theta} - 1}{\theta} + \sum_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \theta \neq 0 \quad \text{or} \tag{9}$$

$$Y = \alpha + \sum_{i=1}^{k} \beta_i \ln X_i + \sum_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \theta = 0$$

In each of the above models, maximum likelihood estimation is used to select the parameter values with the best fit (Williams, 2008). The use of the Box-Cox functional form allows the data to be accommodated in multiple functional forms (Cropper et al., 1988). Certain Box-Cox parameter values are associated with basic functional forms such as the linear, semi-log and double log forms (Haab and McConnell, 2002). Table 2 summarises what the Box–Cox model represents, depending on the parameter value.

Since the Box–Cox regression is able to represent a variety of different functional forms, it can be used to test for the most appropriate functional form (Haab and McConnell, 2002). The Box-Cox regression can also be used as a functional form itself (Cropper et al., 1988).

[3] Only positive variables can be transformed. Thus, dummy variables that can take on a value of zero cannot be transformed.

[4] In this study, represents the Box-Cox transformation parameter on the dependent variable and represents the transformation parameter on independent variables.

4 The Data and Empirical Results

4.1 Study area

The main challenge in defining the study area for the purposes of this study was to find an existing housing development, in the absence[5] of recently constructed social housing developments, that (1) caters for low-income earners, (2) is located in close proximity to a residential neighbourhood (the Walmer one[6]), and (3) is comparable to a typical social housing development as proposed by the South African government. The only viable option was the Walmer (Gqebera) Township. The township is located adjacent to the Walmer neighbourhood, is attractive to low-income earners, and enjoys a vibrant formal property market. An analysis of the traded properties in the township for the period 2005 to 2009 reveals an average sales price of R80 720 (South African Property Transfer Guide, 2011). This is more or less in line with the estimated cost per unit of R66 650 for the proposed New Brighton social housing project in Nelson Mandela Bay.

4.2 The data

The data used in this study were obtained from a variety of sources. Historical sales price data[7] for residential property stands in the neighbourhood of Walmer, Nelson Mandela Bay that were traded at least once during the past 15 years were collected from the Municipal database. All transactions that were not arms-length ones[8] were excluded from the analysis. Data from the Absa house price index were then used[9] to adjust house prices to constant 2009 rands to control for real estate market fluctuations. Information on the structural characteristics of 170 houses (the final dataset) in the Walmer neighbourhood was collected via personal interviews. Due to budget and time constraints, the sample size was limited to 170. The survey took place during January 2010 and respondents were asked to provide information on the structural characteristics at the time of sale.

4.3 The choice of hedonic variables

Previous research conducted by Sirmans et al. (2005) guided the selection of appropriate structural and neighbourhood characteristics for the purposes of this study. Information on the following characteristics were gathered as part of the survey: house size, number of stories, age of house, number of full bathrooms (bath, shower, toilet, basin), number of partial bathrooms, number of bedrooms, swimming pool, staff quarters, bachelor/granny flat, air-conditioning, number of vehicle storage units, irrigation system, separate dining room, number of living rooms, borehole, tennis court, boundary wall, electric access gate, security system, electric fence, distance from Walmer Township[10], distance to closest major shopping centre, distance to closest school and distance to airport. The distance from the subject property to the Walmer Township was measured (to the nearest meter) using Google Maps. The closest house in the sample was located 500m away from

[5] None of the planned social housing developments in the Nelson Mandela Bay area have so far been completed.

[6] The Walmer Township is unique since it was designated to be inside a "whites only" area under the Apartheid Group Areas Act of 1955. The Apartheid regime unsuccessfully attempted to remove the township. The removal was strongly resisted by township residents as well as residents of the Walmer neighbourhood.

[7] Walmer neighbourhood has a total of 2 625 residential properties and a total of 1 326 transactions took place from 1995 – 2009 (excluding repeat sales) (South African Property Transfer Guide, 2011).

[8] Some property transactions are conducted for reasons other than profit maximisation.

[9] Originally, data from the national index were used, but it was suggested by an anonymous referee that the local index may not have followed the national trend. Subsequently, the Port Elizabeth and Uitenhage index has been used to adjust prices. The researchers are grateful for this suggestion and believe that the analysis now reflects local conditions more accurately.

