House price drivers in Dubai: nonlinearity and heterogeneity

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Abstract

Purpose – This paper aims to examine house price drivers in Dubai, addressing nonlinearity and heterogeneity.

Design/methodology/approach – The study applies a combination of linear and nonlinear, as well as quantile regression, specifications to address these concerns and better explain the real-world phenomenon.

Findings – The study shows the double-log quantile regression approach is an overarching description of house price drivers, confirming that not only the price of housing and its determinants are non-linearly related but also that their relationship is heterogeneous across house price quantiles. The findings reveal the prevalence of sub-market differentials in house price sensitivity to house attributes such as size (in square meters), location and type of house, as well as government laws. The study also identifies the peaks and deflation, as well as the rebounding nature of the house price bubble in Dubai.

Research limitations/implications – The data used are limited, in that information on only a few house attributes was available. Future research should include data on other house attributes such as house quality, zip codes and composition.

Practical implications – The findings of this study are expected to suggest results with significant ramifications for researchers, practitioners and policy makers. From a policy perspective, there is an obvious interest in understanding whether the price of housing is affected by different attributes differently along its distribution.

Social implications – This study allows policy makers, developers and buyers of higher-priced houses to behave differently from buyers of lower-priced or medium-priced houses.

Originality/value – Methodologically, it demonstrates alternative linear and nonlinear, as well as quantile regression, specifications to address two increasing concerns in the house price literature: nonlinearity and heterogeneity. Unlike most other studies, this study used a rich data (140,039 day-to-day transactions of 10 years' pooled data). The Dubai housing market presents an interesting case. UAE (Dubai, in particular) is named as the second-hottest marketplace for global residential property investors, ahead of Singapore, the UK and Hong Kong (Savills plc, 2015).

Keywords Nonlinearity, Heterogeneity, Dubai, Double-Log Quantile regression, Hedonic pricing model, House price bubbles

Paper type Research paper

1. Introduction

Many economic studies have used a hedonic regression framework to analyze the relationship between house prices and house attributes (Osland, 2013; Herath and Maier,

JEL classification – R31, R21, R29

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2010; Langrin, 2008; Parkhomenko *et al.*, 2007 and Sirmans *et al.*, 2005). The theoretical underpinning in this framework involves estimating the value of individual attributes of a house and measuring their effect on its price (Malpezzi, 2003). In the hedonic house price literature, the discussion has traditionally been concentrated on, among others, the functional form of the hedonic pricing models (Ekeland *et al.*, 2002; Osland, 2013). In this regard, the two increasing concerns have been issues of nonlinearity and heterogeneity in the relationship between house prices and house attributes. This is vital because house prices can be determined by house attributes differently according to the house price range. A number of studies have addressed nonlinearity by specifying the hedonic house price models using semi-logarithmic, double-logarithmic or Box-Cox transformations, as well as other functional forms (Kam and Marc, 2010; Langrin, 2008; Wan and Bao, 2004). Others have used quantile regression to address the heterogeneous characteristics of housing demand (Zahirovic-Herbert and Gibler, 2014; Zahirovic-Herbert and Chatterjee, 2012; Mak *et al.*, 2010; Zietz *et al.*, 2008; McMillen and Thornes, 2006), arguing that quantile regression addresses heterogeneity by allowing the estimated coefficients of the house attributes to vary along the distribution of house prices. These studies, however, do not consider nonlinearity for the hedonic house price model.

An approach that addresses nonlinearity and heterogeneity in the relationship between house prices and house attributes would be a vital tool with which to probe the relationship. Indeed, a recent study by Kim *et al.* (2015) addressed these two concerns using a Box-Cox quantile regression. However, the Box-Cox model has the disadvantage of not allowing for continuous variables with zero values (Hansen and Benson, 2013; Benson *et al.*, 1998). Moreover, the Box-Cox test is likely to favor nonlinear models, despite this being the incorrect functional form in cases of omitted variables (Parkhomenko *et al.*, 2007). This study examines alternative linear and nonlinear (semi-log, log-log and Box-Cox) specifications, as well as quantile regression specifications, to address nonlinearity and heterogeneity, including the recurring patterns in day-to-day housing data in the presence of an underlying time-trend (and a house price bubble) driving house sale prices.

In this study, a day-to-day transaction of 10 years' pooled data from 140,039 homes sold in Dubai (UAE) is used for the period from January 1, 2007, to March 31, 2016. During this period, real estate has been one of the key drivers of the national economic activity of the UAE, recording a steady and robust performance over the years. The construction sector as a percentage of gross domestic product (GDP) of the UAE reached 10.6 per cent in 2008 and 10.3 per cent in 2011, while for 2015 and 2021, the sector's contribution as a percentage of UAE GDP is projected to be 11.1 and 11.5 per cent, respectively (Dubai Chamber, 2015). As long as the housing (real estate) market is an important driver of growth, the UAE economy will be less resilient to exogenous shocks, such as the 2007 real estate collapse. The price of housing in Dubai has shown fluctuations over the years. From 2002 to 2008, Dubai's property prices almost quadrupled, and large-scale developments turned Dubai into one of the fastest-growing cities in the world (Global Property Guide, 2016). Following the house price boom in 2002-2008, the great recession began to hit Dubai's economy and its housing market until the fourth quarter of 2010/2011[1]. Dubai saw significant price decline in the housing market in these periods. According to the International Monetary Fund (IMF), the fall in residential property prices continued until the end of 2011 (IMF, 2014).

In 2011, the UAE's economy returned to growth and economic activity picked up again. Dubai's GDP rose from AED311,453m (constant 2006 prices) in 2012 to AED337,907m in 2014 (AED: UAE Dirham; based on data from Dubai Chamber, 2015). With the return of confidence in the real estate market, house prices for Dubai increased rapidly from 2012 until the end of 2014. This has led many observers, such as the IMF (IMF, 2014), to believe that

Dubai is in the middle of a speculative bubble in residential real estate prices and to call for government intervention[2]. Such interventions assume that the market is driven primarily by speculation rather than fundamentals. To the best of the author's knowledge, there is no empirical evidence of whether the observed house price changes are due to speculation or changes that can be justified by fundamental values. The rise in house prices could be due to a real demand for housing from end-users and a steady supply of new developments to match it. In such a case, regulatory measures may have a negative effect on "real home demanders" with a genuine interest in purchasing a house, as opposed to "flippers". It is imperative, therefore, to assess the drivers of house prices. This study examines the drivers of house prices using an approach that addresses nonlinearity and heterogeneity in the relationship between house prices and house attributes, using 10 years' pooled data of homes in Dubai.

This study contributes to the existing house price literature in several ways. Methodologically, it demonstrates alternative linear and nonlinear (log, log-log and Box-Cox) specifications, as well as quantile regression specifications, to address two increasing concerns in the house price literature: nonlinearity and heterogeneity in the relationship between house prices and house attributes. From a housing policy perspective, there is an obvious interest in understanding heterogeneous behavior of house prices in assessing the attributes of house prices. It also allows buyers of higher-priced houses to behave differently from buyers of lower-priced houses. Unlike most other studies that have analyzed house prices, the richness of the data (140,039 day-to-day transactions of 10 years' pooled data) makes it possible to assess the relative importance of house characteristics and time-related effects on house prices. To the best of the author's knowledge, this study is the first empirical work to use quantile regression and nonlinear specifications of the hedonic price model to investigate the determinants of house prices in Dubai. The Dubai housing market presents an interesting case. Dubai has been identified as the most internationally invested city for residential real estate in the Middle East. After USA, the UAE (Dubai, in particular) is named as the second-hottest marketplace for global residential property investors, ahead of Singapore, the UK and Hong Kong (Savills plc, 2015).

The following section briefly reviews the literature related to this study. Section 3 discusses the methodological framework within which the hedonic pricing model is applied to house sale prices in Dubai. It discusses the theoretical and empirical framework, as well as the econometric model, used in this study. Section 4 describes the type and source of the data used and provides the empirical estimates of the model. In this section, the empirical results will be interpreted and findings will be discussed. The final section provides conclusion and recommendations.

