



Spatial Dependence in a Hedonic Real Estate Model: Evidence from Jamaica

R. Brian Langrin^{†‡}

Financial Stability Department
Research & Economic Programming Division
Bank of Jamaica

Abstract

The recent global financial crisis has underscored the need for policy makers to closely monitor changes in real estate price levels given the potentially disastrous monetary and financial stability consequences. This paper estimates spatial hedonic price models for housing in Jamaica's most central parishes of Kingston & St. Andrew, using a rich data set spanning from January 2003 to September 2008, in order to construct an efficient regional residential housing price index. Previous hedonic studies using either contiguity-based spatial lag or spatial error models did not find major differences in implicit price estimates when compared with OLS models. However, all these studies controlled for location and neighbourhood effects within the hedonic regressions prior to testing for model comparison. This study finds statistically insignificant difference between the spatial dependence-corrected estimates of implicit prices for housing attributes compared to those estimates obtained using standard OLS, even when location and neighbourhood variables are excluded from the hedonic model. The findings of this study should provide valuable insights for policy analysis.

JEL Classification: C43, C51, O18

Keywords: spatial econometrics, housing price index, hedonic model

[†] Nethersole Place, P.O. Box 621, Kingston, Jamaica, W.I. Tel.: (876) 967-1880. Fax: (876) 967-4265.
Email: brian.langrin@boj.org.jm

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1. Introduction

The recent collapse of housing markets in some advanced economies has renewed international focus on the impact of house price cycles on economic activity and financial stability. Real estate prices can be prone to large swings or ‘boom-bust’ cycles which have a major influence on economic activity and financial stability through their impact on the decisions of households and financial institutions (Kindleberger, 2000; Case *et al.*, 2004). House price booms magnify business cycle upturns and are highly correlated with credit booms (Hofmann, 2001; Borio and Lowe, 2002; Davis and Zhu, 2004). Similarly, sharp declines in house prices have been associated with substantial adverse output and inflation effects which outweigh the impact of busts in other asset prices, such as equities (Helbling and Terrones, 2003; Helbling, 2005). House price busts generally result in substantial declines in the asset quality and profits of financial institutions and, during extreme episodes, wide-spread insolvencies. The well-documented links between fluctuations in house prices and macroeconomic and financial instability, underscores the need for an accurate and reliable measure of house price inflation.

A house is a heterogeneous good whose inherent characteristics e.g. , floor area, number of bedrooms, number of bathrooms, number of floors, existence of a garage and environmental factors e.g., location, distance from the city centre, area of lot and so on are linked to its market value. That each characteristic contributes a measurable percentage of the market value of the unit is at the heart of hedonic real estate price theory which assumes the market value of a property is a function of a set of individual shadow prices associated with each of these characteristics. Hedonic pricing can be used to estimate the market value of a property when transaction data are not available. It can assess the relative desirability of the various characteristics. Additionally, the hedonic price index can be used by financial institutions as a property pricing expert system for credit risk management in line with Basel II regulations (Goui roux and Laferr re, 2006).

This paper estimates the statistical relationship between the value of a property and its characteristics using data from the Kingston Metropolitan Area (KMA) over a specific period. The coefficients or shadow prices from this estimation provide the basis for

projecting the market value of other properties as well as the construction of price indices. The coefficients are kept constant to compute the index over the quarters proceeding the base period, subject to tests of the stability of the parameters over time.

A residential real estate hedonic model is measured in this study by estimating the current value of a region-specific reference stock of dwellings using observed transactions and assessment data on price and non-price characteristics. To determine the evolution of prices, the current value of the reference stock within each region is compared with the value of this stock during a pre-defined base period.¹ This approach to price index construction has an important efficiency advantage in that econometric estimation is required for the base (estimation) period only. The econometric parameters obtained from this initial estimation are then kept constant to compute the index over the quarters proceeding the base period subject to stability tests of time invariance of the parameters.

Spatial dependence of house prices is typically found in real estate data due to the locational clustering of houses with similar valuations. If house prices exhibit spatial correlation, either in the dependent variable or the model residuals, then the standard OLS model can produce spurious results. Many researchers have argued that the existence of spatial autocorrelation in house prices (spatial lag dependence) without correction, results in biased coefficient estimates. Also, the existence of spatially correlated errors among the independent variables without correction, results in inefficient coefficient estimates. Hence, many estimates of implicit prices from past residential real estate hedonic research, which did not account for the spatial nature of the data, may have led to incorrect policy decisions.

A primary objective of this paper is to determine whether estimated implicit prices for a spatial model application to KMA real estate data differ economically from the OLS implicit prices. A row-standardized spatial weights matrix is employed in tests for spatial dependence and estimation of spatial hedonic models. This weights matrix models the contiguity relationships for each price observation based on the 70 communities within

¹ See, for example, Gouriéroux and Laferrère (2006).

the KMA. Previous hedonic studies using either contiguity-based spatial lag or spatial error models did not find significant differences in implicit price estimates when compared with OLS models.² All these studies controlled for location and neighbourhood effects in the hedonic model prior to model comparison. However, *excluding* location and neighbourhood variables before comparison between models allows for more robust testing. In other words, controlling for location and neighbourhood effects in the hedonic regression may account for some or all of the spatial dependence prior to testing for it.

This paper extends the literature of spatial dependence by comparing estimated implicit prices from spatial models and the OLS model when location and neighbourhood variables are excluded from the hedonic model. Obtaining statistically similar results from both models would diminish the importance of taking the spatial dimension of house price data into account in the computation of the hedonic price index for the KMA.

2. Alternative Methodological Approaches

The construction of a real estate price index is typically associated with problems arising from measuring temporal changes in the quality and composition of the housing sample. Houses are heterogeneous goods according to location as well as other characteristics which may change over time. For example, the attributes of the existing housing stock may change significantly due to renovation, depreciation or the construction of new houses with improved qualities. In addition, changes in the composition of the sample of houses to be incorporated in the index between periods, as well as the fact that not all house sales will be captured in the index, could introduce some sample selection bias in the computation.

There are various techniques used to compile real estate transactions to construct a price index. The most common methods can be separated into non-parametric and parametric approaches. The non-parametric methods include, the ‘simple average’ or ‘median’ price approach and the ‘mix-adjustment’ or ‘weighted average price’ approach. Although these

² See Kim, Phipps and Anselin (2003), Wang and Ready (2005), Mueller and Loomis (2008) and Ismail *et al.* (2008).

non-parametric approaches have the advantage of relatively straightforward data requirements, they typically suffer from major problems associated with inadequate measurement of real estate heterogeneity and temporal compositional changes (Case and Shiller, 1987).

Parametric methods, which include the ‘hedonic’, ‘repeat sales’ and ‘hybrid’ approaches, generally overcome the inherent drawbacks of non-parametric methods. Each of these regression-based approaches standardize quality attributes over time in the measurement of price changes which are then used to construct an index of price changes for a constant set of characteristics. Nevertheless, the parametric approaches, depending on the robustness of the specific technique, may still be subject to measurement problems.

Non-parametric Approaches

Simple Average/ Median Price Method

The simple average or median price approach involves the computation of measures of central tendency using a representational distribution of observed real estate prices for each time period. The choice between simple average or median price changes depends directly on the skewness, or existence of outliers, in the distribution of prices in the sample of transactions. If the price distribution was generally heavily skewed, then using the median price index would be preferred (Mark and Goldberg, 1984; Crone and Voith, 1992; Gatzlaff and Ling, 1994; Wang and Zorn, 1997). However, inferences from using either an average or median price index are significantly affected by the failure to control for changes in the quality composition of houses sold over each time period.

Mix- adjustment Method

Alternatively, the mix- adjustment approach relies on the simple measures of central tendency for residential price distributions, which are grouped according to separate sets or “cells” of location and other attributes to construct a mix-adjusted index. Unlike the hedonic approach, changes in the quality of houses across time periods will bias this aggregate measure of prices.

Parametric Approaches

Hedonic Price Method

The hedonic price approach is widely utilized to estimate the relationship between real estate prices and their corresponding hedonic characteristics. This approach has its theoretical foundations in Lancaster's (1966) consumer preference theory and was later extended by using an equilibrium supply and demand framework based on heterogeneous product characteristics (Rosen, 1974). Hedonic price theory assumes the market values of real estate are functions of a set of separate hedonic shadow prices associated with the physical characteristics. These characteristics include location of the property and other attributes, such as, land area, floor area, number of bedrooms, number of bathrooms, number of floors, existence of a garage and so on.

Many studies have applied hedonic techniques to housing markets (Wigren, 1987; Colwell, 1990; Janssen *et al.*, 2001; Buck, 1991; Blomquist *et al.*, 1998; Englund, 1998; Cheshire and Sheppard, 1995; Sivitanidou, 1996; Maurer, Pitzer and Sebastian, 2004; Wen, Jia and Guo, 2005; Goui eroux and Laferr ere, 2006). Assuming that the precise functional form of the hedonic model is known, econometric techniques can be employed to estimate the parameter values associated with each characteristic, revealed from observed prices of heterogeneous houses. These implicit or shadow price estimates are then used to construct the computed average price of a constant-quality stock of residential real estate, consisting of different characteristic compositions.

The three main methods of estimating hedonic models are the time-dummy variable, the characteristics price index and the price imputation methods. The time-dummy variable method pools all periods of transactions prices, including a set of time-dummy variables to represent the specific transaction period, to estimate a single 'constrained' set of hedonic coefficients. Alternatively, the characteristics price index method does not constrain the intercept or a hedonic coefficient to be constant over time, as the hedonic-price model is applied separately to each period. The primary advantage of the characteristics price index method is, unlike the time-dummy variable method, is that it

permits the price index number formula to be determined independent of the hedonic functional form (Diewert, 1976; Triplett, 2004).

The third method, price imputation, is adopted in this paper. It involves the use of the specified hedonic function and current data to estimate the imputed market price for a house with the attributes of a reference stock of houses. Then the difference between the value of the reference stock at the base period and the current estimated value of the reference stock gives the 'pure' price change. Further, the value at the base date can also be imputed and then compared with the current period imputed value. This imputation approach enhances the robustness of the hedonic price index as the conditional expected value of the reference stock is used instead of the observed prices, which could include outliers.

There are some limitations associated with the measurement of 'pure' price changes using the hedonic approach. First, the approach is data intensive, relating to not only prices but also detailed information across hedonic characteristics. If relevant characteristics are not included in measurement or change significantly over time, then the shadow prices of characteristics may be unstable resulting in statistically biased estimates of the price index. Second, different functional forms can be used to specify hedonic equations including the 'linear' model, 'log-linear' model and the 'log-log' ('double-log') model. However, model misspecification produces biased estimates of the price index (Meese and Wallace, 1997). Third, the sample of real estate transactions within a specific period is not random and could vary according to economic conditions if the market is segmented. This could introduce sample selection bias in the computed price index.

Repeat Sales Method

Repeat sales models regress price changes on houses that have been sold more than once to estimate general house price inflation, under the assumption that the hedonic characteristics are unchanged between transactions (Bailey, Muth and Nourse, 1963; Case and Shiller, 1987, 1989; Shiller, 1991, 1993; Goetzmann, 1992; Calhoun, 1996;

Englund, Quigley and Redfearn, 1998; Dreiman and Pennington-Cross, 2004; Jansen *et al.*, 2006). By controlling for quality changes in this manner, the change in price of houses between transactions can be expressed as a simple function of the time intervals between transactions.

The obvious advantage of the repeat sales method over the hedonic price approach is that data requirements are much less detailed, in that information on real estate characteristics are not needed to construct the price index. That is, aside from price changes and the transaction dates, confirmation that the characteristics have remained unchanged is all the additional information required.

However, the omission or 'waste' of information relating to real estate sold only once during the estimation period is viewed as the main disadvantage of the repeat sales method. Omitting single-transaction price data oftentimes lead to an insufficient number of observations for robust estimation of an index for regions where real estate transaction occur relatively infrequently (Abraham and Schauman, 1991; Clapp, Giacotto, and Tirtiroglu, 1991; Cho, 1996). Similarly, problems of sample selection bias are likely to be more serious using the repeat sales method compared to the hedonic price method (Case, Pollakowski and Wachter, 1991; Cho, 1996; Gatzlaff and Haurin, 1997; Meese and Wallace, 1997; Steele and Goy, 1997). Additionally, similar to the drawback of the hedonic price method, model misspecification due to changes in implicit market prices will lead to an inaccurate price index.