[10] On the recommendation of an anonymous referee, an interaction term between the proximity to the Walmer Township and the time of the sale was created (this was the same process followed by Michaels and Smith (1990)). It was found that the coefficient of this interaction term was statistically insignificant, suggesting that the effect of distance has not changed over time. For this reason, the interaction term was excluded from the final analysis.

the township and the furthest house was situated 3 200m away from the township. All distances were measured from the same point, on the outer border of the Walmer Township. Google Maps was also utilised in order to populate the autoregressive term. In each case, the distance from the subject property to the closest three transactions occurring within the prior 6 months was measured. As mentioned, the inverse of these distances were then used to determine the relative influence of prior transactions (within a radius of 3.2km) on each subject property in the sample. These weights were then multiplied by the relevant transaction prices of these neighbouring houses, in an attempt to capture the influence of prior sales on the market price of the subject property.

4.4 The hedonic model results

All models in this study were estimated using Stata Version 11.0. A complete model was estimated first, which included all variables thought to have an influence on the price of a property. Computed variance inflation factors (VIFs) – a test for multicollinearity – did not exceed the threshold value of 5, indicating that there was no severe multicollinearity present in the complete model. Following this, a reduced model, including only the coefficients of variables that were significant at the 5% level, was estimated. For the sake of parsimony, only the reduced model is presented in this paper. Table 3 provides a summary of the descriptive statistics of the variables with significant coefficients.

Seven functional forms were employed for the estimation of the reduced spatial hedonic model – three conventional models (linear, semi-log and double-log) and four Box-Cox transformations (unrestricted, restricted, left-hand side only and right-hand side only). The results of these models are presented in Table 4.

The results from the all the hedonic regressions generally conform to *a priori* expectations. More specifically, the number of stories, the size of the erf, the presence of a pool and the presence of an electric fence all have statistically significant, positive effects on property values in the sample. A very encouraging result is the statistically significant relationship that exists between house prices and distance from the Walmer Township. This significance allows for the calculation of implicit prices and provides evidence that house prices in the suburb of Walmer are, in part, determined by proximity to the township. More specifically, the relationship between house prices in Walmer and distance to the township is positive and significant.

As mentioned above, the Box–Cox transformed regression equation can be used as a test of functional form. The results of these tests are presented in Table 5.

As tests of functional form, the Box-Cox regressions eliminated the standard linear, double log and semi-log forms. As previously mentioned, the Box–Cox regressions can be used as functional forms themselves and based on the results displayed in Table 5, the Box–Cox regressions appear to fit the data best. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to select the appropriate Box-Cox model. Table 6 presents the AIC and BIC values of the four Box-Cox transformations.

According to Table 6, the lhBC had the lowest values for the AIC and the BIC, suggesting it is the most appropriate model. However, because it is preferable to transform both sides of the hedonic equation, the uBC transformation was selected for use in this study, as it had lower AIC and BIC values than the rBC (Williams, 2008). The hedonic function used in this study can thus be represented by the following equation:

$$\frac{y^{\lambda}-1}{\lambda} = \alpha + \sum\nolimits_{z=1}^{k} \beta_z \frac{x_{z^{\theta}-1}}{\theta} + \sum\nolimits_{s=1}^{j} \gamma_s D_s + \epsilon \text{ for } \lambda \text{ and } \theta \neq 0 \tag{10}$$

Equation 10, the unrestricted Box–Cox model, can be used to calculate the implicit price of distance to the Walmer Township. This calculation entails taking the partial derivative of the price Y with respect to distance X:

$$\frac{\partial Y}{\partial X} = \beta_z X_z^{\theta-1} y^{1-\lambda} \tag{11}$$

Based on this formula, the implicit price of distance to Walmer Township can be calculated as:

$$\frac{\partial Y}{\partial X} = 0.005498X^{1.03-1}y^{1-0.272} \tag{12}$$

Using Equation 12, the mean implicit price calculated in this study was R234.49. In other words, distance away from the Walmer Township is valued at R234.49/meter. Using Equation 10 and holding all other variables constant (except for distance to the Walmer Township), reveals a predicted house price of R1 198 816 for a house situated 500m from the township. This same house would increase in value by approximately 49% (or R588 514) when located 3200m away from the township.

4.5 Welfare Estimates

In this section, a household's (with a mean vector of attributes) willingness to pay for a finite change (i.e. discrete improvement) in the distance to Walmer Township characteristic is calculated. In order to define the finite change, impact zones were estimated by creating a dummy variable to indicate whether the subject house was located in the impact area (i.e. the area where proximity to the Walmer Township has a statistically significant, negative effect on Walmer house prices) (Tu, 2005). The impact area was estimated as a 1 999 km radius around the Walmer Township (starting from the outer limit of the township) . At a mean distance away from the Walmer Township of 1 799m for the average house in Walmer, the finite change was estimated to be 200m (i.e. 1 999m – 1 799m).