2. Literature review: toward a conceptual framework

Given that a bubble in the housing market occurs when the current price of a house exceeds its fundamental value (Brunnermeier, 2008; Himmelberg *et al.*, 2005; FRBSF, 2004; Stiglitz, 1990), the difficulty of identifying a bubble is due to the difficulty in accurately estimating these fundamental or intrinsic values. The theoretical literature has not reached a consensus on how to model the fundamental values. In the real estate context, empirical studies often estimate fundamentals by assessing financial ratios (McCarthy and Peach, 2004), by comparing house price indexes with other indexes or by using economic indicators such as regression of actual house prices on a set of supply and demand variables (Nneji *et al.*, 2013; Glindro *et al.*, 2008; Capozza *et al.*, 2002). This study borrows from the economic literature and follows the later approach (to be detailed in the methodology section) within the context of a hedonic regression framework.

The theoretical underpinning in the hedonic regression framework involves estimating the value of individual characteristics of a house and measuring their effect on its price (Malpezzi, 2003). There are many studies that have utilized the hedonic house price model to analyze the determinants of house prices. Sirmans *et al.* (2005) and Herath, and Maier (2010) thoroughly reviewed the literature on the hedonic price method in the housing market context. Other works that have utilized the hedonic pricing framework include Kim *et al.* (2015), Osland (2013), Mak *et al.* (2010), Cebula (2009), Langrin (2008), Zietz *et al.* (2008) and Parkhomenko *et al.* (2007). In the hedonic house price literature, the discussion has been concentrated on two main practical issues: how should we specify the functional form and which house attributes should be included in the model (Ekeland *et al.*, 2002; Osland, 2013)? With regard to the latter, the review by Sirmans *et al.* (2005) categorized the most prevalent house attributes, including structural features (such as square feet and age); internal features (such as number of bedrooms and bathrooms); external features (such as parking space); natural environmental features (such as a lakefront); neighborhood and location; public services; marketing, occupancy and selling factors (such as time-trends); and financing issues.

With regard to the functional forms, linear, semi-logarithmic, double-logarithmic and Box-Cox transformations and other functional forms have been used to specify hedonic house price models (Kam and Marc, 2010; Langrin, 2008; Wan and Bao, 2004). These alternative functional forms may address nonlinearity in the relationship between house prices and house characteristics. However, they do not take into account heterogeneity across different conditional quantiles. While these functional forms answer the question of whether a particular house attribute matters in house price determination, they cannot tell if that attribute influences house prices differently for low-priced houses than for medium- or high-priced houses. Such information is useful for practitioners in the housing market. A number of studies have addressed such heterogeneous characteristics of housing demand using quantile regression analysis. For instance, McMillen and Thornes (2006) used Chicago house transaction data from 1993 to 2005 and suggested that quantile regression has advantages over the conventional mean-based approaches in estimating the house price index; and Zietz *et al.* (2008) applied quantile regression, with and without accounting for spatial autocorrelation, to Provo-Orem (Utah area) data on 1,366 home sales between mid-1999 and mid-2000 and demonstrated that purchasers of higher-priced homes value certain house characteristics differently from buyers of lower-priced homes. Other works that have applied quantile regression in a housing context include those of Mak *et al.* (2010), who used data from 5,947 house transactions in City One Shatin in Hong Kong; Liao and Wang (2012), who used one year's sample data of 46,356 residential properties sold in Changsha city in China; and Zahirovic-Herbert and Gibler (2014), who used house transaction data from Baton Rouge (Louisiana). These studies, however, do not consider nonlinearity for the hedonic house price model.

It is argued that quantile regression addresses heterogeneity by allowing the estimated coefficients of the house attributes to vary along the distribution of the house prices (Kim *et al.*, 2015; Zahirovic-Herbert *et al.*, 2012). Quantile regression complements nonlinear specifications by identifying the implicit prices of house characteristics for different points in the distribution of house prices, rather than estimating the implicit prices of house characteristics, based on parameters of the entire price distribution. The information from such quantile regression estimation provides a better explanation of the real-world phenomenon. It allows house developers and buyers of higher-priced houses to behave differently from buyers of lower-priced houses.

A comprehensive approach that addresses nonlinear relationships between house prices and house attributes, as well as heterogeneous characteristics of housing demand, would be useful and advantageous in probing the relationship. Indeed, a recent study by Kim *et al.* (2015) addressed these two concerns using a Box-Cox quantile regression on housing data from 952 condominium units in Taikoo Shing (Hong Kong) for the year 2010. This study suggests that Box-Cox quantile regression provides a more comprehensive description of the determinants of house prices. The Box-Cox test is likely to favor nonlinear models, despite being the incorrect functional form in cases of omitted variables (Parkhomenko *et al.*, 2007), which might be the case with the data used in this study[3]. This study, therefore, examines alternative linear and nonlinear (semi-log, log-log and Box-Cox) specifications, as well as quantile regression specifications, to address nonlinearity and heterogeneity in the relationship between house prices and attributes. Unlike Kim *et al.* (2015) and most other studies, this study used 10 years' pooled data of 140,039 day-to-day home transactions to examine the recurring pattern in day-to-day data in the presence of an underlying time-trend (and a house price bubble) driving house sale prices. This study is complementary to the existing literature, both theoretically and methodologically. Moreover, such empirical analysis of house prices is missing or limited in Dubai and the UAE. This study is an attempt to fill in this research gap.

3. Methodological framework

The theoretical foundation of hedonic modeling, as argued for the first time by Lancaster (1966), is that an item's utility is simply the aggregated utility of the individual utility of each of its characteristics. This argument is extended by Rosen (1974) to include pricing. Currently, the underlying theory and premise in the housing market context is that a house represents a bundle of both desirable and undesirable attributes to utility-maximizing consumers, all of which contribute to the market value of the house as revealed through a housing market transaction, i.e. house sale. These attributes are what buyers really want and acquire utility from (Herath and Maier, 2010; Sirmans *et al.*, 2005).

Empirically, the hedonic pricing framework has been widely applied in studying house prices in relation to factors attributed to house characteristics (Kim *et al.*, 2015; Osland, 2013; Beck *et al.*, 2012; Sutter *et al.*, 2010; Cebula, 2009; Zietz *et al.*, 2008; Sirmans *et al.*, 2005; Malpezzi, 2003). The hedonic pricing model decomposes the price of the house into the various attributes of the house that affect its sale price. The estimated parameters of the model provide information about the relative contribution of any given house attribute (i.e. implicit price) to the total transaction value of the house. The level of the implicit price reflects the degree of desirability of the attribute (Bazyl, 2009).

3.1 Functional forms: addressing nonlinearity and heterogeneity

Methodologically, the choice of functional form for hedonic price models affects the economic interpretation of the results, contributing to the production of bias in the estimated hedonic coefficients (Langrin, 2008) and thereby in the house price trend. As a result, the question of which functional form to choose and how the functional form should be specified has been a topic of discussion in the hedonic house price literature (Osland, 2013). Economic theory of hedonic prices provides very little theoretical guidance on the appropriate functional relationship between house prices and attributes in the hedonic price function (Lisi, 2013; Taylor, 2003). Theoretically, the hedonic pricing model does not have a definite functional form by definition. It depends on the assumptions arbitrarily chosen by a researcher (Triplett, 2006; Can, 1992; Cassel and Mendelsohn, 1985; Halvorsen and Pollakowski, 1981; Rosen, 1974). As argued in Triplett (2006), imposing some rule for what the hedonic function should be destroys part of the information that market prices convey. Furthermore, no *a* *priori* structural restrictions should be placed on the form of the hedonic functions (Ramalho and Ramalho, 2011; Cropper *et al.*, 1988). This suggests that the hedonic functional form is an empirical issue to be determined from the data analysis and not based on some *a priori* reasoning. In empirical housing studies, several alternative specifications have been adopted for the hedonic function. Predominantly, the specifications differ in the form under which the dependent and the explanatory variables appear in the hedonic equation. A classic hedonic house price model has a linear functional form (Herath and Maier, 2010):

$$P_i = \beta_0 + \sum_{k=1}^{K} \beta_k Y_{ki} + \varepsilon_i \, where \, i = 1, 2, 3, \ldots, N, \tag{1}$$

where P_{i} is the price of house i, Y_k is an array of K (L dichotomous variables, Z_l, and M continuous variables, X_m)[4] that characteristics values explaining the price of house i, β_k is an array of k parameters to be estimated and ε is a residual term with $\varepsilon_i \sim N[0,\sigma^2]$. Though such linear hedonic housing models are still used in the housing literature, there is a belief that hedonic models are nonlinear (Ekeland *et al.*, 2002). Quite often, semi-log (log-linear or linear-log) or double-log forms are used to represent nonlinearity in the relationship between house prices and house attributes. The general functional forms of such models are as in equations (2) and (3):