Hybrid Method

The drawbacks of the repeat sales and hedonic approaches inspired the advancement of a hybrid technique which combines the features of both techniques (Palmquist, 1980; Case, Pollakowski, and Wachter, 1991; Case and Quigley, 1991; Quigley, 1995; Knight, Dombrow, and Sirmans, 1995; Meese and Wallace, 1997; Hill, Knight, and Sirmans, 1997; Englund, Quigley, and Redfearn, 1998). The hybrid method was designed specifically to address the bias and inefficiency problems of the hedonic price and repeat sales approaches. Weighted averages of the hedonic and repeat-sales methods are created

by jointly estimating the hedonic price and repeat sales models and imposing cross equation restrictions. Nevertheless, problems of model misspecification and sample selection bias are still evident in hybrid measurement. Consequently, no clear evidence exists to support the superiority of hybrid models over the other parametric approaches (Case, Pollakowski, and Wachter, 1991).

3. Institutional Context & Data Description

Building an accurate measure of house prices depends critically on the reliability and suitability of data sources. A variety of data sources exist, including transactions and appraisal or assessment data, building permits, land registry, mortgage records, realtors, appraisors and household surveys. The combination of transactions and assessment data represent the most complete data source for the construction of hedonic prices indices and quality-adjusted repeat-sales indices (Pollakowsky, 1995).

The National Housing Trust (NHT), established in 1976, is the largest provider of residential mortgages in Jamaica with over 50.0 per cent market share. All employed persons in Jamaica that are between the ages of 18 and 65 and that earn above minimum wage are required by law to contribute 2.0 per cent of their wages to the Trust. Employers must also contribute 3.0 per cent of their wage bill. In return for their contributions, the NHT facilitates house purchases at concessionary interest rates. Joint financing facilities with private mortgage providers may also be arranged by contributors.

The complete data set consists of 2,271 observations, between 2003 and 2008, on residential mortgages for apartments, houses and townhouses within Jamaica's most central parishes of Kingston & St. Andrew or the KMA.³ This data reflects the overall prices and other primary characteristics for real estate for which NHT is the main mortgage provider. The non-price characteristics covered in the data set are: sale date, postcode, lot size (in square metres), floor area (in square metres), property value, forced sale value, year of construction (1930-1959, 1960-1969, 1970-1979, 1980-1989, 1990-

³ Kingston is the capital and largest city of Jamaica with a total area of 480.0 km² (185.3 square miles). St. Andrew is the parish adjoining Kingston with a total area of 455.0 km² (181.0 square miles).

1999, 2000-2008), type of dwelling (two family house, attached house, semi-detached house, townhouse, studio, apartment), number of floors (1, 2, 3 & over), number of bedrooms (0, 1, 2, 3, 4, 5 & over), number of bathrooms (0, 1, 2, 3, 4 & over), number of laundry rooms (0, 1, 2 & over), number of car ports/garages (0, 1, 2 & over) and existence of a water tank (0, 1).

Location is defined in this paper according to two distinct sets of information variables. In one location variable set, housing data is divided among 20 postcodes dispersed across the KMA.⁴ For the other set of location variables, the data is divided in a more granular manner among 70 community codes, representing relatively smaller parcels of land.

Although using location information on the 70 different community codes instead of the 20 postal codes should result in more robust inferences, there are severe computational limitations arising from inadequate degrees of freedom. For this reason, biased and inefficient estimates of implicit prices cannot be ruled out due to significant heterogeneity as well as overlapping of communities within postal codes (see Table 3). Hence, testing for differences between implicit prices from OLS hedonic estimates compared to spatially corrected estimates will provide evidence of whether potential bias and inefficiency are significant.

Observations are excluded from the final data set for three reasons: incomplete or missing data on characteristics, the existence of more than one house on the property and insufficient number of observations per postcode.^{5,6} A final data set of 1 691 observations, covering 2003 to 2007, is used to estimate the hedonic model.⁷ Observations available

⁴ These are Bull Bay PO, Golden Spring PO, Stony Hill PO, Kingston CSO, Red Hills PO, Kingston 2, Kingston 3, Kingston 4, Kingston 5, Kingston 6, Kingston 7, Kingston 8, Kingston 9, Kingston 10, Kingston 11, Kingston 13, Kingston 16, Kingston 17, Kingston 19 and Kingston 20.

⁵ The floor area was used also as the lot size for apartments.

⁶ The excluded postal codes are: Temple Hall PO, Mount James PO, Lawrence Tavern PO, Mavis Bank PO, Dallas PO, Gordon Town PO, Strathmore PO, Border PO and Kingston 14.

⁷ Other relevant variables reported in the data set include: number of powder rooms, existence of a varandah, existence of a balcony, existence of a storage room, existence of a swimming pool, existence of 24-hour security, among others. However, these variables were excluded because of incomplete coverage over many assessments.

for the first three quarters of 2008 are excluded from the estimation sample but included in the computation of the hedonic price index.

Detached houses account for 46.0 per cent of total dwelling types in the final data set and apartments, the second most frequent occurring dwelling type, account for 30.0 per cent (see Table 1). Other most frequently occurring characteristics include: one floor (79.0 per cent); constructed between 1970 and 1979 (28.0 per cent); two bedrooms (32.0 per cent); one bathroom (54.0 per cent); no carport (67.0 per cent); one laundry area (60.0 per cent); and, no water tank (99.0 per cent). The Kingston 20 postal code, accounting for 22.0 per cent of the final data set, is the most frequently occurring location (see Table 1). Some postal codes are excluded from the final data set due to insufficient observations to constitute a representational sample.

The sample statistics for the initial and final (cleaned) data sets are broadly similar with regard to the variables: ‘number of floors’, ‘number of bedrooms’, ‘number of bathrooms’, ‘number of car ports’ and ‘number of laundry areas’ (see Tables 2a and 2b). The average ‘price’ (in square metres) as well as the average and standard deviation for ‘floor area’ are also similar for both the initial and final data sets. The average, standard deviation and maximum statistics for ‘lot size’ are significantly higher for the initial data set. However, these differences for lot size were primarily due to an outlier lot size of 989 862.34 square metres in the initial data set.

4. The Hedonic Model

The specific methodology that is proposed to construct a real estate index for Jamaica is based on the approach used to compute official housing price indexes by the National Institute of Statistics and Economic Studies (INSEE)⁸ in France (Gouriéroux and Laferrère, 2006). The French indexes are constructed by estimating the value of ‘reference stocks’ of dwellings in each homogeneous zone (region). Hence, a price index is computed for each zone as the ratio of the current estimated value of a reference stock of dwellings to its value at the base period of the index. Specifically, observed

⁸ Institut National de la Statistique et des Etudes Economiques.

transactions within each quarter are used to estimate the current value of each reference dwelling by way of hedonic econometric models. The main advantage of this approach is that the marginal contribution (shadow price) of each house characteristic remains constant and is, thus, immune from the problem of sample selection bias.

Functional Form and the Box-Cox Transformation

The semi-log and double-log functional forms are the more popular hedonic specifications. However, selecting the most appropriate functional form for the hedonic model is important for minimizing any bias in the estimated hedonic coefficients and, by extension, the real estate price index. The Box-Cox (1964) model nests the linear, semi-log and double-log functional forms. The Box-Cox transformation is represented by $Y^{(\lambda)} = Y^\lambda - 1/\lambda$. The linear model results if $\lambda = 1$, $Y^\lambda - 1/\lambda \rightarrow Y - 1$; and if $\lambda \rightarrow 0$, $Y^\lambda - 1/\lambda \rightarrow \log(Y)$. Consider the application of the following *unrestricted* Box-Cox transformation to the hedonic price equation:

$$P_i^{(\lambda_1)} = P_0 + \sum_{t=1}^T \theta_t A_{t,i} + \sum_{q=1}^3 \kappa_q Q_{q,i} + \sum_{k=1}^K \alpha_k Z_{k,i} + \sum_{m=1}^M \beta_m X_{m,i}^{(\lambda_2)} + \varepsilon_i \quad \text{for } \lambda_1 \text{ and } \lambda_2 \neq 0. \quad [1]$$

where P_i represents the price per square metres of dwelling i , $A_{t,i}$ is a dummy variable for the year of sale for i , $Q_{q,i}$ is a dummy for the quarter of sale for i , $Z_{k,i}$ are dichotomous observations on K variables for which the Box-Cox transformation does not apply (i.e., dummy variables), $X_{m,i}$ are continuous observations on M variables which are subject to the Box-Cox transformation (i.e., lot size and floor area), $\varepsilon_i \sim N[0, \sigma^2]$, λ_1 denotes the Box-Cox transformation parameter on the dependent variable and λ_2 denotes the Box-Cox transformation parameter on the independent continuous variables.⁹ The *restricted* Box-Cox transformation requires that $\lambda_1 = \lambda_2$. The linear model results when $\lambda_1 = \lambda_2 = 1$, while the log-log model results when $\lambda_1 = \lambda_2 = 0$. Further, a left-side semi-log model arises when $\lambda_1 = 0$ and $\lambda_2 = 1$, while the right-side semi-log arise when $\lambda_1 = 1$ and $\lambda_2 = 0$.¹⁰ The log likelihood function for a sample of n observations is:

⁹ Other forms of unrestricted Box-Cox models include: transformation on the dependent variable only and transformation on the independent variables only.

¹⁰ The Box-Cox model represents a reciprocal functional form when the transformation parameter equals -1.

$$\ln L(\lambda_1, \lambda_2, \theta, \kappa, \alpha, \beta; A, Q, Z, X) = \frac{-n}{2} (\ln(2\pi) - \ln \sigma^2) + (\lambda_1 - 1) \sum_{i=1}^n \ln(P_i) - \frac{1}{2\sigma^2} \sum_{i=1}^n \varepsilon_i^2. \quad [2]$$

This study employs the Greene (1993) likelihood ratio (LR) test of the appropriateness of only the unrestricted Box-Cox, linear, semi-logarithmic and double-logarithmic functional forms. The LR (Box-Cox) test statistic is $-2(\ln L^* - \ln L) \sim \chi_J^2$, where $\ln L^*$ is the log-likelihood evaluated at the restricted estimates.¹¹ This test rejects, at the 5.0 per cent critical value of 3.84, the null hypotheses that the estimated Box-Cox parameters are equal to 0 or 1. However, as mentioned in Parkomenko *et al.* (2007), the Box-Cox test is likely to favour nonlinear models despite being the incorrect functional form in cases of omitted and misspecified variables. Hence, similar to Li, Prud'Homme and Yu (2006), the preferred model is evaluated according to signs of coefficients, value of coefficients as well as out-of-sample goodness-of-fit measures (see Table 4 and Tables 5 – 9 in Appendix). The specific goodness-of-fit measures used are: Akaike's Information Criteria (AIC), Schwartz Criteria (SC) and Hannan-Quinn criterion (HQ).

Table 4. Goodness of Fit Statistics

Criterion	Double-log	Semi-log (lh)	Semi-log (rh)	Linear	Box-Cox
AIC	0.79	0.85	18.01	18.13	-11.37
SC	0.97	1.03	18.19	18.31	-11.18
HQ	0.85	0.92	18.07	18.20	-11.30

All out-of-sample goodness-of-fit statistics indicate that the Box-Cox model produces the best specification (see Table 4). The double-log model ranks second, followed by the left side semi-log model, the right side semi-log model and the linear model, respectively. The double-log model is chosen as the preferred specification as the coefficient values and signs are, by far, more reasonable when compared to the Box-Cox specification, for all the groups of characteristics (see Tables 5 – 9 in Appendix).

¹¹ J is equal to the number of restrictions imposed on the model.

