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Testing for Persistence with Breaks and Outliers in South African House Prices

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ABSTRACT

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Abstract

This study examines the time series behaviour of South African house prices within a fractional integration modelling framework while identifying potential breaks and outliers. We used quarterly data on the six house price indexes, namely affordable, luxury, middle-segment (all sizes, large, medium and small sizes), covering the periods 1966:Q1-2012:Q1 for the different middle-segments, 1966:Q3-2012:Q1 for the luxury segment and 1969:Q4-2012:Q1 for the affordable segment. In general, there is persistence in South African house prices with breaks identified. Our results show that in the cases of affordable and luxury, shocks will be transitory, disappearing in the long run, while for the remaining four series of the middle-segment, shocks will be permanent. Hence, for the middle-segment series strong policy measures must be adopted in the event of negative shocks, in order to recover the original trends.

Keywords: House prices, persistence, breaks, fractional integration, South Africa

JEL Classification: C16 R21

1. Introduction

Housing accounts for a large share of household expenditures and assets and a significant part of economic activity. Around half the net wealth of private households in the US and other developed countries such as the UK consists of real estate, of which the own home constitutes a substantial part (Schindler, 2012). In South Africa, housing accounts for 29.4% of

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household assets and 21.68% of total wealth (Das et al., 2011). By affecting the net wealth of households and their capacity to borrow and spend, as well as profitability and employment in the construction and real estate industries, developments in house prices have major economic implications (Maier and Herath, 2009; Posedel and Vizek, 2010). Monetary policy moves may translate to mortgage market rate changes; housing demand may change during the business cycle and housing might be a hedge against inflation (Demary, 2010, Inglesi-Lotz and Gupta, forthcoming). Asset price bubbles have potential negative effects on the economy. The departure of asset prices from fundamentals can lead to inappropriate investments that decrease the efficiency of the economy (Mishkin, 2007). Furthermore, the origin of the current global financial crisis has quite clearly demonstrated the importance of the housing market for the financial system and the economy. The importance of housing is also reflected in the great number of papers published on house price modelling.

Understanding the time series behaviour of house prices is critical in the assessment of the impact of house price shocks and structural breaks on households, firms and the general economy. Further, house intermediaries rely on price series to manage their activity, therefore investigating the statistical characteristics of prices is of paramount importance for their management (Garcia and Raya, 2011). Two important features commonly observed in house price data are persistence across time and breaks in the series (Alexander and Barrow, 1994; Gil-Alana and Barros, 2012). Persistence is a measure of the extent to which short term shocks[1] in current market conditions lead to permanent future changes (MacDonald and Taylor, 1993; Malpezzi, 1999). Modelling the degree of persistence is important in that it reflects the stability of the macroeconomic variable of the relevant country (Holmes and Grimes, 2008; Barros et al. 2011). Furthermore, the persistence of house price shocks may be

[1]A shock is an event which takes place at a particular point in the series, and it is not confined to the point at which it occurs (Gil-Alana and Barros 2012).

transmitted to other sectors and macroeconomic aggregates. Such shocks could be transitory or persistent.[2] A prior knowledge of the persistent behaviour of house prices can help real estate agents reap the benefit of positive effects, or avoid the drawbacks of a negative effect (Gil-Alana and Barros, 2012). Information on persistence is critical for policy decisions in the event of an exogenous shock, when different policy measures have to be taken depending on the degree of persistence (Himmelberg et al., 2005).

The definition of persistence is inadequate without considering the influence of breaks and outliers. Ignoring structural changes may have effects on statistical inference as well as investment allocation implications. On statistical grounds, it is shown that ignoring structural breaks in financial or economic time series can have persistence or long memory effects (Mikosch and Stărică, 2004, Hillebrand, 2005) and can have implications about the existence of higher order unconditional moments such as kurtosis or tail index (Mikosch and Stărică, 2004; Andreou and Ghysels, 2005) as well as forecasting (Pesaran and Timmerman, 2004). From an economic perspective, structural breaks can affect the returns and volatility of an economic time series, risk management measures as well as asset allocations (Andreou and Ghysels, 2005, 2006, 2009; Horváth, et al., 2006; Pettenuzzo and Timmerman, 2011). Breaks and outliers in house price data may reflect shocks in house prices due to changes in monetary or fiscal policies, fluctuations in world prices, financial liberalization and other major economic events. If house prices are stationary I(0), shocks to house prices will be transitory and following major structural breaks in house prices, the price of houses will return to its original equilibrium with the disruptions only having a temporary impact. However, if house