Semi-log (log-liner) model:

$$lnP_i = \beta_0 + \sum_{k=1}^{K} \beta_k Y_{ki} + \varepsilon_i \, where \, i = 1, 2, 3, \ldots, N. \tag{2}$$

Double-log model (DLM):

$$lnP_i = \beta_0 + \sum_{l=1}^{L} \beta_l Z_{li} + \sum_{m=1}^{M} \beta_m \, lnX_{mi} + \varepsilon_i \, where \, i = 1, 2, 3, \ldots, N. \tag{3}$$

Although all of the above functional forms are popular hedonic model specifications, each having its strong points, there has been an increasing concern that they all have weaknesses in the sense that all restrict the ways in which the hedonic function can be specified. This has led researchers to consider flexible functional forms, particularly the Box-Cox model (Box and Cox, 1964), which nests all the above three functional forms:

$$P_i^{\lambda_1} = \beta_0 + \sum_{l=1}^{L} \beta_l Z_{li} + \sum_{m=1}^{M} \beta_m X_{mi}^{(\lambda_2)} + \varepsilon_i \, where \, i = 1, 2, 3, \ldots, N, \tag{4}$$

with the Box-Cox transformation of P and the independent continuous variables (X_m) as follows:

$$P^{(\lambda_1)} = \begin{cases} \dfrac{P^{\lambda_1} - 1}{\lambda_1}, \, for \, \lambda_1 \neq 0 \\ \ln(P), \, for \, \lambda_1 = 0 \end{cases} \quad and \quad X^{(\lambda_2)} = \begin{cases} \dfrac{X^{\lambda_2} - 1}{\lambda_2}, \, for \, \lambda_2 \neq 0 \\ \ln(X), \, for \, \lambda_2 = 0 \end{cases},$$

where λ_1 and λ_2, respectively, denote the Box-Cox transformation parameter on the dependent and the independent continuous variables. With various combination of λ_1 and λ_2

values, the above transformation [equation (4)] embeds several popular functional forms (Kam and Marc, 2010). The point is the Box-Cox, as a nonlinear estimation technique, can allow us to simultaneously estimate the model parameters (the β's), λ_1 and λ_2, and let the data decide which functional form is the best. A maximum-likelihood unrestricted Box-Cox hedonic model provides a flexible functional form and hence seems an attractive choice in the hedonic price model. However, the Box-Cox model has the disadvantage of not allowing for continuous variables with zero values (Hansen and Benson, 2013; Benson *et al.*, 1998). Moreover, the Box-Cox test is likely to favor nonlinear models despite being the incorrect functional form in cases of omitted and mis-specified variables (Parkhomenko *et al.*, 2007). Similar to Langrin (2008) and Li *et al.* (2006), therefore, the preferred model is evaluated according to signs of coefficients and value of coefficients, as well as out-of-sample goodness-of-fit measures (see the subsection below).

Although the above alternative functional forms can address nonlinearity in the relationship between house prices and house attributes, they do not take into account heterogeneity across different price quantiles (such as the low-, medium- or high-priced houses). Indeed, studies (Kim *et al.*, 2015; Liao and Wang, 2012; Mak *et al.*, 2010; Zietz *et al.*, 2008; McMillen and Thornes, 2006; Koenker, 2005) have empirically demonstrated that the relationship between house prices and house attributes varies across quantiles and the response of house prices to various house characteristics varies across price quantiles. Such heterogeneous characteristics of housing demand can be addressed using quantile regression analysis (Kim *et al.*, 2015; Zahirovic-Herbert *et al.*, 2012). Quantile regression allows the house price determination to vary across the different quantiles of the conditional distribution of house prices and the effect of a particular house characteristic (such as house size) to be different across the different quantiles. Such information is useful for practitioners in the housing market; it provides them with a more comprehensive relationship between house prices and attributes, allowing developers and buyers of low-priced houses to behave differently from buyers of medium- or high-priced houses.

Methodologically, quantile regression is preferred compared to the alternative approach in that it first subdivides the sample according to the unconditional distribution of the response variable and subsequently performs least squares regression for each subsample. While least squares models relationships of the independent variables and the conditional mean of the dependent variable (Mak *et al.*, 2010), quantile regression models generalize the concept of an unconditional quantile to a quantile that is conditioned on one or more covariates, and hence, it is more comprehensive. Quantile regression[5] uses the full sample and avoids the truncation problem that the alternative approach usually encounters. The superiority of quantile regression also stems from its superior capability in handling heteroscedasticity and unobserved heterogeneity (Liao and Wang, 2012; Koenker, 2005; Koenker and Hallock, 2001). Moreover, quantile regression estimates are more robust against outliers compared with least squares regressions (Koenker, 2005).

The quantile regression for the equation (1) is described by equation (5):

$$P_i = \beta_{0q} + \sum_{k=1}^{K} \beta_{kq} Y_{ki} + \varepsilon_i \, where \, i = 1, 2, 3, \ldots, N, \tag{5}$$

where β_{kq} instead of β_k is used to make clear the different choices of q (quantile) estimates at different values of β. Equation (5) can be specified for the various functional forms described earlier [equations (2)-(4)]. Unlike the least squares regression (which minimizes $\Sigma_i \, \varepsilon_i^2$) and the least absolute deviation (LAD) regression (which minimizes $\Sigma_i \, |e_i|$), the quantile regression is based on the minimization of weighted absolute deviations (Koenker and Hallock, 2001). It minimizes $\Sigma_i q|\varepsilon_i| + \Sigma_i (1 - q)|\varepsilon_i|$, giving the asymmetric penalties $q|\varepsilon_i|$ for underprediction and $(1-q)|\varepsilon_i|$ for overprediction. Accordingly, the *qth* quantile regression estimator $\hat{\beta}_q$ minimizes over β_q the objective function:

$$Q(\beta_q) = \sum_{i:P_i \geq \hat{P}_i}^{N} q\left|P_i - \hat{P}_i\right| + \sum_{i:P_i < \hat{P}_i}^{N} (1 - q)\left|P_i - \hat{P}_i\right|,$$

where $0 < q < 1$ and $\hat{P}_i = P_i - [\beta_{0q} + \Sigma_{k=1}^{K} \beta_{kq} Y_{ki}]$. In contrast to least squares and maximum likelihood, the computational implementation of quantile regression uses linear programming methods.

Neither the quantile regression nor the alternative nonlinear specifications single-handedly address the two increasing concerns in the house price literature: nonlinearity and heterogeneity in the relationship between house prices and attributes. This study used a combination of alternative linear and nonlinear (log, log-log and Box-Cox) specifications and quantile regression specifications to address the two problems. While the quantile regression helps to address the issue of heterogeneous characteristics of housing demand, the increasing concern in the housing literature that hedonic function can be nonlinear is addressed by comparing different linear and nonlinear models.

Typical econometric issues that can arise from estimating hedonic house price models using quantile regression analyses are problems associated with heteroscedasticity and spatial correlations (Zietz *et al.*, 2008). With regard to the former, the estimated parameter β_{kj} and standard errors, for the jth independent variable, are estimated by bootstrapping using the "sqreg" command in Stata. Such standard errors are significantly less sensitive to heteroscedasticity. Because of the way location dummy variable is used in this study, the issue of spatial autocorrelation dependence and the possible spillover effects of location on other parameters cannot be ruled out in this study, as priced houses may not be all clustered geographically (Zietz *et al.*, 2008). This is due to the possibility of the overlapping of important house attributes represented by these location dummy variables. Use could have been made of zip codes of the house (with its corresponding latitude and longitude coordinates) for a more robust result. However, such information is not available in the data set used in this study.

3.2 The empirical model and operational hypotheses

As discussed earlier in this paper, the choice of the hedonic functional form is an empirical issue to be determined from the data analysis and not based on some *a priori* reasoning. A typical approach in the choice of functional form is to compare the out-of-sample goodness-of-fit measures from alternative functional forms and then pick up the best-fitting model (Zietz *et al.*, 2008; Langrin, 2008 and Li *et al.*, 2006). In this study, therefore, both the linear, semi-logarithmic, double-logarithmic and unrestricted Box-Cox functional forms are estimated using the Dubai house transaction data, and Akaike's information criterion (AIC) and Bayesian information criterion (BIC) are used as model selection criteria. Moreover, the preferred model is evaluated according to the estimated signs and values of coefficients. Subsequently, the selected model is estimated at selected quantile values to address the problem of heterogeneity.