Table 10. Regression Results for Double-Log Model using HCC-Robust Standard Errors

Variables	Coefficient	Standard error	P-value
Constant	10.4067	0.3076	0.000
YEAR 2003		<i>Reference</i>	
YEAR 2004	0.0966	0.0297	0.001
YEAR 2005	0.1460	0.0319	0.000
YEAR 2006	0.2986	0.0291	0.000
YEAR 2007	0.5339	0.0259	0.000
QUARTER 1	-0.1352	0.0240	0.000
QUARTER 2	-0.0944	0.0229	0.000
QUARTER 3	-0.0802	0.0246	0.001
QUARTER 4		<i>Reference</i>	
DETACHED		<i>Reference</i>	
SEMI-DETACHED	0.0232	0.0526	0.659
ATTACHED	-0.0867	0.0759	0.254
TOWNHOUSE	0.1075	0.0558	0.054
2-FAMILY HOUSE	0.0976	0.0834	0.242
APARTMENT	0.1735	0.0589	0.003
STUDIO	0.1290	0.0881	0.144
ONE FLOOR		<i>Reference</i>	
TWO FLOORS	0.0742	0.0405	0.067
THREE FLOORS	0.1213	0.0961	0.207
FLOOR AREA	-0.5139	0.0556	0.000
LOT SIZE	0.1026	0.0252	0.000
CONSTRUCTED <1960		<i>Reference</i>	
CONSTRUCTED 1960-1969	0.0744	0.0399	0.063
CONSTRUCTED 1970-1979	0.1383	0.0375	0.000
CONSTRUCTED 1980-1989	0.1828	0.0429	0.000
CONSTRUCTED 1990-1999	0.3363	0.0472	0.000
CONSTRUCTED 2000-2007	0.4346	0.0482	0.000
0 BEDROOMS	-0.3545	0.1828	0.053
1 BEDROOM		<i>Reference</i>	
2 BEDROOMS	-0.0002	0.0340	0.995
3 BEDROOMS	-0.0552	0.0549	0.315
4 BEDROOMS	-0.1920	0.0623	0.002
5 & OVER BEDROOMS	-0.3228	0.0765	0.000
0 BATHROOMS	0.1352	0.0853	0.113
1 BATHROOM		<i>Reference</i>	
2 BATHROOMS	0.2165	0.0324	0.000
3 BATHROOMS	0.3528	0.0479	0.000
4 & OVER BATHROOMS	0.4295	0.0741	0.000
0 CAR PORTS		<i>Reference</i>	
1 CAR PORT	0.0081	0.0277	0.770
2 & OVER CAR PORTS	0.1349	0.0595	0.024
0 LAUNDRY AREAS	-0.0592	0.0198	0.003
1 LAUNDRY AREA		<i>Reference</i>	
2 & OVER LAUNDRY AREAS	0.0208	0.0718	0.772
WATERTANK	0.1580	0.0664	0.017
LOC1_Bull Bay	-0.2337	0.0730	0.001
LOC2_Golden Spring	-0.1926	0.0841	0.022
LOC3_Kingston10	0.1925	0.0327	0.000
LOC4_Kingston 11	-0.5411	0.0397	0.000
LOC5_Kingston 13	-0.4769	0.0649	0.000
LOC6_Kingston 16	-0.5910	0.0718	0.000
LOC7_Kingston 17	0.0500	0.0562	0.374
LOC8_Kingston 19	0.1699	0.0398	0.000
LOC9_Kingston 2	-0.2627	0.0426	0.000
LOC11_Kingston 3	-0.1748	0.0456	0.000
LOC12_Kingston 4	-0.3768	0.0819	0.000
LOC13_Kingston 5	0.0525	0.0824	0.524
LOC14_Kingston 6	0.2983	0.0372	0.000
LOC15_Kingston 7	-0.2030	0.0693	0.003
LOC16_Kingston 8	0.2521	0.0319	0.000
LOC17_Kingston 9	0.0902	0.0993	0.364
LOC18_Central Sorting Off.	-0.1271	0.0950	0.181
LOC19_Red Hills	0.1456	0.0620	0.019
LOC20_Stony Hill	0.1558	0.1451	0.283
LOC21_Kingston 20		<i>Reference</i>	
Number of Observations	1691		
Adjusted R-squared	0.63		
Log likelihood	-612.80		

Residual Tests for Correct Functional Form

Tests of the residuals from the double-log estimation reveal the presence of heteroskedasticity. The White (W) Test rejects the null hypothesis of no heteroskedasticity with $W = 90.42$. However, the Breusch-Godfrey Serial Correlation LM Test cannot reject the null hypothesis of no serial correlation in the residuals at various lag orders. Hence, the double-log model is estimated using White (1980) Heteroskedasticity Consistent Covariances (HCC) (see Table 10). The CUSUM Test and CUSUM-of-Squares Test of the double-log model provide evidence of parameter and residual variance stability over the estimation period (see Figures 1 & 2 in Appendix).

Spatial Analysis

Spatial correlation between locational data is defined by the moment condition:

$$\text{cov}(x_i, x_j) = E(x_i x_j) - E(x_i) \cdot E(x_j) \neq 0, \forall i \neq j \quad [3]$$

where i and j are locations and x_i and x_j represent values for random variables at the specific locations (see Anselin and Bera, 1998). This covariance is spatial when i, j pairs are non-zero based on the structure, interaction or arrangement of the observations in the data set.

The two types of spatial dependence, spatial lag dependence and spatial error dependence, are determined by the underlying spatial data generating process (DGP) of house prices (see Anselin, 1988). If the DGP exhibits a spatial lag process, a spatial autoregressive (SAR) model is appropriate. The SAR model is modelled by including a spatially lagged dependent variable in the model as specified by:

$$\begin{aligned} y &= \rho W y + X \beta + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I_n) \end{aligned} \quad [4]$$

where ρ is the spatial autoregressive parameter and W is the $n \times n$ weighting matrix and β is a vector of estimated coefficients.

If the DGP exhibits spatial dependence in the errors, a spatial errors model (SEM) is used. The SEM is typically appropriate when measurement error is systemically related to location. The SEM is specified by:

$$\begin{aligned} y &= X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + u \\ u &\sim N(0, \sigma^2 I_n) \end{aligned} \quad [5]$$

where λ is a coefficient on the spatially correlated errors.

The general specification of the spatial model (SAC) incorporates both the spatial lagged dependent variable as well as a spatially correlated error structure, as shown by:

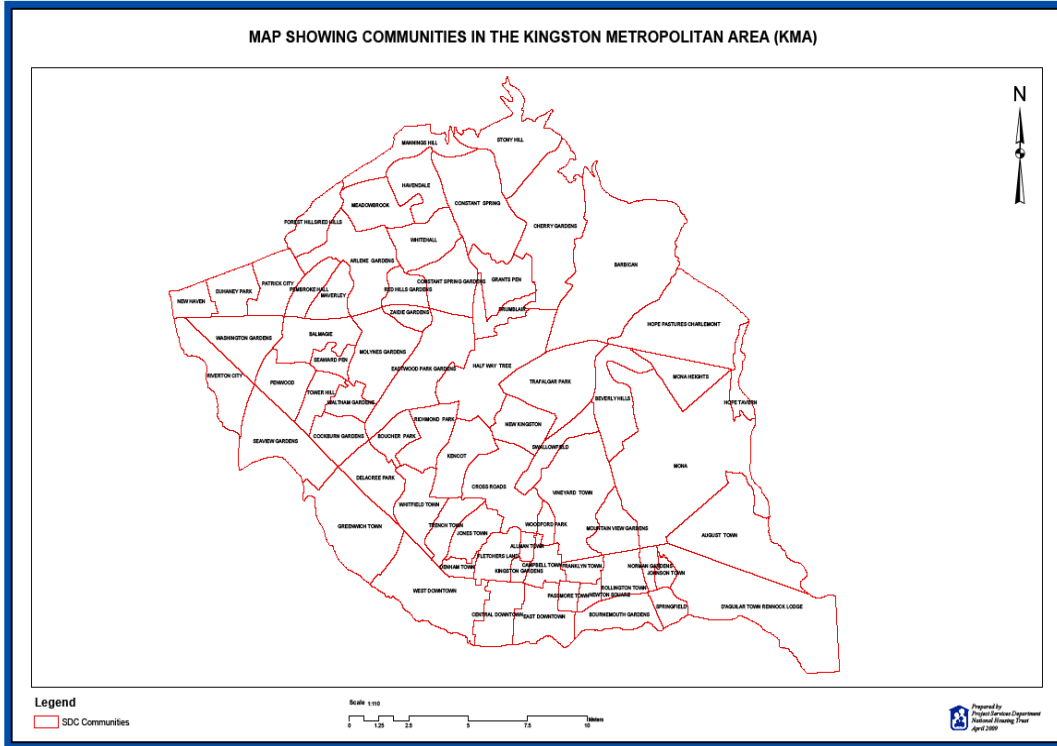
$$\begin{aligned} y &= \rho W_1 y + X\beta + \varepsilon \\ \varepsilon &= \lambda W_2 \varepsilon + u \\ u &\sim N(0, \sigma^2 I_n) \end{aligned} \quad [6]$$

where W_1 and W_2 are weighting matrices corresponding to the spatial lag process and the spatial error process, respectively. W_1 and W_2 are constructed differently to avoid identification problems when estimating equation [6].

The choice of covariance structure requires that an appropriate spatial weights matrix, W , is constructed. Weights may be based on contiguity or on distance. Based on information on the borders separating the 70 communities represented in the data set, a spatial contiguity weighting matrix is used. The weights matrix captures the similarities in characteristics between houses in a given community. Non-zero elements in the weights matrix correspond to two neighbouring communities separated by a border (see Chart 1). A non-zero element in row i , $w_{ij}=1$, defines community j as being adjacent to community i and $w_{ij}=0$, otherwise. The spatial weights matrix is then row-standardized so that the elements of each row sum to one to allow for ease of estimation.¹²

¹² The MATLAB code used for estimating the spatial models is obtained in the *Spatial Econometrics Toolbox* by James LeSage, available for download at <http://www.spatial-econometrics.com>.

Chart 1.



To determine whether spatial dependence must be accounted for when estimating the hedonic model, equation [1] is estimated in double-logs using OLS as well as the SAR, SEM and SAC procedures, excluding the location and time dummy variables (see Table 11). The spatial estimations indicate large and significant values for ρ and λ which imply strong spatial dependence in both the dependent variable and residual errors. However, there is only small improvement in the adjusted R^2 for the spatial regressions compared to the OLS regression. Additionally, the estimates of implicit prices for the spatial regressions are very similar to the OLS estimates.

The Moran's I -, Lagrange Multiplier (LM) and Likelihood Ratio (LR) tests are also computed to determine the presence of spatial dependence in the OLS errors (see Table 12).¹³ The results from these tests for spatial autocorrelation indicate that each reject the null hypothesis of no spatial correlation in the OLS errors at the 1.0 per cent level.

¹³ For the description of these procedures see Anselin (1988).

Table 11. Comparison of Regression Results for OLS and Spatial Models
(excluding time and location dummy variables).