[2] A shock is considered to have a transitory or short term effect, if after a number of periods the series returns back to its original performance level. On the other hand, a shock is considered to have a persistence or long term impact if its short run impact is carried over forward to set a new trend in performance. A shock is known to have a transitory or short term effect, if after a number of periods the series returns back to its original performance level. On the other hand, a shock is known to have a persistence or long term impact if its short run impact is carried over forward to set a new trend in performance.

prices contain a unit root (i.e., if it is nonstationary I(1)), shocks to house prices will have persistent effects with the disruptions in the housing prices having a permanent impact on economic activity (Gil-Alana and Barros, 2012).

Several researches have been conducted on house prices for various economies around the world.[3] Although, the basic objective of most of these studies is not to test for unit root characteristics of house prices, most of these studies usually perform preliminary analysis to determine the unit root characteristics of house prices and in some cases investigate cointegrating relationships between regional house prices. As far as South Africa, our country of study is concerned, a number of studies have been conducted for the housing sector focusing on forecasting housing prices or the impact of monetary policy on housing prices or "ripple" effects or the impact of housing prices on consumption and output or the hedging property of housing or the short and long-run relationship between house and stock prices (a few recent examples: Gupta and Das, 2008; Das et al., 2009; Gupta et al., 2010; Das et al., 2010; Balcilar et al., 2011; Das et al., 2011; Simo-Kengne et al., 2012; Aye et al., forthcoming; Balcilar et al., forthcoming; Iglesi-Lotz and Gupta, forthcoming; Peretti et al., forthcoming). However, none of these studies except Gil-Alana and Barros (2012) investigated fractional integration and breaks together for housing. Therefore, this study extends the previous studies on South Africa based on I(0) and I(1) hypotheses to the fractional I(d) case, which, in turn, permits the examination of the dependence of house prices between periods. Specifically, we employ a fractional integration model adopted by Caporale and Gil-Alana (2007; 2008) and Gil-Alana and Barros (2012) which incorporates breaks and outliers in the analysis of South Africa's house price persistence.

[3] For a detailed literature review in this regard, refer to Gil-Alana and Barros (2012) and Peretti et al., (forthcoming).

2. Methodology

One characteristic of many economic and financial time series is their nonstationary nature. There exists a variety of models to describe such nonstationarity. Until the 1980s a standard approach was to impose a deterministic (linear or quadratic) function of time, thus assuming that the residuals from the regression model were stationary $I(0)$. Later on, and especially after the seminal work of Nelson and Plosser (1982), there was a general agreement that the nonstationary component of most series was stochastic, and unit roots (or first differences, $I(1)$) were commonly adopted. However, the $I(1)$ case is merely one particular model to describe such behaviour. In fact, the number of differences required to get $I(0)$ may not necessarily be an integer value but any point in the real line. In such a case, the process is said to be fractionally integrated or $I(d)$. The $I(d)$ models belong to a wider class of processes called long memory. We can define long memory in the time domain or in the frequency domain.

Let us consider a zero-mean covariance stationary process $\{x_t, t = 0, \pm 1, ...\}$ with autocovariance function $\gamma_u = E(x_t x_{t+u})$. The time domain definition of long memory states that $\sum_{u=-\infty}^{\infty} |\gamma_u| = \infty$. Now, assuming that x_t has an absolutely continuous spectral distribution, so that it has spectral density function

$$f(\lambda) = \frac{1}{2\pi}\left(\gamma_0 + 2\sum_{u=1}^{\infty} \gamma_u \cos(\lambda u)\right), \tag{1}$$

the frequency domain definition of long memory states that the spectral density function is unbounded at some frequency in the interval $[0, \pi]$. Most of the empirical literature has concentrated on the case where the singularity or pole in the spectrum takes place at the 0-frequency. This is the standard case of $I(d)$ models of the form:

$$(1-L)^d x_t = u_t, \qquad t = 0, \pm 1, \ldots, \tag{2}$$

where L is the lag-operator $(Lx_t = x_{t-1})$ and u_t is $I(0)$ defined, as a covariance stationary process with spectral density function that is positive and finite at the zero frequency. The polynomial $(1-L)^d$ in equation (2) can be expressed in terms of its binomial expansion, such that, for all real d,