The basic empirical model in this study is specified by the flexible functional form model, unrestricted Box-Cox model (UBCM), as in equation (6):

$$\left.\begin{aligned} PRICE_i^{\lambda_1} = \beta_0 + \sum_{t=1}^{T} \beta_t YEAR_{t,i} + \sum_{t=1}^{T} \beta_q QUARTER_{q,i} + \sum_{t=1}^{L} \beta_l LOCATION_{l,i} \\ + \beta_h HOUSE\,TYPE_i + \beta_m MORTGAGE_i + \beta_{tr} TRANSACTION_i + \beta_{sqmt} \cdot SQMT_i^{(\lambda_2)} + \varepsilon_i \end{aligned}\right\} \quad (6)$$

where $PRICE_i$ is the price of house i, expressed in January 2003 constant AED; $YEAR_{t,i}$ is a vector of dummy variables for the year house i was sold; and $QUARTER_{q,i}$ is a vector of dummy variables for the quarter house i was sold. These time-control variables (quarter and year) are used to account for potential annual and seasonal variations in house price. $LOCATION_{l,i}$ is a vector of dummy variables for the location of house i; $HOUSETYPE_i$ is a dummy variable for the type of house i (villa versus apartment); $MORTGAGE_i$ is a dummy variable for UAE federal mortgage cap law; $TRANSACTION_i$ is a dummy variable for Dubai Land Department (DLD) transaction fee law; $SQMT_i$ is the area in square meters of house I; λ_1 and λ_2, respectively, represent the Box-Cox transformation parameter on the dependent variable, P_i, and the independent continuous variable, $SQMT_i$. See Table AI (Appendix) for the definitions of the variables.

The literature on the relationship between house prices and house attributes (Julia and Earl, 2013; Beck *et al.*, 2012; McCord *et al.*, 2012; Herath and Maier, 2010; Laurice and Bhattacharya, 2005; Sirmans *et al.*, 2005; Malpezzi, 2003) suggests that many housing attributes affect house prices[6]. These literatures give rise to the operational hypotheses set for this study:

H1. House price is an increasing function of the size of its area in square meters (i.e. $\beta_{sqmt} > 0$).

H2. There are sub-market differentials in house price sensitivity to housing locations, where locations with better amenities are expected to increase house prices (i.e. $\beta_1 > 0$ for waterfront and city center locations; and $\beta_1 < 0$ for countryside, industrial area and new area locations).

H3. There are sub-market differentials in house price sensitivity to housing types, where villa houses earn a higher house price premium than apartments (i.e. $\beta_h > 0$).

No hypotheses on the year and quarterly dummies are immediately clear at the outset (i.e. no expected sign on β_t and β_q). Two other variables, a UAE federal mortgage cap law dummy and a DLD transaction fee law dummy, are also included in the empirical model as extraneous variables to proxy government policy interventions.

4. Empirical analysis and findings

4.1 Data type and sources

This study uses house price data from Dubai city. The data are 10 years' pooled data of home sales from January 1, 2007, to March 31, 2016. It is manually extracted from the DLD website. The website lists daily transactions of flats (apartments) and villas ("detached houses"), including the sale price, location[7] and area size (in square meters), of each home sold on a day-to-day basis. Information on 140,438 home transactions was made available for the 10-year period; of these, 47 were not included in the empirical analysis of this study, mainly because of missing or unsuitable location information. An additional 336 and 16 home transactions were eliminated because of outliers in house sale price and in house area size[8]. Finally, information on 140,039 homes is compiled to generate the data used in the empirical analysis of this study[9]. Nominal house prices were converted into constant (or real) values using the monthly house sale price index obtained from REIDIN[10] Dubai.

4.2 Definition of variables and summary statistics

This study used all the available information available in the DLD data source, including time-control (quarter and year) variables. Table AI (Appendix) formally defines the variables used in the analysis of this study. Despite the limitations of certain variables on house attributes, this study attempts to examine the drivers of house prices using a diverse (yet available) set of variables taking into account nonlinearity and heterogeneity in the relationship between house prices and attributes.

Table AII (see Appendix) presents the summary statistics of the variables used in the empirical analysis. The overall average real house prices was AED646,646, or about AED5,562/m^2. The average house sold was 115 m^2 in size, apartment-flat located near to the waterfront and sold in the first quarter of 2013. On average, 73 per cent of the housing units were sold before the UAE federal mortgage cap law came into effect, while 70 per cent were sold before the DLD doubled property transaction fees from 2 to 4 per cent.

The quantile values reported in Table AII show that the mean real sale price of houses associated with the fourth quantile point is 142 per cent higher than the mean price of houses associated with the third quarter, while the increase from the second to the third quantile point is only about 74 per cent. The result suggests a higher variability (relative to average sale price) in the sale price of houses associated with higher quantile points. The house sale price associated with the bottom 10 per cent quantile point is on average AED127,340 in real terms with a 95 per cent confidence interval covering from AED126,844.20 to AED127,836. This confidence interval, for instance, is much narrower compared to that of the fourth quantile point and the 90 per cent quantile point (top 10 per cent).

For the independent variables, the reported quantile values are averages of the values that are associated with the given quantile point of the dependent variable, real house price. Houses with sale prices in the 90 per cent quantile point have on average square footage of 246.62 m^2 compared to a square footage of 48.48 for houses associated with the 10 per cent quantile point. Remarkably, 93 per cent of houses associated with the 90 per cent quantile point are located near to the waterfront, while this figure is only 9 per cent for houses associated with the 10 per cent quantile point. The majority (77 per cent) of houses associated with the 10 per cent quantile point are located in the countryside, far from the city center. Similarly, about 66 per cent of the houses associated with the first quantile point are located in the countryside and only 3 per cent of the houses associated with the 90 per cent quantile point are located in the countryside. Most house sale transactions were made in the first quarter of 2013, and these transactions are consistently higher at all quantile points, except for the houses associated with the first quarter with a higher proportion of houses sold in 2007.

4.3 Empirical analysis

This section discusses the empirical estimation results of the models applied in this study. Starting with comparison of the alternative model estimations, the findings from the preferred model will be discussed.

4.3.1 Addressing nonlinearity (model comparison). As mentioned earlier in this paper, the choice of the hedonic functional form is an empirical issue to be determined from the data analysis and not based on some *a priori* reasoning. This paper, therefore, compares alternative model estimations. To address the problem of nonlinearity, various linear and nonlinear functional forms are specified and regression estimation results are presented in Table AIII (Appendix). A comparison of the results from these alternative specifications shows that the model that best fits the data used in this study is the DLM. This is evidenced from the comparison of the goodness-of-fit measures (Table I), where DLM specification gives a better fit compared to its alternatives, as it generates the lowest AIC) and BIC. The choice of the DLM is also intuitive given that its estimated coefficients are more reasonable in values and signs. In particular, the estimates from the double-log specification yielded estimates similar to those obtained from the UBCM with $\lambda_1 = -0.051 \approx 0$ and $\lambda_2 = 0.009 \approx 0$, a transformation with more economic meaning.

4.3.2 Addressing nonlinearity. To address the heterogeneity problems, the DLM is estimated at selected quantile points. The results are presented in Table II. The variation of the DLM regression coefficients for each of the covariates at different quantile points is plotted in Figure A1[11] (Appendix). The figure shows how the effects of each covariate vary across quantiles and contrasts them with the overall DLM estimates[12]. It also shows how the magnitude of the effects at various quantiles differs considerably from the DLM coefficients, even in terms of the confidence intervals around each coefficient.

This suggests the appropriateness of the quantile regression approach to describe house price determinants in the Dubai housing market. This is also confirmed by formal cross-equation hypothesis tests[13], which clearly reject (at 1 per cent significance) equality of the estimated coefficients across the quantiles, except for the year 2007 and year 2013 variables, which can only be rejected at 10 and 5 per cent, respectively.