Variables	OLS	SAR	SEM	SAC
Constant	4.0300 **	3.4089 **	4.3702 **	4.5589 **
SEMI-DETACHED	0.0155	0.0248	0.0145	0.0076
ATTACHED	-0.0072	-0.0123	-0.0204	-0.0244
TOWNHOUSE	0.1226 **	0.1060 **	0.0966 **	0.0665 **
2-FAMILY HOUSE	0.0248	0.0293	0.0375	0.0364
APARTMENT	0.2032 **	0.1598 **	0.1335 **	0.0899 **
STUDIO	0.1455 **	0.1154 **	0.0961 **	0.0372
TWO FLOORS	0.0355	0.0222	0.0128	0.0078
THREE FLOORS	-0.0025	-0.0181	-0.0222	-0.0030
FLOOR AREA	-0.4167 **	-0.4443 **	-0.4747 **	-0.5035 **
LOT SIZE	0.1570 **	0.1382 **	0.1132 **	0.0902 **
CONSTRUCTED 1960-1969	0.1373 **	0.1321 **	0.1247 **	0.1154 **
CONSTRUCTED 1970-1979	0.1549 **	0.1494 **	0.1386 **	0.1233 **
CONSTRUCTED 1980-1989	0.1929 **	0.1878 **	0.1640 **	0.1412 **
CONSTRUCTED 1990-1999	0.2419 **	0.2432 **	0.2235 **	0.1955 **
CONSTRUCTED 2000-2007	0.2619 **	0.2630 **	0.2428 **	0.2111 **
0 BEDROOMS	-0.0910	-0.0911	-0.0996	-0.0932
2 BEDROOMS	-0.0472 *	-0.0343 **	-0.0241	0.0027
3 BEDROOMS	-0.0870 **	-0.0718 **	-0.0461 *	-0.0008
4 BEDROOMS	-0.1664 **	-0.1416 **	-0.1037 **	-0.0410
5 & OVER BEDROOMS	-0.2522 **	-0.2212 **	-0.1739 **	-0.0951 **
0 BATHROOMS	0.0321	0.0395	0.0649	0.0800
2 BATHROOMS	0.1119 **	0.1043 **	0.0988 **	0.0823 **
3 BATHROOMS	0.1994 **	0.1835 **	0.1682 **	0.1314 **
4 & OVER BATHROOMS	0.2232 **	0.2091 **	0.1843 **	0.1358 **
1 CAR PORT	0.0162	0.0167	0.0164	0.0088
2 & OVER CAR PORTS	0.0369	0.0378	0.0355	0.0257
0 LAUNDRY AREAS	-0.0445 **	-0.0436 **	-0.0457 **	-0.0421 **
2 & OVER LAUNDRY AREAS	-0.0786	-0.0625	-0.0451	-0.0466
WATERTANK	0.0737	0.0718	0.0812	0.0843 *
rho (ρ)	-	0.2199 **	-	-0.7280 **
lambda (λ)	-	-	0.4850 **	0.9983 **
Number of Observations	1691	1691	1691	1691
R-squared	0.4457	0.4540	0.4775	0.5215
Adjusted R-squared	0.4360	0.4444	0.4684	0.5132
Log likelihood	-	1049	1067	2090

** - significant at the 1% level; * - significant at the 5% level.

Table 12. Comparison of Results of Spatial Dependence Tests
(excluding time and location dummy variables).

	Moran-I Test	LM Test	LR Test
Computed Value	0.0644	387.7355	96.2010
Statistic	22.3238	-	-
Marginal Probability	0.0000	0.0000	0.0000
Chi-squared (0.01) Value	-	17.6110	6.6350

The Student t -test statistic is used to compare the difference in estimated implicit prices between the OLS hedonic model and the spatial hedonic models. This test statistic is computed as the difference between the two slopes divided by the standard error of the difference between the slopes, denoted as:

$$t = \frac{\hat{\beta}_1 - \hat{\beta}_2}{s_{\hat{\beta}_1 - \hat{\beta}_2}} \sim t_{n-4} \text{ and } s_{\hat{\beta}_1 - \hat{\beta}_2} = \sqrt{s_{\hat{\beta}_1}^2 + s_{\hat{\beta}_2}^2}.$$

Table 13. Results of Student t -test for Difference in Implicit Price Estimates.

Variables	OLS vs. SAR	OLS vs. SEM	OLS vs. SAC
Constant	5.6163 **	-3.1044 **	-2.9714 **
SEMI-DETACHED	-0.2207	0.0255	0.1938
ATTACHED	0.0984	0.2567	0.3369
TOWNHOUSE	0.4585	0.7438	1.6047
2-FAMILY HOUSE	-0.0822	-0.2332	-0.2200
APARTMENT	1.2654	2.2498 **	3.4956 **
STUDIO	0.5680	0.9872	2.1152 **
TWO FLOORS	0.4751	0.8132	1.0079
THREE FLOORS	0.1705	0.2167	0.0069
FLOOR AREA	0.5010	1.1215	1.6147
LOT SIZE	0.5703	1.4389	2.1080 **
CONSTRUCTED 1960-1969	0.1607	0.3991	0.6821
CONSTRUCTED 1970-1979	0.1647	0.5054	0.9783
CONSTRUCTED 1980-1989	0.1436	0.8319	1.4856
CONSTRUCTED 1990-1999	-0.0338	0.5007	1.2632
CONSTRUCTED 2000-2007	-0.0285	0.5005	1.3460
0 BEDROOMS	0.0029	-1.5501	0.0207
2 BEDROOMS	-0.5500	-0.9899	-2.1993 **
3 BEDROOMS	-0.4518	-1.2365	-2.6612 **
4 BEDROOMS	-0.6325	-1.6174	-3.2777 **
5 & OVER BEDROOMS	-0.6806	-1.7416	-3.5368 **
0 BATHROOMS	-0.0904	-0.4045	-0.6032
2 BATHROOMS	0.3901	0.6689	1.5249
3 BATHROOMS	0.5278	1.0320	2.2696 **
4 & OVER BATHROOMS	0.2380	0.6913	1.5761
1 CAR PORT	-0.0286	-0.0214	0.4000
2 & OVER CAR PORTS	-0.0258	-0.0223	0.2022
0 LAUNDRY AREAS	-0.0660	0.0844	-0.1652
2 & OVER LAUNDRY AREAS	-0.2211	-0.4289	-0.4179
WATERTANK	0.0283	-0.1162	-0.1673

** - significant at the 1% level

The results of the t -test indicate that the statistical differences between implicit price estimates from the OLS regression and the SAR and SEM regressions are all insignificant, except for the ‘Apartment’ coefficient estimate in the SEM regression (see Table 13). Notwithstanding, the value of the ‘Apartment’ coefficient estimate is still very similar across all regressions and the results reveal the same relative ranking across the types of dwelling represented in each model. Although there are relatively more differences between implicit price estimates of the SAC regression and the other regressions, by and large, the differences are not economically significant. These results imply that using the OLS hedonic implicit prices are appropriate in the construction of the housing price index for KMA.

Base Period Estimation of the Reference Stock

To compute the characteristics’ or implicit prices of the reference stock in the base period, transactions and assessment data are used for the period 2003 to 2007. The OLS implicit prices of characteristics are calculated based on the following hedonic equation:

$$\ln(P_i) = \ln(P_0) + \sum_{t=1}^T \theta_t A_{t,i} + \sum_{q=1}^3 \kappa_q Q_{q,i} + \sum_{k=1}^K \alpha_k Z_{k,i} + \sum_{m=1}^M \beta_m \ln(X_{m,i}) + \varepsilon_i \quad [7]$$

The hedonic coefficients on the $K + M$ variables are imputed prices relative to reference characteristics. A reference dwelling, possessing specified reference characteristics, is determined. The characteristics of the reference dwelling correspond, for the most part, with the most frequent occurring characteristic in the base period data. These characteristics are: detached house, one floor, one bedroom, one bathroom, zero carports, one laundry room and zero water tanks, located in Kingston 20 and constructed between 1930 and 1959.

Current Value of Reference Dwelling

In order to compute the current value of the reference dwelling, transactions and assessment data for the current quarter are used to estimate the price of the reference dwelling, $P_{0,\tau}$. The price per square metres of dwelling j sold in quarter τ is:

$$\ln(P_{j,\tau}) = \ln(P_{0,\tau}) + \sum_{k=1}^K \alpha_{k,\tau} Z_{k,i,\tau} + \sum_{m=1}^M \beta_{m,\tau} \ln(X_{m,j,\tau}) + \varepsilon_{j,\tau} \quad [8]$$

Assuming the $\alpha_{k,\tau}$ and $\beta_{m,\tau}$ parameters are known and rearranging [8] allows for estimation of the ‘reference dwelling equivalent price’, denoted as $\tilde{P}_{j,\tau}$, using current transactions data:

$$\text{Ln}(\tilde{P}_{j,\tau}) = \text{Ln}(P_{j,\tau}) - \sum_{k=1}^K \alpha_{k,\tau} Z_{k,j,\tau} - \sum_{m=1}^M \beta_{m,\tau} \text{Ln}(X_{m,j,\tau}), \quad [9]$$

or:

$$\text{Ln}(\tilde{P}_{j,\tau}) = \text{Ln}(P_{0,\tau}) + \varepsilon_{j,\tau} \quad [10]$$

Then, an average ‘reference dwelling equivalent price’, denoted as $\hat{P}_{0,\tau}$, may be estimated using the J_τ transactions occurring during the current quarter:

$$\text{Ln}(\hat{P}_{0,\tau}) = \frac{1}{J_\tau} \sum_{j=1}^{J_\tau} \text{Ln}(\tilde{P}_{j,\tau}) \quad [11]$$

Following Gouriéroux and Laferrère (2006), the term $\sum_{t=1}^T \theta_t A_{t,i} + \sum_{q=1}^3 \kappa_q Q_{q,i}$ and the parameters $\alpha_{k,\tau}$ and $\beta_{m,\tau}$ are assumed to be time invariant for five years following their estimation. This time invariance assumption allows the replacement of $\alpha_{k,\tau}$ and $\beta_{m,\tau}$ with $\hat{\alpha}_k$ and $\hat{\beta}_m$. This conjecture will be checked periodically by testing for parameter stability. Hence, hedonic house prices can be computed quarterly using the simple formula:

$$\begin{aligned} \text{Ln}(\tilde{P}_{j,\tau}) &\approx \text{Ln}(P_{j,\tau}) - \sum_{k=1}^K \hat{\alpha}_k Z_{k,j,\tau} - \sum_{m=1}^M \hat{\beta}_m \text{Ln}(X_{m,j,\tau}) \\ &= \text{Log} \left[\frac{P_{j,\tau}}{\exp \left(\sum_{k=1}^K \hat{\alpha}_k Z_{k,j,\tau} - \sum_{m=1}^M \hat{\beta}_m \text{Ln}(X_{m,j,\tau}) \right)} \right]. \end{aligned} \quad [12]$$

Then, the log of the price per square foot of the reference dwelling is computed as:

$$\text{Ln}(\hat{P}_{0,\tau}) = \frac{1}{J_\tau} \sum_{j=1}^{J_\tau} \text{Ln}(\tilde{P}_{j,\tau}) = \frac{1}{J_\tau} \text{Ln} \left(\prod_{j=1}^{J_\tau} \tilde{P}_{j,\tau} \right), \quad [13]$$

or:

$$\text{Ln}(\hat{P}_{0,\tau}) = \frac{1}{J_\tau} \left(\prod_{j=1}^{J_\tau} \tilde{P}_{j,\tau} \right)^{\frac{1}{J_\tau}}. \quad [14]$$

Current Value of the Reference Stock

The current value of properties in the reference housing stock is calculated by adjusting the average “reference dwelling equivalent price” for differences in characteristics:

$$\hat{P}_{i,\tau}^* = \exp \left(\text{Ln}(\hat{P}_{0,\tau}) + \sum_{k=1}^K \hat{\alpha}_k Z_{k,i} + \sum_{m=1}^M \hat{\beta}_m \text{Ln}(X_{m,i}) \right) \Psi_i, \quad [15]$$

where Ψ_i denotes the floor area of dwelling i and characteristics vectors, $Z_{k,i}$ and $X_{m,i}$, are time invariant as determined in the reference stock.

The total value of the reference housing stock during time period τ is simply the sum of the N individual estimated property values:

$$\hat{W}_\tau = \sum_{i=1}^N \hat{P}_{i,\tau}^*. \quad [16]$$

Quarterly Computation of the Hedonic Housing Price Index for Each Region

The actual index for each region, r , measures the change in the value of the respective reference housing stock relative to its value estimated for the base period:

$$I_{t,r} = \frac{\hat{W}_{r,\tau}}{W_{r,0}} = \frac{\sum_{i=1}^N \exp \left(\text{Ln}(\hat{P}_{0,r,\tau}) + \sum_{k=1}^K \hat{\alpha}_{k,r} Z_{k,i,r} + \sum_{m=1}^M \hat{\beta}_{m,r} \text{Ln}(X_{m,i,r}) \right) \Psi_{i,r}}{\sum_{i=1}^N \exp \left(\text{Ln}(\hat{P}_{0,r,0}) + \sum_{k=1}^K \hat{\alpha}_{k,r} Z_{k,i,r} + \sum_{m=1}^M \hat{\beta}_{m,r} \text{Ln}(X_{m,i,r}) \right) \Psi_{i,r}}. \quad [17]$$

Hence, the index for each region is computed as the change in the geometric mean value of prices for each period, τ , relative to geometric mean value of prices for the base period, 0. In order to be comparable, the two mean values must refer to the same quality level. This is attained by imputing prices for the missing houses. The imputed prices indicate the prices the average consumer would have paid in the current period, for a house with characteristics of the reference stock. The geometric means of the two periods are then compared in order to derive the quality adjusted price change.