The first-order approximation of the average household's willingness to pay (WTP) to move 200m further away from the Walmer Township, using the implicit price of R234.49 per meter obtained from Equation 12, equals R46 898. This WTP value was also estimated by calculating the discrete change associated with a 200m increase in distance from the Walmer Township (Haab and McConnell, 2002). The basic expression for the discrete change is given by WTP = h(z*) – h(z), where z* represents the new vector of attributes (i.e. an increase in distance of 200m away from the Walmer Township) and z represents the original vector. The welfare effects are calculated at the mean price (Haab and McConnell, 2002). Specifying h(z) as the mean house price and h(z*) = $(p^\lambda + \lambda(z * (\theta) + z(\theta))\beta)^{1/\lambda}$, enables us to calculate the discrete change. The results of the first-order approximations as well as the discrete change estimates for the linear, semi-log, lhBC, rhBC and the uBC are presented in Table 7.

It is interesting to note that the first-order approximations using the marginal values are all quite close to the estimates of the discrete change.

5 Conclusion

This paper finds that the Walmer Township has a statistically significant negative impact on Walmer property prices. More specifically, the Walmer Township's impact on surrounding property values shows that a typical house in the Walmer neighbourhood located 500m from the township would experience a 49% rise in value if located 3200m away. The study also shows that the average household, if located in the impact zone, is willing to pay between R10 092 and R48 459 to move 200m further away from the Walmer Township. In addition, the paper also finds that the number of stories, a swimming pool, an electric fence, the size of the erf and property values in the immediate surrounding area all have a significant effect on the value of a property in the Walmer neighbourhood.

One of the main shortcomings of this study is that it uses one residential neighbourhood in Nelson Mandela Bay as its locus – this limits the extent to which the study's results can be generalised nationally. Also, in addition to the formally traded houses, the Walmer Township also comprises of informal "shack dwellings" – these are located at the back of the township (i.e. they are further away from the Walmer neighbourhood compared to the formal houses). In this study it was impossible to separate or disentangle the distance effects of the two dwelling types on the property prices in the Walmer neighbourhood. Finally, a fairly small data set was used in the study.

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Table 1: Top twenty characteristics appearing most often in hedonic pricing model studies

Variable	Appearances	No. of times positive	No. of times negative	No. of times insignificant
Lot Size	52	45	0	7
Ln Lot Size	12	9	0	3
Square Feet	69	62	4	3
Ln Square Feet	12	12	0	0
Brick	13	9	0	4
Age	78	7	63	8
No. Stories	13	4	7	2
No. Bathrooms	40	34	1	5
No. Rooms	14	10	1	3
Bedrooms	40	21	9	10
Full Baths	37	31	1	5
Fireplace	57	43	3	11
Air-conditioning	37	34	1	2
Basement	21	15	1	5
Garage Spaces	61	48	0	13
Deck	12	10	0	2
Pool	31	27	0	4
Distance	15	5	5	5
Time On Market	18	1	8	9
Time Trend	13	2	3	8

Source: Sirmans et al. (2005)

Table 2: Possible Box-Cox functional forms

Box – Cox model:	**Parameter Value:**	**Functional Form:**
Restricted Box-Cox	$\lambda = 1$	Linear
	$\lambda = 0$	Log–log
Left hand Box–Cox	$\lambda = 0$	semi–log
	$\lambda = 1$	Linear
Right hand Box–Cox	$\theta = 1$	Linear
	$\theta = 0$	semi log
	$\theta = -1$	Reciprocal
Unrestricted Box–Cox	$\lambda = \theta$	Restricted Box–Cox
	$\theta = 1$	Left hand Box–Cox
	$\lambda = 1$	Right hand Box–Cox

Table 3: Summary Statistics

Variable	**Unit of measurement**	**Min**	**Max**	**Mean**	**Standard deviation**
Sales price	Rands	193600	4926800	1626395	774758
Structural characteristics					
Stories	Number of	1	2	1.18	0.387
Swimming pool	Yes = 1 No = 0	0	1	0.8	0.401
Electric fence	Yes = 1 No = 0	0	1	0.26	0.442
Erf size	Square meters	380	4600	1776.4	629
Neighbourhood characteristic					
Distance to Walmer Township	Meters	500	3200	1799	599