4.3.3 Regression results. This section discusses the regression results presented in Table II. The coefficient of determination for the overall DLM estimation indicates that about 74 per cent of the variation in house prices is explained by the model, and the joint F-statistic is significant at the 1 per cent level. This yields evidence regarding the strength of the DLM estimation for the overall data. Unlike the R^2 values, which provide a global goodness of fit, the pseudo-R^2 values in the quantile regression provide a local goodness of fit (Baur *et al.*, 2004). The pseudo-R^2 for the quantile regression estimations is about 50 per cent, marginally varying between 0.47 and 0.52 across the different quantiles. These are acceptable values given that they are only measuring local fit. The result suggests uniformity in performance at all quantile points.

Most of the estimated coefficients display results with high levels of statistical significance. The estimated coefficient for square footage is positive and highly significant in the overall DLM estimation and at all quantile points. A 1 per cent increase in total house area results in a 1 per cent increase in the house price, interestingly without major difference in the elasticities across quantiles. The positive and significant effect of total house area is consistent with prior expectations; however, similarity in magnitude of the effects across the different quantile points is enlightening.

For the house type variable, estimated coefficient signs are positive and strongly significant in all the models. The magnitude of effect of this variable in the overall DLM estimation generally differs from those obtained at various quantile points, and these values vary across the different quantile points. The effect of house type is higher at lower quantile points. Relative to villas, being an apartment is expected to cause about a 112 per cent

Table I.
Goodness-of-fit statistics: model comparison

Criterion	LRM*	LSSLM	RSSLM	DLM	UBCM
AIC	4,099,677	209,612	4,143,761	157,003	3,803,999
BIC	4,099,833	209,828	4,143,967	157,210	3,804,019
Adjusted-R^2	0.5449	0.6192	0.3762	0.7384	–
LR (Box-Cox)	−2,499,891			−1,902,374	−1,901,998

Note: *LRM denotes linear regression model, DLM denotes double-log model, LSSLM means left-side semi-log model, RSSLM means right-side semi-log model and UBCM refers to the unrestricted Box-Cox model

Table II. Regression estimation for DLM and quantile models

Variable name: *dependent variable – Ln(Real Price)*	DLM coefficients[a]	10th percentile coefficients	1st -quartile coefficients	Median coefficients	3rd quartile coefficients	90th percentile coefficients
Ln(square meter)	1.026***	0.995***	1.022***	1.031***	1.025***	1.005***
House type dummy	0.973***	1.123***	0.992***	0.927***	0.800***	0.768***
Location dummies						
Waterfront	0.417***	0.205***	0.339***	0.433***	0.535***	0.612***
Country side	−0.104***	−0.188***	−0.163***	−0.130***	−0.076***	−0.023**
City center	0.513***	0.668***	0.558***	0.481***	0.442***	0.764***
New area	0.252***	0.071***	0.166***	0.264***	0.350***	0.366***
Quarterly dummies						
Quarter 1	−0.008**	0.010**	0.003	−0.010***	−0.007*	−0.020***
Quarter 2	−0.025***	−0.003	−0.005	−0.026***	−0.017***	−0.018***
Quarter 4	0.012***	0.009	0.012***	0.002	0.018***	0.012**
Year dummies						
Year 2007	0.081***	0.040	0.064**	0.106***	0.116***	0.150***
Year 2008	0.011	−0.112***	−0.101***	0.018	0.113***	0.190***
Year 2009	0.052**	0.064*	0.013	0.058**	0.089***	0.104**
Year 2010	0.111***	0.065*	0.032	0.095***	0.168***	0.238***
Year 2011	0.092***	−0.040	−0.022	0.077***	0.152***	0.270***
Year 2012	0.070***	−0.043	0.090	0.063**	0.116***	0.148***
Year 2013	0.117***	0.059	0.068**	0.117***	0.145***	0.150***
Year 2014	−0.017***	−0.059***	−0.012	0.005	−0.017	−0.003
Year 2015	−0.024***	−0.179***	−0.069***	−0.029***	−0.018	0.030*
UAE Federal mortgage cap	−0.067***	−0.012	−0.009	−0.064**	−0.106***	−0.090**
DLD transaction fee	0.016**	−0.021*	−0.010	0.010	0.034***	0.011
Constant term	7.205***	6.922***	7.036***	7.203***	7.509***	7.788***
Pseudo-R^2	0.7384 (AdjustedR^2)	0.4653	0.5165	0.5232	0.5062	0.4862

Notes: [a] Standard errors are estimated but suppressed in this table; *, **, *** indicate statistical significance at the 10%, 5% and 1% confidence levels respectively; to save space, marginal effects are calculated but not presented increase in the price of a house at the 0.10 quantile point, while the effect is only about a 77 per cent increase at the 0.90 quantile point. In contrast to prior expectations, apartments are associated with a higher premium compared to villa houses, with larger premiums on houses at lower quantile points.

Location is found to be an important factor in the valuation of a house unit in Dubai. All of the location dummy variables are statistically significant and have the expected sign in the overall DLM estimation and at all quantile points. As anticipated, locations with better amenities are found to increase house prices. Specifically, houses located near waterfronts, in the city center and in newly developed areas are priced higher relative to houses located near industrial areas (the base category). On the other hand, houses located in the countryside are priced lower than houses located near industrial areas. A close look at the overall DLM and quantile regression estimation results reveals some interesting findings. Despite their expected sign and significance effect, the results show that the magnitude of effects of the location variables vary between the overall DLM and quantile regression estimation, as well as across the different quantile points. In particular, the effect of a house being located near to a waterfront varies considerably across quantile points, having a stronger effect on house prices at higher quantiles, with the median estimate higher than the overall DLM estimate. For instance, being near to a waterfront is expected to cause about a 61 per cent increase in the price of a house at the 0.90 quantile point, while the effect is only about a 21 per cent increase in price at the 0.10 quantile point and a 42 per cent increase in price in the overall DLM estimation. For houses located in newly developed areas, the effects are much stronger at higher quantile points, with the overall DLM effect marginally less than the median estimate. In contrast, being located in the countryside has a stronger (but negative) effect on house prices at lower quantile points. With regard to houses located in the city center, the result does not show an orderly effect across various quantile points, with a 76.4 per cent (highest) increase in house prices at the 0.90 quantile point, a 67 per cent increase at the 0.10 quantile point and a 44 per cent (lowest) increase in houses at the 0.75 quantile point. These findings are enlightening to house developers.

Both the UAE mortgage cap law and the DLD transaction fee law dummies are found to be statistically significant at the 1 and 5 per cent significance levels, respectively, in the overall DLM estimation. However, the former is not significant at lower quantile points (at the 0.10 and 0.25 quantile points), while the latter is insignificant at the 0.25, 0.50 and 0.90 quantile points. The UAE mortgage cap variable has a negative effect on the price of houses at the 0.50, 0.75 and 0.90 quantile points, with a stronger effect at the 0.75 quantile point. Selling a house after the UAE federal mortgage cap causes about 11 and 9 per cent increase in the price of a house at the 0.75 and 0.90 quantile points, respectively, while the increase for the overall DLM estimation is only about 7 per cent, which is roughly similar to the median estimate. Unlike its effect of increasing house prices in the overall DLM estimation and at the 0.75 quantile point, higher property transaction fees seem to suppress house sale price at the 0.10 quantile point. Selling a house after the DLD transaction fee causes about a 3.4 per cent decrease in the price of a house. This result seems rational in the Dubai housing market context where house sales are largely based on cash transactions – from purchasers' own resources or financed from abroad.

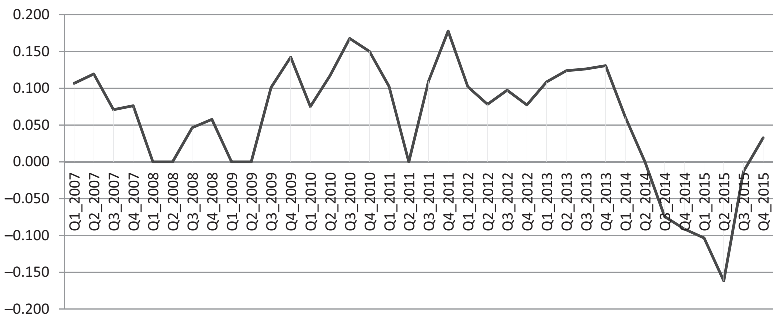
Apart from the year 2008, all of the annual time-dummy variables have significant effects and are positive for the years between 2007 and 2013, while being negative for the years 2014 and 2015 in the overall DLM estimation, with house prices peaking at 11 per cent in 2010 and 12 per cent in 2013 relative to the base year 2016. Noticeably, the effects of annual time-dummy variables vary between the overall DLM and quantile regression estimation, as well as across the different quantiles of conditional distributions, with much stronger and positive effects at higher quantile points (at 0.75 and 0.90 quantile points). Relative to Quarter 3 (the base category), quarterly dummy variables have an increasing effect on house prices in Quarter 4 and a decreasing effect in Quarter 2 and Quarter 1 (except at 010 quantile point). This trend is observed in both the overall DLM and quantile regression estimations, with observed variation in the magnitude of effect across the different quantile points.