Quarterly Computation of the Aggregate Hedonic Housing Price Index

The computation of the aggregate hedonic price index for quarter τ is computed in three simple steps:

- 1) First, compute the geometric mean of the ‘reference dwelling equivalent prices’ for each region:

$$\text{Ln}(\hat{P}_{0,r,\tau}) = \frac{1}{J_\tau} \sum_{j=1}^{J_\tau} \text{Ln}(P_{j,r,\tau}) - \sum_{k=1}^K \hat{\alpha}_{k,r} \bar{Z}_{k,i,r,\tau} - \sum_{m=1}^M \hat{\beta}_{m,r} \text{Ln}(\bar{X}_{m,r,\tau}) \quad [18]$$

where $\bar{Z}_{k,i,r,\tau}$ and $\bar{X}_{m,j,r,\tau}$ represent the means of the respective variables for the J_τ transactions of the current period τ .¹⁴

- 2) Then, compute the price sub-index for each region:

$$I_{t,r} = \exp(\text{Ln}(\hat{P}_{0,r,\tau}) - \text{Ln}(\hat{P}_{0,r})) \times 100. \quad [19]$$

- 3) Finally, compute the aggregate price index as a weighted average of the regional sub-indices, where the weights are the value of the reference stock at the base period for each of the R regions:

$$I_t = \frac{\hat{W}_t}{\hat{W}_0} = \sum_{r=1}^R \left(\frac{\hat{W}_r}{\sum_{r=1}^R \hat{W}_{r,0}} \right) \times I_{t,r}. \quad [20]$$

5. Discussion of Hedonic Regression Results

The hedonic regression results for double-log model using HCC-robust standard errors indicate reasonably strong out-of-sample goodness-of-fit values. The adjusted-R² of the model is 0.63. The joint F-statistic is 52.75 with a p -value of 0.000. The individual p -values indicate that most coefficients (approximately 3/4) are significant at the 10.0 per cent level (see Table 10).

¹⁴ The computation of the implicit price of each dwelling of the reference stock is not required to compute the index at date t .

All of the annual time-dummy variables have positive and monotonically increasing values showing constant 'price per square metres' appreciation for each successive year following the reference year, 2003. Similarly, in terms of construction year-dummy variables, prices are progressively higher for each of the five decades following 1959. The quarterly dummy variables indicate that prices are, on average, highest during the December quarter and lowest during the March quarter. The 'type of dwelling' coefficient signs and values indicate that the prices of apartments and town houses are higher compared to the reference, 'detached houses'. In contrast, 'price per square metres' of other types of dwellings are not statistically discernable from detached house prices.

The regression results also show that the existence of two floors would have a positive influence on price relative to single-floor dwellings. However, additional floors (i.e., 3 or more) does not change the price per square metres of the dwelling relative to the reference category, one floor. Furthermore, consistent with expectations, a larger lot size results in a higher price. Greater floor area, on the other hand, decreases the price per square metres. Consistent with this result, additional bedrooms over three bedrooms (i.e., four bedrooms and five & over bedrooms) result in a decline in price per square metres. Contrary to the effect of increasing the number of bedrooms, additional bathrooms over one bathroom increases the price per square metres.

Furthermore, two & over car ports increase the price compared to the reference zero car ports. In addition, zero laundry areas decrease the price and two & over laundry areas increase the price, relative to the reference category, 'one laundry area'. The existence of a water tank also has a positive influence on price.

Most of the location dummy variables are statistically significant. As anticipated, the price per square metres in the more affluent Kingston 6 and Kingston 8 postal codes are higher relative to the base location category, Kingston 20. The signs on the other location dummy variables are also reasonable.

Quarterly index values for Kingston & St. Andrew are computed using the parameters of the double-log functional form and equation [15] over the quarters 2003:2 – 2008:3 (see Figure 2).¹⁵ The index reflects a trend increase over the period, with an overall increase of approximately 44.0 per cent. The most significant calendar year increase of 15.5 per cent occurred during 2007. Between end-2007 and 15 August 2008, the index declined by 18.15 per cent.

6. Concluding Remarks

The hedonic price imputation regression method was used in this paper to construct a quality-adjusted residential real estate index for KMA. The main advantage of this hedonic approach is that the marginal contribution of each house characteristic remains constant over time and is thus, immune from the problem of sample selection bias. This price imputation approach to price index construction also has an important efficiency advantage in that econometric estimation is required for the base (estimation) period only.

A rich database including characteristics and price data was obtained from the NHT covering the quarters 2003:2 to 2008:3. Various hedonic specifications were applied in order to select the most appropriate functional form. The double-log model was chosen as the preferred specification based on primarily on coefficient values and signs as well as goodness-of-fit criteria.

Obviously, biased or inefficient hedonic coefficient estimates could result in major errors concerning policy decisions. This paper contributes to the literature of spatial dependence by comparing estimated implicit prices from spatial models and the OLS model when location and neighbourhood effects are not controlled in the hedonic model. Excluding location and neighbourhood variables before comparison between models allows for more robust testing. The regression results from the OLS model and the spatial models indicate that taking the spatial dimension of house price data into account in the computation of the hedonic price index for KMA is not economically important.

¹⁵ This series includes in-sample data between 2003:2 and 2007:4 as well as out-of-sample data, available up to 15/08/2008.

REFERENCES

- Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Dordrecht: Kluwer.
- Anselin, L. and A. Bera (1998). Spatial Dependence in Linear Regression Models. In *Handbook of Applied Economic Statistics*, eds., A. Ullah and D.E.A. Giles, pp. 237-289. New York: Marcel Dekker, Inc.
- Anselin, L. (2005). Exploring Spatial Data with GeoDa: A Workbook. Available at <http://www.geoda.uiuc.edu/pdf/geodaworkbook.pdf>.
- Abraham, J.M., and W.S. Schauman (1991). New Evidence on House Prices from Freddie Mac Repeat Sales. *American Real Estate and Urban Economics Association Journal*, 19, 333-352.
- Bailey, M. J., Muth, R. F., Nourse, H. O. (1963). A Regression Method for Real Estate Price Index Construction. *Journal of the American Statistical Association*, 58, 933-942.
- Blomquist, G.C., M.C. Berger, J.P. Hoehn (1998). New Estimates of Quality of Life in Urban Areas. *American Economic Review*, 78, 89-107.
- Borio, C., and P. Lowe (2002). Assessing the Risk of Banking Crisis. *BIS Quarterly Review*, 43-54.
- Box, G.P. and D.R. Cox (1964). An Analysis of Transformations. *Journal of the Royal Statistical Society*, 26(2), 211-52.
- Calhoun, C.A. (1996). OFHEO House Price Indexes: HPI Technical Description. OFHEO Working Paper.
- Case, B., Clapp, R., Dubin & M., Rodriguez (2004). Modelling Spatial and Temporal House Price Patterns: A Comparison of Four Models. *Journal of Real Estate Finance and Economics*, 29, 167-191.
- Case, B., and J.M. Quigley (1991). The Dynamics of Real Estate Prices. *The Review of Economics and Statistics*, 73, 50-58.
- Case, B., H.O. Pollakowski, and S.M. Wachter (1991). On Choosing among House Price Index Methodologies. *American Real Estate and Urban Economics Association Journal*, 19, 286- 307.
- Case, K.E., and R.J. Schiller (1987). Prices of Single Family Homes Since 1970: New Indexes for Four Cities. *New England Economic Review*, September-October, 45-56.
- Case, K.E., and R.J. Schiller (1989). The Efficiency of the Market for Single Family Homes. *American Economic Review*. 79, 125-137.
- Cheshire, P. and S. Sheppard (1995). On the Price of Land and the Value of Amenity. *Econometrica*, 62, 247-67.

- Cho, M. (1996). House Price Dynamics: a Survey of Theoretical and Empirical Issues. *Journal of Housing Research*, 7, 145–172.
- Clapp, J.M., C. Giaccotto, and D. Tirtiroglu (1991). Housing Price Indices Based on All Transactions Compared to Repeat Subsamples. *American Real Estate and Urban Economics Association Journal*, 19, 270-285.
- Colwell, P.F (1990). Power Lines and Land Values. *Journal of Real Estate Research*, 5, 117-127.
- Crone, T.M., and R.P. Voith (1992). Estimating House Price Appreciation: A Comparison of Methods. *Journal of Housing Economics*, 2, 324-338.
- Davis, E. P. and H. Zhu (2004). Bank Lending and Commercial Property Cycles: Some Cross-Country Evidence. *BIS Working Paper No. 150*.
- Diewert, W.E. (1976). Exact and Superlative Index Numbers. *Journal of Econometrics*, 4, 115-145.
- Dreiman, M.H. and A. Pennington-Cross (2004). Alternative Methods of Increasing the Precision of Weighted Repeated Sales House Price Indices. *Journal of Real Estate Finance and Economics*, 28, 299-317.
- Englund, P. (1998). Improved Price Indexes for Real Estate: Measuring the Course of Swedish Housing Prices. *Journal of Urban Economics*, 44, 171-196.
- Englund, P., J. M. Quigley and C. L. Redfean (1998). Improved Price Indexes for Real Estate: Measuring the Course of Swedish Housing Prices. *Journal of Urban Economics*, 44, 171-196.
- Gatzlaff, D. H., Haurin, D. R. (1997). Sample Selection Bias and Repeat Sales Index Estimates. *Journal of Real Estate Finance and Economics*, 14, 33-49.
- Gatzlaff, D.H., and D.C. Ling (1994). Measuring Changes in Local House Prices: An Empirical Investigation of Alternative Methodologies. *Journal of Urban Economics*, 40, 221-244.
- Goetzmann W.N. (1992). The Accuracy of Real Estate Indices: Repeat Sales Estimators. *The Journal of Real Estate Finance and Economics*, 5, 5-53.
- Gouriéroux, C. and A. Laferrère (2006). Managing Hedonic Housing Price Indexes: The French Experience. Paper presented at the OECD-IMF Workshop on Real Estate Price Indexes, Paris, November 6-7.
- Greene, William (1993). *Econometric Analysis*. A Simon & Schuster Company.
- Helbling, T. (2005). Housing Price Bubbles - a Tale Based on Housing Price Booms and Busts., *BIS Working Paper No.21*.
- Helbling, T. and M. Terrones (2003). Real and Financial Effects of Bursting Asset Price Bubbles. *IMF World Economic Outlook*, Chapter II, April.

- Hill, R. C., J. R. Knight, and C. F. Sirmans (1997). Estimating Capital Asset Prices. *Review of Econometrics and Statistics*, 79, 226-233.
- Hofmann, B. (2001). The Determinants of Private Sector Credit in Industrialised Countries: Do Property Prices Matter? *BIS Working Paper* No. 108.
- Ismail, S., A. Iman, N. Kamaruddin, H. Ali, I. Sipan and R. Naveneethan (2008). Spatial Autocorrelation in Hedonic Models: Empirical Evidence for Malaysia. Working Paper, Universiti Teknologi Malaysia, Department of Property Management, Faculty of Geoinformation Sciences and Engineering.
- Jansen S., P. De Vries, H. Coolen, C. Lamain and P. Boelhouwer (2006). Developing a House Price Index for the Netherlands: a Practical Application of Weighted Repeat Sales. Working Paper, ENHR Congress.
- Janssen, C. and J. Soderberg (2001). Robust Estimation of Hedonic Models of Price and Income for Investment Property. *Journal of Property Investment & Finance*, 19, 342-360.
- Kim, C., T. Phipps and L. Anselin (2003). Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Analysis. *Journal of Environment, Economics and Management*, 45, 24-39.
- Kindleberger, Charles P. (2000). *Manias, Panics, and Crashes: A History of Financial Crises*. New York: Wiley.
- Knight, J.R., J. Dombrow, and C.F. Sirmans (1995). A Varying Parameters Approach to Constructing House Price Indexes. *Real Estate Economics*, 23, 187-205.
- Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, 74, 132-157.
- Li, W., M. Prud'Homme and K. Yu (2006). Studies in Hedonic Resale Housing Price Indexes. Paper presented at the OECD-IMF Workshop on Real Estate Price Indexes, Paris, November 6-7.
- Mark, J. H., Goldberg, M. A. (1984). Alternative Housing Price Indices: An Evaluation. *AREUEA Journal*, 12, 31-49.
- Maurer, R., M. Pitzer and S. Sebastian (2004). Construction of a Transaction-Based Real Estate Index for the Paris Housing Market. Working Paper Series: Finance and Accounting 68, Department of Finance, Goethe University Frankfurt am Main.
- Meese, R. and N. Wallace (1997). The Construction of Residential Housing Price Indices: A Comparison of Repeat-Sales, Hedonic-Regression and Hybrid Approaches. *Journal of Real Estate Finance and Economics*, 14, 51-73.
- Mueller, J. and J. Loomis (2008). Spatial Dependence in Hedonic Property Models: Do Different Corrections for Spatial Dependence Result in Economically Significant Differences in Estimated Implicit Prices? *Journal of Agricultural and Resource Economics*, 33, 212-231.