Table 4: Regression results

Variable	Model						
	Linear	**Semi-log**	**Double-log**	**lhBC model**	**rhBC model**	**rBC model**	**uBC model**
Constant	-850912.6 (239532.7)[b]	12.7 (0.15)[b]	8.14 (1.223)[b]	99.91	-214272.7	-5.521	111.84
Structural Characteristics							
Stories	304642.1[a] (114285.1)[b]	0.2055[a] (0.07)[b]	0.213[a] (0.074)[b]	9.53[a] (8.907)[c]	284338.1[a] (7.535)[c]	66.82[a] (8.182)[c]	9.545[a] (8.914)[c]
Swimming pool	359880.5[a] (113581.4)[b]	0.316[a] (0.07)[b]	0.369[a] (0.073)[b]	13.599[a] (17.622)[c]	355489[a] (9.941)[c]	81.004[a] (18.162)[c]	13.74[a] (17.497)[c]
Electric fence	277279.2* (100928.7)[b]	0.1416[a] (0.062)[b]	0.167[a] (0.065)[b]	7.19[a] (6.51)[c]	273190.7[a] (7.491)[c]	46.18[a] (7.903)[c]	7.26[a] (6.454)[c]
Erf size	623.14[a] (70.95)[b]	0.0003[a] (0.00004)[b]	0.348[a] (0.058)[b]	0.016[a] (58.051)[c]	109.24[a] (65.696)[c]	7.84[a] (48.215)[c]	0.013[a] (57.537)[c]
Neighbourhood Characteristics							
Distance to Walmer Township	234.72[a] (73.17)[b]	0.00015[a] (0.0000448)[b]	0.248[a] (0.074)[b]	0.00699[a] (11.594)[c]	41.018[a] (9.673)[c]	3.756[a] (12.652)[c]	0.005498[a] (11.398)[c]
Autoregressive term	0.1418[a] (0.065)[b]	0.000000062 (0.00000004)[b]	0.074 (0.071)[b]	0.000003[a] (3.33)[c]	0.00524[a] (5.17)[c]	0.105 (2.622)[c]	0.00000207[a] (3.337)[c]
R-squared	0.48	0.47	0.41				
F-statistic	25.57	24.61	19.26				
Transformation Parameters							
λ				0.2713 (0.1011)[b]	---	0.394[a] (0.096)[b]	0.272[a] (0.101)[b]
θ				---	1.23 (0.323)[b]	0.394[a] (0.096)[b]	1.03[a] (0.296)[b]
Log likelihood				-2467.04	-2489.3	-2471.7	-2467.03

Notes: [a] Significant at the 1-percent level
[b] Standard errors in parentheses
[c] Chi–square values in parenthesis[1]

[1] The Box-Cox produced probability values for the coefficients on the basis of chi–square tests (as the use of ordinary least squares estimates of variance may produce inaccurate measures of significance when used with Box-Cox transformations) (Williams, 2008).

Table 5: Hypothesis tests for Box–Cox transformations

Transformation	λ	θ	**Ho Equation**	**Chi² statistic for rejecting Ho when X =**			**Standard functional forms rejected**
				1	**0**	**-1**	
lhBC	0.27123		λ=X	45.10	7.61	198.83	Semi-log and linear
rhBC		1.23	θ=X	0.58	28.91	60.76	Semi-log and reciprocal
rBC	0.394	0.394	θ=λ=X	35.78	16.82	203.91	Linear and log-log
uBC	0.272	1.03	θ=λ=X	45.11	26.15	213.24	Linear and log-log

Table 6: AIC and BIC values

Model	**AIC**	**BIC**
lhBC	4936	4939
rhBC	4980	4983
rBC	4945	4948
uBC	4938	4944

Table 7: Welfare measures for a change in distance

Functional form	**Coefficient:**β	**Marginal Value***	**First Approximation using marginal value****	**Discrete Change**
Linear ($\lambda = \theta = 1$)	234.72	234.72	46944	46944
Semi-log ($\lambda = 0, \theta = 1$)	0.0001468	238.75	47750	48459
lhBC ($\lambda = 0.271, \theta = 1$)	0.0069873	234.81	46692	47457
rhBC ($\lambda = 1, \theta = 1.2302$)	41.01798	230.34	46068	10092
uBC ($\lambda = 0.272, \theta = 1.033$)	0.005498	234.49	46898	38033

Notes: *Marginal value = $\beta X^{\theta-1} Y^{1-\lambda}$
** Marginal value * 200