Interestingly, all the seasonal (quarterly dummies) and annual (year dummies) variations are found to be statistically significant in both estimations. Consequently, a closer look is taken at the price trend with an alternative DLM specification. In this specification, all the independent variables remained as before, except quarterly fixed effects (Q1_2007-Q4_2015) are used in place of the quarterly and year dummies. The first quarter of year 2016 (the final quarter for the data used) is used as the reference group. The estimation result is presented in Table AIV (Appendix), where other results are present but suppressed. For better clarity, the estimation results in Table AIV are plotted in Figure 1. The results highlight the ups and downs of Dubai house prices in the study period. It shows a time-varying house price premium of 14.2 per cent in the fourth quarter of 2009, 17 per cent in the third quarter of 2010, 18 per cent (the highest) in the fourth quarter of 2011 and 13 per cent in the fourth quarter of 2013, as compared to the first quarter of 2016. On the other hand, a major drop (16.2 per cent) in the time-dependent house price premium was observed in the second quarter of 2015, as compared to the first quarter of 2016.

A similar estimation is made to describe the quarterly fixed effect on house sale prices at various quantile points. The estimation results are plotted in Figure 2. The result shows the presence of a time-varying house price trend at specific quantile points, and the magnitude of variation varies across the different quantile points. In particular, a greater fluctuation is observed at a higher quintile point (at 0.75 and 0.90 quantile points). A comparison of Figures 1 and 2 also shows that the magnitude of variation varies between the overall DLM and the quantile estimations.

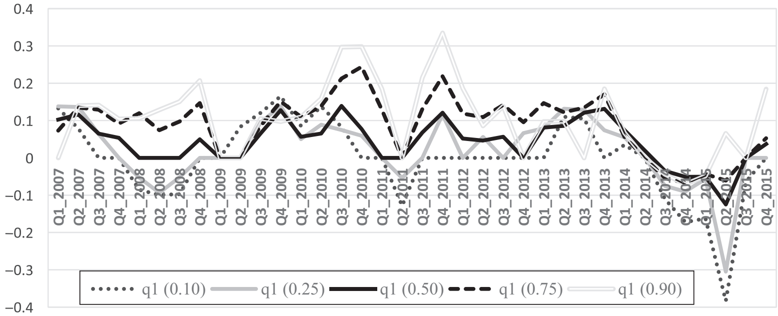
5. Conclusions and recommendations

This study addresses two increasing concerns in the house price literature: nonlinearity and heterogeneity in the relationship between house prices and attributes. It demonstrates how a combination of linear and nonlinear (semi-log, log-log and Box-Cox) and quantile regression specifications can address these concerns and better explains the real-world phenomenon. Using 10 years' pooled data from 140,039 home sales in Dubai city, the study shows that the



Note: Quarterly fixed variables (Q1_2008, Q2_2008, Q1_2009, Q2_2009, Q2_2014 and Q3_2015) are not statistically significant and hence suppressed to 0 values

Figure 1.
Estimated quarterly fixed effect on house sale prices (overall DLM)



Note: Quarterly fixed variables that are not statistically significant are suppressed to 0 values

Figure 2.
Estimated quarterly fixed effect on house sale prices (quantile models)

double-log quantile regression approach provides an overarching description of house price drivers, confirming that the price of housing and its determinants are not only nonlinearly related but also their relationship is heterogeneous across house price quantiles. Using the methodology developed, the study examines the drivers of house prices in the relationship between house prices and attributes, including the recurring patterns in day-to-day housing data in the presence of an underlying time-trend driving house sale prices.

The findings suggest various insights. In addition to higher house price variability being observed at higher quantile points, the quantile regression highlights the fact that there are noticeable differences in the way particular house attributes affect house prices across different price quantiles. Specifically, house type is found to be an important factor in house price determination and apartments are associated with a higher premium compared to villa houses, with a greater premium on houses at lower quantile points. This result contrasts with prior expectations, as privacy of villas was hypothesized to command higher prices. With regard to house location, results vary across the different quantiles of conditional distributions. The finding enlightens house developers in that it indicates that home buyers are more concerned about house location and are willing to offer higher prices for houses located near water, in city centers or in newly developed areas, with larger offer price disparity at the higher quantile points. In contrast, they are not willing to opt for houses located in the countryside unless a bigger discount is offered to them, with larger discount disparity at the lower quantile points of the distribution and considerably smaller disparity at higher quantile points.

Total area of the house (in square meters) is found to be the only variable that appears to have effects that do not vary along the entire conditional price distribution. Although the positive and significant effect of total house area is consistent with prior expectations, the similarity in magnitude of the effect of total area across different quantile points is enlightening to practitioners in the Dubai housing market in that buyers of higher-priced homes appear not to price house areas differently from buyers of lower-priced homes or medium-priced houses, and vice versa. The empirical results also show that the effects of the mortgage cap and transaction fee variables vary between the overall DLM and quantile regression estimation, as well as across the different quantiles of conditional distributions. This suggests that a “one size fits all” regulatory measure may cause unintended consequences. This result is important in the Dubai housing market context, where house sales are largely based on cash transactions – from purchasers’ own resources or financed from abroad. Noticeably, the effects of annual time-dummy variables vary across the different quantiles of conditional distributions, with much stronger and positive effects at higher quantile points. Such variation in the magnitude of effect of the quarterly dummy variables is also observed across the different quantile points. Specifically, the study shows the presence of ups and downs of Dubai housing prices and the presence of time-varying house price premium over the years. It also shows the rebounding nature of housing price as of the second quarter of 2015. Hence, caution needs to be exercised.

Overall, the methodology used in this study illuminates the way a particular house attribute can affect one quantile over another quantile, allowing buyers of higher-priced houses to behave differently from buyers of lower-priced houses or medium-priced houses, and vice versa. The results suggest that substantial robust information can be gained by using nonlinear specification of quantile regression techniques to analyze the relationship between house prices and attributes. The findings of this study are expected to suggest results with significant ramifications for practitioners, policy makers and researchers. From a policy perspective, there is an obvious interest in understanding whether the price of housing is affected by different attributes differently along its distribution.

Future work is needed to assess the relevance of the approach used in this study and the findings obtained in other contexts. The data used in this study are limited, in that information on only a few characteristics of the houses sold was available. Future research should include data on other house attributes, in addition to those used in this study. Inclusion of data such as house quality, zip codes (with their corresponding latitude and longitude coordinates) and house composition (such as number of bed rooms and bath rooms) in future research will clarify whether the watched price changes and whether changes in time-varying house price premium are due to changes in quality over time, changes in location or changes in composition of houses sold. In particular, data on house quality (building construction and age of the house) can be used to adjust house price for quality. Moreover, given the way the location dummy variable is used in this study, the issue of spatial dependence and the possible spillover effects of location on other parameters cannot be ruled out because of heterogeneity and the possibility of overlap of important house attributes represented by these location dummies. Instead, use of location coordinates should result in more robust inferences. These are areas of improvements for future house price research in Dubai. Following the methodology used in this study, appropriate functional specification tests can also be conducted even at each quantile point.

Notes

1. Based the house price index data provided by REIDIN.
2. To prevent the occurrence of such "real estate bubbles" and cool down the real estate market, the Central Bank of the UAE introduced several measures, including the federal mortgage cap on December 28, 2013 [Central Bank of the United Arab Emirates (UAE), 2013]. In addition, the DLD doubled property transaction fees from 2 to 4 percent on October 6, 2013 (Dubai Land Department, 2013).
3. The data set used in this study, as described in the methodology section, does not include information other than that used in the study. Information on house attributes such as house quality, house composition and zip codes with their corresponding latitude and longitude coordinates (to address issues of spatial dependence and the possible spillover effects of location on other parameters) is not available in the data set used and is missing in the analysis of this study.
4. Z_{li} are dummy (dichotomous) or categorical observations on L variables that are not subject to the Box-Cox transformation [equation (4)], and χ_{mi} are continuous observations on M variables for which the Box-Cox transformation will be applied.
5. Quantiles and percentiles are used synonymously. That is, the 90 quantile is the 90th percentile.