- Palmquist, R.B. (1980). Alternative Techniques for Developing Real Estate Price Indexes. *Review of Economics and Statistics*, 62, 442-448.
- Parkhomenko, A., R. Anastasia and O. Maslivets (2007). Econometric Estimates of Hedonic Price Indexes for Personal Computers in Russia. Working Paper, Higher School of Economics.
- Pollakowsky, H. (1995). Data Sources for Measuring House Price Change. *Journal of Housing Research*, 6, 377 – 387.
- Quigley, J. M. (1995). A Simple Hybrid Model for Estimating Real Estate Price Indices. *Journal of Housing Econometrics*, 4, 1-12.
- Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, 82, 34-55.
- Shiller, R. J. (1991). Arithmetic Repeat Sales Price Estimators. *Journal of Housing Economics*, 1, 110-126.
- Shiller, R. J. (1993). Measuring Asset Values for Cash Settlement in Derivative Markets: Hedonic Repeated Measures Indices and Perpetual Futures. *Journal of Finance*, 43, 911-931.
- Sivitanidou, R. (1996). Do Office-Commercial Firms Value Access to Service Employment Centers? A Hedonic Value Analysis within Polycentric Los Angeles. *Journal of Urban Economics*, 40, 125-149.
- Steele, M., and R. Goy (1997). Short Holds, the Distributions of First and Second Sales, and Bias in the Repeat-Sales Price Index. *Journal of Real Estate Finance and Economics*, 14, 133-154.
- Triplett, J. (2004). *Handbook on Hedonic Indexes and Quality Adjustments in Price Indexes*. OECD Publishing.
- Wang, L. and R. Ready (2005). Spatial Econometric Approaches to Estimating Hedonic Property Value Models. Working Paper, The Pennsylvania State University, Department of Agricultural Economics and Rural Sociology.
- Wang, F.T. and P. M. Zorn (1997). Estimating House Price Growth with Repeat Sales Data: What's the Aim of the Game? *Journal of Housing Economics*, 6, 93-118.
- Wen, H., S. Jia and X. Guo (2005). Hedonic Price Analysis of Urban Housing: An Empirical Research of Hangzhou, China. *Journal of Zhejiang University SCIENCE*, 6, 907-914.
- White, H. (1980). Heteroskedasticity-Consistent Covariance Matrix and a Direct Test for Heteroskedasticity. *Econometrica*, 48, 817-838.
- Wigren, R. (1987). House Prices in Sweden: The Significance of Attributes. *Scandinavian Housing and Planning Research*, 4, 243–261.

Table 1. Description of Variables

Variable	Description	Proportion
PRICE	Sale price of unit per square foot	-
LNFLLOORAREA	Surface area of unit in square feet	-
LNLOTSIZE	Surface area of lot in square feet	-
DETACHED	= 1, if unit is detached; = 0, otherwise	46%
SEMIDETACHED	= 1, if unit is semi-detached; = 0, otherwise	3%
ATTACHED	= 1, if unit is attached; = 0, otherwise	2%
TOWNHOUSE	= 1, if unit is a townhouse; = 0, otherwise	13%
2FAMHOUSE	= 1, if unit is a two family house; = 0, otherwise	1%
APARTMENT	= 1, if unit is an apartment; = 0, otherwise	30%
STUDIO	= 1, if unit is a studio; = 0, otherwise	3%
1FLOOR	= 1, if unit has one floor; = 0, otherwise	79%
2FLOORS	= 1, if unit has two floors; = 0, otherwise	20%
3OVERFLOORS	= 1, if unit has three or more floors; = 0, otherwise	1%
CONSTR<60	= 1, if unit was constructed prior to 1960; = 0, otherwise	5%
CONSTR60	= 1, if unit was constructed between 1960 & 1969; = 0, otherwise	23%
CONSTR70	= 1, if unit was constructed between 1970 & 1979; = 0, otherwise	28%
CONSTR80	= 1, if unit was constructed between 1980 & 1989; = 0, otherwise	18%
CONSTR90	= 1, if unit was constructed between 1990 & 1999; = 0, otherwise	15%
CONSTR00	= 1, if unit was constructed between 2000 & 2007; = 0, otherwise	11%
0BED	= 1, if unit has no bedroom; = 0, otherwise	0.3%
1BED	= 1, if unit has one bedroom; = 0, otherwise	20%
2BED	= 1, if unit has two bedrooms; = 0, otherwise	32%
3BED	= 1, if unit has three bedrooms; = 0, otherwise	24%
4BED	= 1, if unit has four bedrooms; = 0, otherwise	15%
5OVERBED	= 1, if unit has 5 or more bedrooms; = 0, otherwise	8%
0BATH	= 1, if unit has no bathroom; = 0, otherwise	1%
1BATH	= 1, if unit has one bathrooms; = 0, otherwise	54%
2BATH	= 1, if unit has two bathrooms; = 0, otherwise	34%
3BATH	= 1, if unit has three bathrooms; = 0, otherwise	10%
4OVERBATH	= 1, if unit has four or more bathrooms; = 0, otherwise	2%
0CARPORT	= 1, if unit has no carport; = 0, otherwise	67%
1CARPORT	= 1, if unit has one carport; = 0, otherwise	32%
2OVERCARPORT	= 1, if unit has two carports; = 0, otherwise	2%
0LAUND	= 1, if unit has no laundry room; = 0, otherwise	39%
1LAUND	= 1, if unit has one laundry room; = 0, otherwise	60%
2OVERLAUND	= 1, if unit has two or more laundry areas; = 0, otherwise	1%
WATERTANK	= 1, if unit has a water tank; = 0, otherwise	1%
LOC0_K20	= 1, if unit is located in Kingston 20 ; = 0, otherwise	22%
LOC1_BB	= 1, if unit is located in Bull Bay P O ; = 0, otherwise	1%
LOC2_GS	= 1, if unit is located in Golden Spring P O ; = 0, otherwise	1%
LOC3_K10	= 1, if unit is located in Kingston 10 ; = 0, otherwise	12%
LOC4_K11	= 1, if unit is located in Kingston 11 ; = 0, otherwise	6%
LOC5_K13	= 1, if unit is located in Kingston 13 ; = 0, otherwise	1%
LOC6_K16	= 1, if unit is located in Kingston 16 ; = 0, otherwise	1%
LOC7_K17	= 1, if unit is located in Kingston 17 ; = 0, otherwise	4%
LOC8_K19	= 1, if unit is located in Kingston 19 ; = 0, otherwise	6%
LOC9_K2	= 1, if unit is located in Kingston 2 ; = 0, otherwise	7%
LOC11_K3	= 1, if unit is located in Kingston 3 ; = 0, otherwise	6%
LOC12_K4	= 1, if unit is located in Kingston 4 ; = 0, otherwise	1%
LOC13_K5	= 1, if unit is located in Kingston 5 ; = 0, otherwise	5%
LOC14_K6	= 1, if unit is located in Kingston 6 ; = 0, otherwise	9%
LOC15_K7	= 1, if unit is located in Kingston 7 ; = 0, otherwise	1%
LOC16_K8	= 1, if unit is located in Kingston 8 ; = 0, otherwise	14%
LOC17_K9	= 1, if unit is located in Kingston 9 ; = 0, otherwise	1%
LOC18_CSO	= 1, if unit is located in Kingston C S O ; = 0, otherwise	1%
LOC19_RH	= 1, if unit is located in Red Hills P O ; = 0, otherwise	1%
LOC20_SH	= 1, if unit is located in Stony Hill P O ; = 0, otherwise	0.4%

Table 2a. Summary Statistics for Initial Data Set = 2 271 Obs.

Variable	Mean	Standard Deviation	Minimum	Maximum
PRICE	4,209.77	3,642.63	106.28	74,525.75
FLOORAREA	1,174.35	784.42	55.74	9,798.31
LOTSIZE	5,441.97	29,845.21	72.29	989,862.34
NO. OF FLOORS	1.24	0.45	1.00	4.00
NO. OF BEDROOMS	2.73	1.48	0.00	16.00
NO. OF BATHROOMS	1.63	0.81	0.00	8.00
NO. OF CARPORTS	0.34	0.54	0.00	9.00
NO. OF LAUNDRY ROOMS	0.61	0.51	0.00	3.00

Table 2b. Summary Statistics for Final Data Set = 1 691 Obs.

Variable	Mean	Standard Deviation	Minimum	Maximum
PRICE	4,016.08	2,686.45	106.28	46,953.05
FLOORAREA	1,152.53	794.79	100.10	9,798.31
LOTSIZE	3,450.01	5,612.14	205.00	88,190.00
NO. OF FLOORS	1.21	0.42	1.00	3.00
NO. OF BEDROOMS	2.63	1.35	0.00	15.00
NO. OF BATHROOMS	1.59	0.78	0.00	6.00
NO. OF CARPORTS	0.35	0.52	0.00	3.00
NO. OF LAUNDRY ROOMS	0.62	0.50	0.00	3.00

Table 3. Communities of Kingston & St. Andrew¹⁶

Postal Code	Communities Represented in Data Set
Kingston 2	<i>Rollington Town</i> , Franklyn Town, Doncaster, Norman Gardens, Springfield, Manley Meadows, <i>Mountain View</i> and <i>Vineyard Town</i> .
Kingston 3	Hampden Park, Rollington Town, Deanery Road, <i>Mountain View</i> , <i>Vineyard Town</i> and Nannyville Gardens.
Kingston 4	Allman Town, Arnold Road, Woodford Park and Kingston Gardens.
Kingston 5	New Kingston, Trench Town, South Camp Road, <i>Trafalgar Park</i> , Lady Musgrave, Swallowfield, Kensington and Maxfield Avenue.
Kingston 6	Acadia, Barbican, Beverly Hills, Liguanea, Sandhurst, Long Mountain, Hope Pastures, Mona and Papine.
Kingston 7	Elleston Flats, Hermitage, Gordon Town and August Town.
Kingston 8	Dunrobin, Whitehall, Olivier Mews, Merrivale, <i>Constant Spring</i> , Grants Pen, Norbrook, Drumblair and Oaklands.
Kingston 9	Havendale, Old Stony Hill and Rockview.
Kingston 10	Dunrobin, Eastwood Park, Hagley Park, Molyne Road, Waterloo, <i>Trafalgar Park</i> , Half Way Tree, Hope Road and <i>Constant Spring</i> .
Kingston 11	Waterhouse, Olympic Gardens, Waltham Park, Hagley Park, Delacree, Kencot, Seaward Gardens, Cockburn Gardens and Tower Hill.
Kingston 13	Spanish Town Road, Delacree Park, Maxfield Gardens, Whitfield Town, Tivoli Gardens and Swimmers Pen
Kingston 16	Franklyn Town, Rae Town and Browns Town.
Kingston 17	Harbour View and <i>Bull Bay</i> .
Kingston 19	Havendale, Hughenden, <i>Queensbury</i> , Meadowbrook, <i>Calabar Mews</i> , Forrest Hills and Red Hills.
Kingston 20	Duhaney Park, Pembroke Hall, Cooreville Gardens, Seaward Gardens, Zaidie Gardens, Glendale, <i>Calabar Mews</i> , Washington Boulevard, Patrick City and <i>Queensbury</i> .
Kingston CSO	Down Town Kingston, Campbell Town and Beverly Gardens.
Red Hills PO	Belvedere, Plantation Heights and Rock Hall.
Stony Hill PO	Boone Hall, Fort George Estate and <i>Constant Spring</i> .
Golden Spring PO	Golden Spring, Golden Meadows and Boone Hall.
Bull Bay PO	<i>Bull Bay</i> , Copacabana, Camrose and Winsor Lodge.