6. Information on many of the suggested attributes is not available in the data set (Section 4) used in this study. For instance, quality of the house in the form of building construction and the age of the house (Curto *et al.*, 2015; Knight *et al.*, 2000), zip codes with their corresponding latitude and longitude coordinates (Zietz *et al.*, 2008) and composition of the house such as number of bed rooms and bath rooms (Sirmans *et al.*, 2005) are important factors in house price determination, yet they are not available. For instance, if information on house quality (building construction and age of the house) was available, house price would have been adjusted for quality. Likewise, information on zip codes (with their corresponding latitude and longitude coordinates) could have been used to control for spatial dependence and the possible spillover effects of location on other parameters.
7. Information on location (region) of the house is coded using Google Maps. Using these maps, the houses are grouped in five zones. This is used to create five spatial location dummy variables for the empirical analysis. The Google mapping of the location of the sample houses can be accessed upon request from gbekele@ud.ac.ae.
8. Extreme high and low values are identified using Nick Cox's *extremes* Stata command and assessment of the descriptive statistics of the data. Accordingly, outlying cases that do not fall within the population of interest are excluded from this study. Consequently, 336 homes (priced above AED100,000,000 or below AED170) and 16 homes (with area size above 5,000 m^2 or below 2 m^2) were removed.
9. The data set used in this study can be accessed upon request from gbekele@ud.ac.ae.
10. REIDIN's index methodology covers both sides of the market – supply (asking) and demand (realized) sides – which indicates a fair average. Both transactions and asking prices are used in the index calculation, with the application of the moving average method to remove fluctuations.
11. Figure 1 presents the quantile regression coefficients for each explanatory variable in the model, with their 90 per cent confidence intervals (shaded area) and the dashed line indicating the DLM regression coefficient.
12. For instance, the figure (see the second and third graphs on the top row in Figure 1) illustrates how the effects of square footage and house type vary at various quantile points.
13. The Stata command "sqreg" followed by "test [q10 = q25 = q50 = q75 = q90] list of covariate" is used for the cross-equation hypothesis tests.

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Appendix

Variable name	Definition
Dependent variable	
Price	Sale price of the transacted housing unit, expressed in current AED
Ln(price)	Logarithm of sale price of the transacted housing unit, expressed in current AED
Real price	Sale price of the transacted housing unit, expressed in January 2003 constant AED
Ln(real price)	Logarithm of sale price of the transacted housing unit, expressed in January 2003 constant AED
Square meter	Size (total area) of the house in square meters
Square meter^2	The square of size of the house
Ln(square meter)	Logarithm of size of the house
Ln(square meter^2)	Logarithm of the square of size of the house
House type	House type dummy: 1 if house is flat, 0 if villa
Location Dummies	
Water front	1 if house is located across from or adjacent to water front
Country side	1 if house is located at country side far from the city center
Industrial area	1 if house is located in or near to industrial places
City center	1 if house is located in or near to the city center
New area	1 if house is located in new areas of the city
Quarter dummies	
Quarter1	1 if house was sold in quarter 1 (January through March)
Quarter2	1 if house was sold in quarter 2 (April through June)
Quarter3	1 if house was sold in quarter 3 (July through September)
Quarter4	1 if house was sold in quarter 4 (October through December)
Year dummies	
Year 2007	1 if house was sold in year 2007
Year 2008	1 if house was sold in year 2008
Year 2009	1 if house was sold in year 2009
Year 2010	1 if house was sold in year 2010
Year 2011	1 if house was sold in year 2011
Year 2012	1 if house was sold in year 2012
Year 2013	1 if house was sold in year 2013
Year 2014	1 if house was sold in year 2014
Year 2015	1 if house was sold in year 2015
Year 2016	1 if house was sold in year 2016
UAE Federal mortgage cap dummy	1 if house was sold before 28 December 2013, the date UAE Federal Mortgage Cap Law was effected; 0 otherwise
DLD transaction fee dummy	1 if house was sold before 6 October 2013, the date (effected) DLD doubled property transaction fees; 0 otherwise

Table AI.
Variable definition

Variable name	MIN	MAX	MEAN	SD	Mean at QUANTILES (in accordance with real price of house) Bottom 10%	Quarters First quarter	Second quarter	Third quarter	Fourth quarter	Top 10%
Price	239.82	8.24E + 07	1,322,347	1,594,728	265,607.30	353,380.20	741,072.20	1,310,853	2,884,141	4,201,073
Ln(price)	5.48	18.23	13.73	0.85	12.38	12.69	13.47	14.03	14.73	15.11
Real price	91.19	5.27E + 07	646,645.50	815,837.40	127,339.90	170,391.70	347,437.90	604,141.40	1,464,642	2,182,945
95% confidence					126,844.20	169,932.80	346,804.40	603,151.80	1,451,142	2,153,008
Interval for real price					127,835.70	170,850.60	348,071.40	605,131.00	1,478,141	2,212,882
Ln(real price)	4.51	17.78	13.02	0.83	11.68	11.99	12.74	13.30	14.06	14.47
Square Meter	2	4,995.39	114.93	101.03	48.48	55.96	87.36	124.02	192.39	246.62
Square Meter^2	4	2.50E + 07	23,414.69	167,247.70	3,042.90	4,113.73	9,938.92	20,098.90	59,508.54	102,281
Ln(square meter)	0.69	8.52	4.54	0.62	3.78	3.94	4.38	4.72	5.12	5.35
Ln(square meter^2)	1.39	17.03	9.07	1.23	7.57	7.88	8.76	9.43	10.23	10.70
House type dummy	0	1	0.95	0.21	0.98	0.99	0.96	0.91	0.96	0.99
Location Dummies										
Water front	0	1	0.50	0.50	0.09	0.13	0.50	0.73	0.86	0.93
Country side	0	1	0.44	0.44	0.77	0.66	0.26	0.11	0.04	0.03
Industrial area	0	1	0.23	0.23	0.08	0.12	0.08	0.02	0.01	0.00
City center	0	1	0.03	0.03	0.00	0.00	0.00	0.01	0.02	0.00
New area	0	1	0.32	0.32	0.06	0.09	0.15	0.14	0.08	0.04

(*continued*)

Table AII. Basic statistics and quantiles of variables, 140,039 observations

Table AII.
Basic statistics and quantiles of variables, 140,039 observations

					Mean at QUANTILES (in accordance with real price of house)					
							Quarters			
Variable name	MIN	MAX	MEAN	SD	Bottom 10%	First quarter	Second quarter	Third quarter	Fourth quarter	Top 10%
Quarter dummies										
Quarter 1	0	1	0.45	0.45	0.28	0.30	0.29	0.27	0.27	0.28
Quarter 2	0	1	0.44	0.44	0.27	0.26	0.24	0.25	0.26	0.27
Quarter 3	0	1	0.41	0.41	0.21	0.21	0.21	0.22	0.22	0.22
Quarter 4	0	1	0.43	0.43	0.24	0.23	0.26	0.26	0.25	0.23
Year dummies										
Year 2007	0	1	0.31	0.31	0.14	0.17	0.09	0.08	0.08	0.08
Year 2008	0	1	0.27	0.27	0.13	0.10	0.09	0.07	0.06	0.06
Year 2009	0	1	0.25	0.25	0.05	0.06	0.07	0.07	0.07	0.07
Year 2010	0	1	0.31	0.31	0.08	0.09	0.10	0.11	0.14	0.15
Year 2011	0	1	0.27	0.27	0.08	0.06	0.06	0.08	0.10	0.11
Year 2012	0	1	0.34	0.34	0.13	0.10	0.12	0.14	0.15	0.16
Year 2013	0	1	0.37	0.37	0.14	0.15	0.16	0.18	0.18	0.18
Year 2014	0	1	0.35	0.35	0.12	0.14	0.15	0.14	0.12	0.11
Year 2015	0	1	0.31	0.31	0.11	0.12	0.12	0.11	0.07	0.06
Year 2016	0	1	0.14	0.14	0.02	0.02	0.02	0.02	0.01	0.01
UAE mortgage cap dummy	0	1	0.73	0.44	0.74	0.72	0.70	0.73	0.79	0.81
DLD transaction fee dummy	0	1	0.70	0.46	0.72	0.69	0.67	0.70	0.76	0.78

Variable name	LRM[a] Coefficients (SE[b])	LSSLM[a] Coefficients (SE[b])	RSSLM[a] Coefficients (SE[b])	DLM[a] Coefficients (SE[b])	UBCM[a] Coefficients (SE[b])
Dependent variable	*Real price*	*Ln(real price)*	*Real price*	*Ln(real price)*	$\boldsymbol{\lambda}1 = -0.051$ and $\lambda 2 = 0.009$
Square meter	6,367.65***	0.007***	–	–	0.970** (transformed)
Square meter^2	−0.30***	−1.75E-06***	–	–	0.293** (transformed)
Ln(square meter)	–	–	807,739.70***	1.026***	–
Ln(square meter^2)	–	–	Cor. with Ln (SQMT)	Cor. with Ln (SQMT)	–
House type dummy	1,212,104.00**	0.945***	932,029.80***	0.973***	1.054*** Non transformed
Location[c] dummies					
Water front	232,700.30***	0.612***	147,880.10***	0.417***	0.466***
Country side	−33,041.15***	−0.109***	−25,395.84***	−0.104***	−0.116***
City center	456,890.90***	0.751***	435,343.50***	0.513***	0.593***
New area	114,912.90***	0.393***	30,305.78***	0.252***	0.276***
Quarter[d] dummies					
Quarter1	−3,180.05	−0.010**	3,794.95	−0.008**	−0.009**
Quarter2	−9,517.39**	−0.032***	4,357.53	−0.025***	−0.026***
Quarter4	−707.66	0.021***	−6,852.83	0.012***	0.012***
Year dummies					
Year 2007	117,755.80***	0.061**	120,575.70***	0.081***	0.091***
Year 2008	75,243.18**	0.018	60,509.25*	0.011	0.011
Year 2009	48,516.49	0.049**	61,493.62*	0.052**	0.061**
Year 2010	127,855.90***	0.105***	134,668.70***	0.111***	0.128***
Year 2011	122,717.60***	0.062**	187,930.70***	0.092***	0.112***
Year 2012	149,424.50***	0.073**	112,068.40***	0.070***	0.080***
Year 2013	114,337.30***	0.122***	104,713.70***	0.117***	0.123***
Year 2014	108,651.60	3.08E−04	−11,896.93	−0.017***	−0.028**
Year 2015	−21,888.08*	−0.068***	−17,428.75	−0.024***	−0.075***
UAE Federal mortgage cap dummy	−32,799.70	−0.059**	−36,677.65	−0.067***	−0.076***
DLD transaction fee dummy	−22205.12**	0.023**	−18,064.87	0.016**	0.017**
Constant term	−1,402,309.00***	11.017***	−4,026,110.00***	7.205***	6.457**

Notes: [a] LRM denotes linear regression model, DLM denotes double-log model, LSSLM means left-side semi-log model, RSSLM means right-side semi-log model, UBCM refers to unrestricted Box-Cox model. [b] standard errors are estimated but suppressed in this table; *, **, *** indicate statistical significance at the 10%, 5% and 1% confidence level respectively; [c] industrial area is used as reference category; these areas are often associated with air pollution brought by the industrial activities. [d] quarter 3 is used as a reference category; unlike all other months, Quarter 3 (July-September) is mostly a summer vacation time and most people travel out of Dubai; moreover, this period often coincides with "Ramadan" timing in the UAE

Table AIII. Regression estimation for linear and non-linear box-cox models

Variable	Coefficient	Variable	Coefficient
Q1_2007	0.107***	Q3_2011	0.110***
Q2_2007	0.119***	Q4_2011	0.178***
Q3_2007	0.071***	Q1_2012	0.102***
Q4_2007	0.076***	Q2_2012	0.078***
Q1_2008	0.018	Q3_2012	0.097***
Q2_2008	−0.010	Q4_2012	0.077***
Q3_2008	0.046*	Q1_2013	0.109***
Q4_2008	0.058**	Q2_2013	0.124***
Q1_2009	0.002	Q3_2013	0.126***
Q2_2009	0.022	Q4_2013	0.131***
Q3_2009	0.101***	Q1_2014	0.061***
Q4_2009	0.142***	Q2_2014	0.002
Q1_2010	0.075***	Q3_2014	−0.074***
Q2_2010	0.117***	Q4_2014	−0.091***
Q3_2010	0.168***	Q1_2015	−0.103***
Q4_2010	0.150***	Q2_2015	−0.162***
Q1_2011	0.103***	Q3_2015	−0.013
Q2_2011	−0.002	Q4_2015	0.033***

Table AIV.
DLM estimation of quarterly fixed effects[a]

Notes: Adjusted R^2 is 0.7410, F-value is 9107.82, Prob > F = 0; other results are present but suppressed; [a]other results are present but suppressed in this table; *, **, ***indicate statistical significance at the 10%, 5% and 1% confidence level

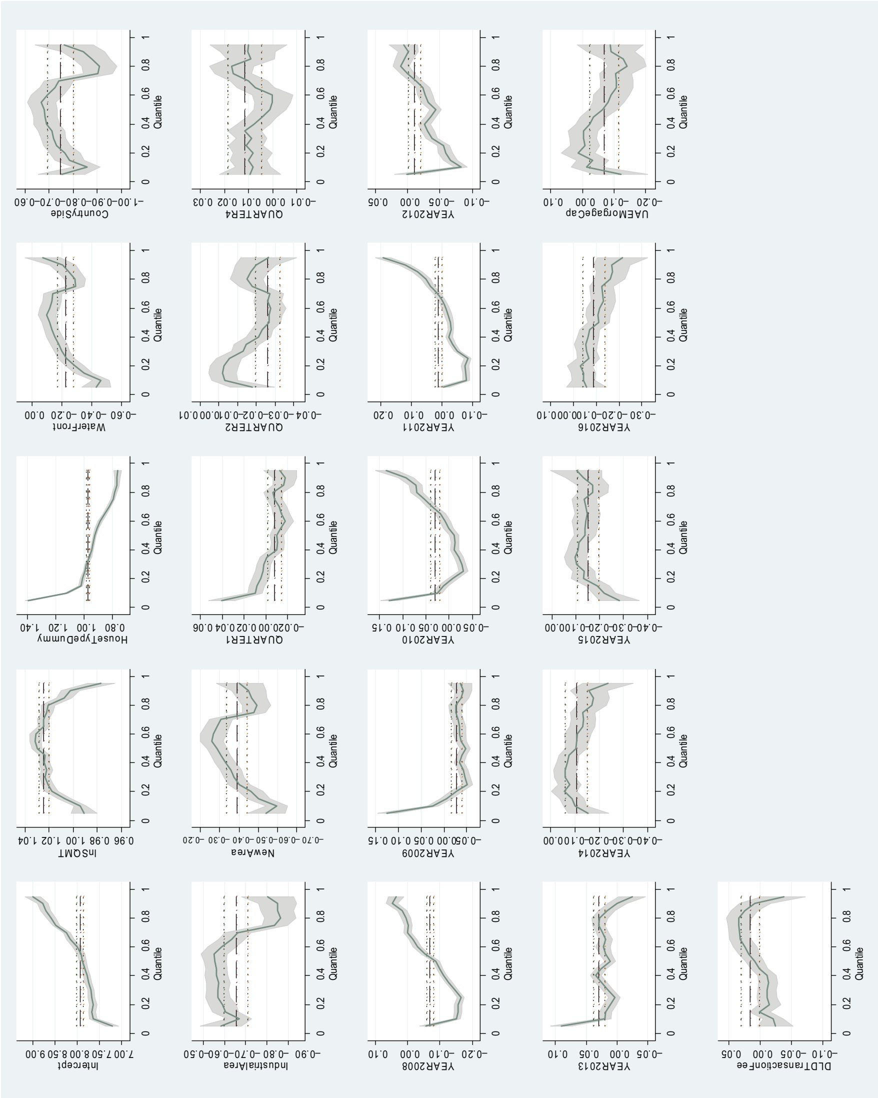

Figure A1.
Plotting coefficients
for each regressor by
quantiles

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