¹⁶ Communities in italics are listed under two or more postal codes.

Table 5. Regression Results for Double Log Model

Variables	Coefficient	Standard error	P-value
Constant	10.407	0.209	0.000
YEAR 2003	<i>Reference</i>		
YEAR 2004	0.097	0.029	0.001
YEAR 2005	0.146	0.032	0.000
YEAR 2006	0.299	0.030	0.000
YEAR 2007	0.534	0.029	0.000
QUARTER 1	-0.135	0.027	0.000
QUARTER 2	-0.094	0.025	0.000
QUARTER 3	-0.080	0.024	0.001
QUARTER 4	<i>Reference</i>		
DETACHED	<i>Reference</i>		
SEMI-DETACHED	0.023	0.058	0.688
ATTACHED	-0.087	0.072	0.227
TOWNHOUSE	0.107	0.050	0.032
2-FAMILY HOUSE	0.098	0.075	0.191
APARTMENT	0.174	0.049	0.000
STUDIO	0.129	0.074	0.082
ONE FLOOR	<i>Reference</i>		
TWO FLOORS	0.074	0.038	0.052
THREE FLOORS	0.121	0.126	0.335
FLOOR AREA	-0.514	0.033	0.000
LOT SIZE	0.103	0.020	0.000
CONSTRUCTED <1960	<i>Reference</i>		
CONSTRUCTED 1960-1969	0.074	0.037	0.044
CONSTRUCTED 1970-1979	0.138	0.034	0.000
CONSTRUCTED 1980-1989	0.183	0.040	0.000
CONSTRUCTED 1990-1999	0.336	0.042	0.000
CONSTRUCTED 2000-2007	0.435	0.045	0.000
0 BEDROOMS	-0.354	0.167	0.034
1 BEDROOM	<i>Reference</i>		
2 BEDROOMS	0.000	0.033	0.995
3 BEDROOMS	-0.055	0.046	0.231
4 BEDROOMS	-0.192	0.054	0.000
5 & OVER BEDROOMS	-0.323	0.063	0.000
0 BATHROOMS	0.135	0.112	0.229
1 BATHROOM	<i>Reference</i>		
2 BATHROOMS	0.216	0.027	0.000
3 BATHROOMS	0.353	0.042	0.000
4 & OVER BATHROOMS	0.430	0.078	0.000
0 CAR PORTS	<i>Reference</i>		
1 CAR PORT	0.008	0.026	0.756
2 & OVER CAR PORTS	0.135	0.074	0.070
0 LAUNDRY AREAS	-0.059	0.020	0.003
1 LAUNDRY AREA	<i>Reference</i>		
2 & OVER LAUNDRY AREAS	0.021	0.107	0.845
WATERTANK	0.158	0.088	0.073
LOC1_Bull Bay	-0.234	0.085	0.006
LOC2_Golden Spring	-0.193	0.115	0.095
LOC3_Kingston10	0.192	0.033	0.000
LOC4_Kingston 11	-0.541	0.041	0.000
LOC5_Kingston 13	-0.477	0.077	0.000
LOC6_Kingston 16	-0.591	0.079	0.000
LOC7_Kingston 17	0.050	0.051	0.323
LOC8_Kingston 19	0.170	0.042	0.000
LOC9_Kingston 2	-0.263	0.041	0.000
LOC11_Kingston 3	-0.175	0.042	0.000
LOC12_Kingston 4	-0.377	0.112	0.001
LOC13_Kingston 5	0.053	0.046	0.251
LOC14_Kingston 6	0.298	0.038	0.000
LOC15_Kingston 7	-0.203	0.087	0.020
LOC16_Kingston 8	0.252	0.034	0.000
LOC17_Kingston 9	0.090	0.098	0.357
LOC18_Central Sorting Off.	-0.127	0.102	0.212
LOC19_Red Hills	0.146	0.109	0.182
LOC20_Stony Hill	0.156	0.138	0.258
LOC21_Kingston 20	<i>Reference</i>		
Number of Observations	1691		
Adjusted R-squared	0.627427		
Log likelihood	-612.8017		

Table 6. Regression Results for Left-Side Semi-Log Model

Variables	Coefficient	Std. Error	Prob.
Constant	8.073	0.062	0.000
YEAR 2003	Reference		
YEAR 2004	0.109	0.030	0.000
YEAR 2005	0.152	0.033	0.000
YEAR 2006	0.305	0.031	0.000
YEAR 2007	0.537	0.030	0.000
QUARTER 1	-0.151	0.027	0.000
QUARTER 2	-0.103	0.025	0.000
QUARTER 3	-0.084	0.025	0.001
QUARTER 4	Reference		
DETACHED	Reference		
SEMI-DETACHED	-0.003	0.058	0.962
ATTACHED	-0.120	0.072	0.097
TOWNHOUSE	0.046	0.050	0.353
2-FAMILY HOUSE	0.106	0.077	0.171
APARTMENT	0.075	0.041	0.067
STUDIO	0.100	0.068	0.145
ONE FLOOR	Reference		
TWO FLOORS	0.029	0.039	0.451
THREE FLOORS	0.037	0.130	0.776
FLOOR AREA	0.000	0.000	0.000
LOT SIZE	0.000	0.000	0.005
CONSTRUCTED <1960	Reference		
CONSTRUCTED 1960-1969	0.100	0.038	0.009
CONSTRUCTED 1970-1979	0.139	0.036	0.000
CONSTRUCTED 1980-1989	0.202	0.041	0.000
CONSTRUCTED 1990-1999	0.355	0.044	0.000
CONSTRUCTED 2000-2007	0.450	0.046	0.000
0 BEDROOMS	-0.383	0.173	0.027
1 BEDROOM	Reference		
2 BEDROOMS	-0.096	0.032	0.003
3 BEDROOMS	-0.217	0.045	0.000
4 BEDROOMS	-0.386	0.052	0.000
5 & OVER BEDROOMS	-0.515	0.062	0.000
0 BATHROOMS	0.203	0.116	0.080
1 BATHROOM	Reference		
2 BATHROOMS	0.161	0.028	0.000
3 BATHROOMS	0.316	0.043	0.000
4 & OVER BATHROOMS	0.451	0.081	0.000
0 CAR PORTS	Reference		
1 CAR PORT	-0.019	0.027	0.470
2 & OVER CAR PORTS	0.165	0.079	0.038
0 LAUNDRY AREAS	-0.051	0.021	0.014
1 LAUNDRY AREA	Reference		
2 & OVER LAUNDRY AREAS	0.008	0.111	0.944
WATERTANK	0.174	0.091	0.056
LOC1_Bull Bay	-0.231	0.087	0.008
LOC2_Golden Spring	-0.208	0.120	0.083
LOC3_Kingston10	0.176	0.034	0.000
LOC4_Kingston 11	-0.540	0.042	0.000
LOC5_Kingston 13	-0.475	0.079	0.000
LOC6_Kingston 16	-0.619	0.081	0.000
LOC7_Kingston 17	0.053	0.052	0.311
LOC8_Kingston 19	0.150	0.043	0.001
LOC9_Kingston 2	-0.222	0.043	0.000
LOC11_Kingston 3	-0.188	0.043	0.000
LOC12_Kingston 4	-0.428	0.116	0.000
LOC13_Kingston 5	0.068	0.047	0.150
LOC14_Kingston 6	0.281	0.039	0.000
LOC15_Kingston 7	-0.166	0.090	0.066
LOC16_Kingston 8	0.237	0.035	0.000
LOC17_Kingston 9	0.106	0.101	0.295
LOC18_Central Sorting Off.	-0.120	0.105	0.256
LOC19_Red Hills	0.152	0.112	0.174
LOC20_Stony Hill	0.156	0.142	0.273
LOC21_Kingston 20	Reference		
Number of Observations	1691		
Adjusted R-squared	0.601653		
Log likelihood	-669.3584		

Table 7. Regression Results for Right-Side Semi-Log Model

Variables	Coefficient	Std. Error	Prob.
Constant	17435.040	1144.673	0.000
YEAR 2003		Reference	
YEAR 2004	466.636	157.703	0.003
YEAR 2005	604.585	176.793	0.001
YEAR 2006	1255.719	165.703	0.000
YEAR 2007	2367.595	156.811	0.000
QUARTER 1	-577.830	145.472	0.000
QUARTER 2	-417.647	134.191	0.002
QUARTER 3	-228.245	132.834	0.086
QUARTER 4		Reference	
DETACHED		Reference	
SEMI-DETACHED	-311.638	316.630	0.325
ATTACHED	-444.709	393.064	0.258
TOWNHOUSE	370.340	273.907	0.177
2-FAMILY HOUSE	725.364	408.937	0.076
APARTMENT	663.973	268.058	0.013
STUDIO	519.239	405.615	0.201
ONE FLOOR		Reference	
TWO FLOORS	574.709	208.887	0.006
THREE FLOORS	340.063	689.168	0.622
FLOOR AREA	-3035.676	179.469	0.000
LOT SIZE	623.730	110.745	0.000
CONSTRUCTED <1960		Reference	
CONSTRUCTED 1960-1969	25.820	202.004	0.898
CONSTRUCTED 1970-1979	296.427	188.933	0.117
CONSTRUCTED 1980-1989	502.545	217.529	0.021
CONSTRUCTED 1990-1999	1452.557	231.371	0.000
CONSTRUCTED 2000-2007	1751.441	245.042	0.000
0 BEDROOMS	-1675.819	915.017	0.067
1 BEDROOM		Reference	
2 BEDROOMS	176.998	178.011	0.320
3 BEDROOMS	363.462	252.107	0.150
4 BEDROOMS	10.665	297.067	0.971
5 & OVER BEDROOMS	145.280	345.871	0.675
0 BATHROOMS	-36.430	614.639	0.953
1 BATHROOM		Reference	
2 BATHROOMS	1044.762	149.523	0.000
3 BATHROOMS	1447.690	230.172	0.000
4 & OVER BATHROOMS	1726.193	425.744	0.000
0 CAR PORTS		Reference	
1 CAR PORT	125.639	142.937	0.380
2 & OVER CAR PORTS	772.224	407.118	0.058
0 LAUNDRY AREAS	-282.400	110.075	0.010
1 LAUNDRY AREA		Reference	
2 & OVER LAUNDRY AREAS	-69.549	583.603	0.905
WATERTANK	577.713	481.808	0.231
LOC1_Bull Bay	-1160.870	462.822	0.012
LOC2_Golden Spring	-642.167	631.021	0.309
LOC3_Kingston10	1071.664	182.701	0.000
LOC4_Kingston 11	-1544.552	222.378	0.000
LOC5_Kingston 13	-1274.059	419.563	0.002
LOC6_Kingston 16	-1330.422	430.777	0.002
LOC7_Kingston 17	366.862	276.927	0.185
LOC8_Kingston 19	785.006	229.468	0.001
LOC9_Kingston 2	-511.108	226.544	0.024
LOC11_Kingston 3	-420.746	230.058	0.068
LOC12_Kingston 4	-631.364	613.419	0.304
LOC13_Kingston 5	1411.075	250.506	0.000
LOC14_Kingston 6	1472.316	206.997	0.000
LOC15_Kingston 7	-752.509	478.461	0.116
LOC16_Kingston 8	1399.060	185.743	0.000
LOC17_Kingston 9	463.679	535.362	0.387
LOC18_Central Sorting Off.	-182.960	557.584	0.743
LOC19_Red Hills	808.839	597.233	0.176
LOC20_Stony Hill	784.642	753.803	0.298
LOC21_Kingston 20		Reference	
Number of Observations	1691		
Adjusted R-squared	0.497425		
Log likelihood	6.13E+09		

Table 8. Regression Results for Linear Model

Variables	Coefficient	Std. Error	Prob.
Constant	3616.896	346.963	0.000
YEAR 2003		Reference	
YEAR 2004	516.958	167.918	0.002
YEAR 2005	621.693	188.066	0.001
YEAR 2006	1287.072	176.343	0.000
YEAR 2007	2364.753	166.977	0.000
QUARTER 1	-663.176	154.702	0.000
QUARTER 2	-459.303	142.795	0.001
QUARTER 3	-235.521	141.423	0.096
QUARTER 4		Reference	
DETACHED		Reference	
SEMI-DETACHED	-406.522	326.403	0.213
ATTACHED	-522.057	406.572	0.199
TOWNHOUSE	122.502	279.326	0.661
2-FAMILY HOUSE	733.523	435.043	0.092
APARTMENT	79.665	229.165	0.728
STUDIO	395.061	385.703	0.306
ONE FLOOR		Reference	
TWO FLOORS	137.121	219.604	0.533
THREE FLOORS	-354.742	731.424	0.628
FLOOR AREA	-0.903	0.113	0.000
LOT SIZE	0.017	0.012	0.140
CONSTRUCTED <1960		Reference	
CONSTRUCTED 1960-1969	190.532	214.790	0.375
CONSTRUCTED 1970-1979	252.589	200.612	0.208
CONSTRUCTED 1980-1989	598.773	229.737	0.009
CONSTRUCTED 1990-1999	1553.663	245.621	0.000
CONSTRUCTED 2000-2007	1794.728	260.957	0.000
0 BEDROOMS	-1870.605	973.450	0.055
1 BEDROOM		Reference	
2 BEDROOMS	-430.385	181.052	0.018
3 BEDROOMS	-754.333	252.102	0.003
4 BEDROOMS	-1362.851	295.141	0.000
5 & OVER BEDROOMS	-1324.873	347.943	0.000
0 BATHROOMS	409.991	652.460	0.530
1 BATHROOM		Reference	
2 BATHROOMS	621.293	155.671	0.000
3 BATHROOMS	1013.132	244.188	0.000
4 & OVER BATHROOMS	1476.457	458.155	0.001
0 CAR PORTS		Reference	
1 CAR PORT	-129.642	151.270	0.392
2 & OVER CAR PORTS	663.706	446.646	0.138
0 LAUNDRY AREAS	-231.013	117.075	0.049
1 LAUNDRY AREA		Reference	
2 & OVER LAUNDRY AREAS	-122.541	623.108	0.844
WATERTANK	593.821	512.960	0.247
LOC1_Bull Bay	-1101.094	489.444	0.025
LOC2_Golden Spring	-676.405	673.962	0.316
LOC3_Kingston10	939.674	192.633	0.000
LOC4_Kingston 11	-1510.836	236.610	0.000
LOC5_Kingston 13	-1274.760	446.414	0.004
LOC6_Kingston 16	-1533.924	457.882	0.001
LOC7_Kingston 17	436.518	294.415	0.138
LOC8_Kingston 19	645.101	242.368	0.008
LOC9_Kingston 2	-265.498	240.529	0.270
LOC11_Kingston 3	-494.502	244.759	0.044
LOC12_Kingston 4	-922.620	651.845	0.157
LOC13_Kingston 5	1482.152	266.187	0.000
LOC14_Kingston 6	1292.306	218.014	0.000
LOC15_Kingston 7	-475.013	508.489	0.350
LOC16_Kingston 8	1226.635	196.225	0.000
LOC17_Kingston 9	623.611	570.353	0.274
LOC18_Central Sorting Off.	-168.794	592.992	0.776
LOC19_Red Hills	799.486	631.286	0.206
LOC20_Stony Hill	736.679	801.756	0.358
LOC21_Kingston 20		Reference	
Number of Observations	1691		
Adjusted R-squared	0.411919		
Log likelihood	-15274.18		

Table 9. Regression Results for Unrestricted Box-Cox Model

Variables	Coefficient	Std. Error	Prob.
Constant	1.1513	0.0062	0.0000
YEAR 2003	<i>Reference</i>		
YEAR 2004	-0.0002	0.0001	0.1629
YEAR 2005	0.0002	0.0001	0.2240
YEAR 2006	0.0003	0.0001	0.0489
YEAR 2007	0.0005	0.0001	0.0000
QUARTER 1	-0.0002	0.0001	0.2126
QUARTER 2	-0.0003	0.0001	0.0278
QUARTER 3	-0.0001	0.0001	0.2187
QUARTER 4	<i>Reference</i>		
DETACHED	<i>Reference</i>		
SEMI-DETACHED	0.0009	0.0002	0.0000
ATTACHED	0.0007	0.0003	0.0187
TOWNHOUSE	0.0010	0.0002	0.0000
2-FAMILY HOUSE	-0.0001	0.0004	0.8813
APARTMENT	0.0015	0.0002	0.0000
STUDIO	0.0014	0.0003	0.0000
ONE FLOOR	<i>Reference</i>		
TWO FLOORS	0.0001	0.0001	0.4175
THREE FLOORS	0.0009	0.0003	0.0134
FLOOR AREA	-0.0100	0.0053	0.0579
LOT SIZE	0.0080	0.0046	0.0841
CONSTRUCTED <1960	<i>Reference</i>		
CONSTRUCTED 1960-1969	0.0000	0.0001	0.7232
CONSTRUCTED 1970-1979	0.0001	0.0001	0.4751
CONSTRUCTED 1980-1989	0.0001	0.0001	0.4381
CONSTRUCTED 1990-1999	0.0000	0.0002	0.8751
CONSTRUCTED 2000-2007	0.0000	0.0002	0.9825
0 BEDROOMS	-0.0009	0.0006	0.1558
1 BEDROOM	<i>Reference</i>		
2 BEDROOMS	-0.0002	0.0001	0.1148
3 BEDROOMS	-0.0006	0.0002	0.0009
4 BEDROOMS	-0.0007	0.0002	0.0013
5 & OVER BEDROOMS	-0.0010	0.0002	0.0001
0 BATHROOMS	0.0004	0.0006	0.5408
1 BATHROOM	<i>Reference</i>		
2 BATHROOMS	0.0006	0.0001	0.0000
3 BATHROOMS	0.0008	0.0002	0.0000
4 & OVER BATHROOMS	0.0009	0.0003	0.0065
0 CAR PORTS	<i>Reference</i>		
1 CAR PORT	0.0003	0.0001	0.0019
2 & OVER CAR PORTS	0.0006	0.0004	0.1610
0 LAUNDRY AREAS	0.0000	0.0001	0.9923
1 LAUNDRY AREA	<i>Reference</i>		
2 & OVER LAUNDRY AREAS	-0.0003	0.0005	0.5668
WATERTANK	0.0000	0.0005	0.9717
LOC1_Bull Bay	-0.0002	0.0005	0.6873
LOC2_Golden Spring	-0.0003	0.0010	0.7728
LOC3_Kingston10	-0.0001	0.0002	0.6670
LOC4_Kingston 11	-0.0006	0.0001	0.0000
LOC5_Kingston 13	-0.0005	0.0002	0.0217
LOC6_Kingston 16	-0.0007	0.0003	0.0167
LOC7_Kingston 17	0.0000	0.0002	0.9263
LOC8_Kingston 19	0.0001	0.0002	0.6957
LOC9_Kingston 2	-0.0005	0.0002	0.0085
LOC11_Kingston 3	-0.0002	0.0002	0.2739
LOC12_Kingston 4	-0.0002	0.0006	0.7126
LOC13_Kingston 5	-0.0012	0.0001	0.0000
LOC14_Kingston 6	0.0001	0.0002	0.6647
LOC15_Kingston 7	-0.0005	0.0004	0.2386
LOC16_Kingston 8	0.0000	0.0002	0.9351
LOC17_Kingston 9	-0.0006	0.0004	0.1335
LOC18_Central Sorting Off.	-0.0008	0.0005	0.1346
LOC19_Red Hills	-0.0003	0.0006	0.5936
LOC20_Stony Hill	-0.0008	0.0005	0.0718
LOC21_Kingston 20	<i>Reference</i>		
LAMDA 1	-0.8390	0.0247	0.0000
LAMDA 2	-0.1110	0.0050	0.0000
Number of Observations	1691		
Log likelihood	9672		
Avg. log likelihood	6		

Figure 1. CUSUM Test for Parameter Stability in Double-Log Model

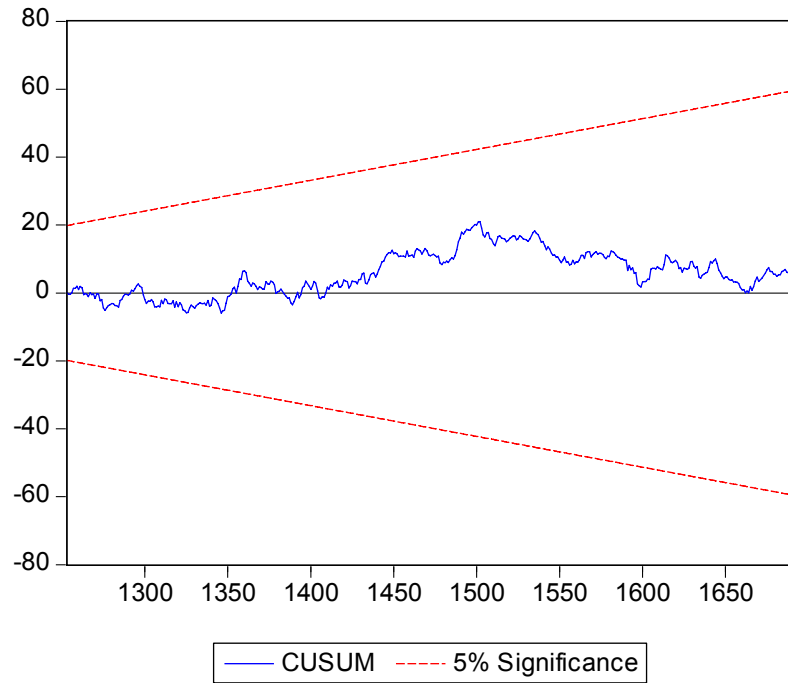


Figure 2. CUSUM-of-Squares Test for Parameter Stability in Double-Log Model

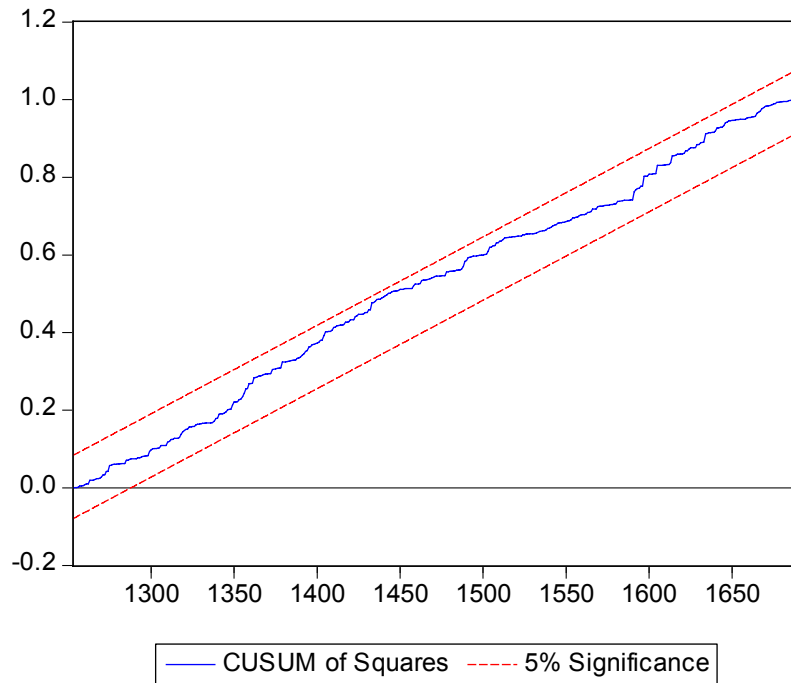


Figure 3. Quarterly Hedonic Price Index for Kingston & St. Andrew