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots,$$

and thus

$$(1-L)^d x_t = x_t - d x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \ldots$$

In this context, d plays a crucial role since it indicates the degree of dependence of the time series: the higher the value of d is, the higher the level of association will be between the observations (Barros et al. 2011). The above process also admits an infinite Moving Average (MA) representation such that

$$x_t = \sum_{k=0}^{\infty} a_k u_{t-k},$$

where

$$a_k = \frac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)},$$

and $\Gamma(x)$ represents the Gamma function. Thus, the impulse responses are also clearly affected by the magnitude of d, and the higher the value of d is, the higher the responses will be. If d is smaller than 1, the series is mean reverting, with shocks having temporary effects, and disappearing in the long run. On the other hand, if $d \geq 1$, shocks have permanent effects unless strong policy actions are adopted. Processes with $d > 0$ in equation (2) display the property of "*long memory*", characterised because the spectral density function of the process is unbounded at the origin. However, fractional integration may also occur at other frequencies away from 0, as in the case of seasonal or cyclical models.

In this study, we estimate the fractional differencing parameter d using the Whittle function in the frequency domain (Dahlhaus, 1989) along with a testing procedure developed by Robinson (1994) that permits us to test the null hypothesis $H_0 : d = d_0$ in equation (2) for any real value d_0, where x_t in equation (2) can be the errors in a regression model of the form:

$$y_t = \beta^T z_t + x_t, \qquad t = 1,2,..., \tag{3}$$

where y_t is the observed time series, β is a $(k \times 1)$ vector of unknown coefficients and z_t is a set of deterministic terms that might include an intercept (i.e., $z_t = 1$), an intercept with a linear time trend $(z_t = (1,t)^T)$, or any other type of deterministic processes such as dummy variables to examine the potential presence of outliers/breaks.[4]

On the other hand, it has been argued that fractional integration may be a spurious phenomenon caused by the presence of breaks in the data (Cheung, 1993; Diebold and Inoue, 2001; Giraitis et al., 2001; Mikosch and Stărică, 2004; Granger and Hyung, 2004, Ohanissian et al, 2008). Thus, we also employed a procedure that determines endogenously the number of breaks and the break dates in the series. This method, of Gil-Alana's (2008), is based on minimising the residual sum of the squares at different break dates and different (possibly fractional) differencing parameters.[5] The general model can be described as follows:

$$y_t = \beta_i^T z_t + x_t; \quad (1-L)^{d_i} x_t = u_t, \quad t = 1,...,T_b^{\,i}, \quad i = 1,...nb, \tag{4}$$

[4] This method is described in appendix 1 of Gil-Alana and Barros (2012).
[5] This method is described in appendix 2 of Gil-Alana and Barros (2012).

where nb is the number of breaks, y_t is the observed time series, the $\beta_i's$ are the coefficients on the deterministic terms, the $d_i's$ are the orders of integration for each sub-sample, u_t is $I(0)$ and the $T_b^i's$ correspond to the unknown break dates. Given the difficulties in distinguishing between models with fractional orders of integration and those with broken deterministic trends, it is important to consider estimation procedures for fractional unit roots in the presence of broken deterministic terms (Barros et al., 2012).

3. Data and Empirical Results

We used seasonally adjusted quarterly house price indexes, with the data being obtained from the Amalgamated Bank of South Africa (ABSA). ABSA categorizes housing into three price segments, namely luxury (ZAR 3.5 million – ZAR 12.8million), middle (ZAR 480,000 – ZAR 3.5 million) and affordable (below ZAR 480,000 and area between 40 square metres - 79 square metres). The middle-segment is further categorized into three more segments based on sizes, namely large-middle (221 square metres – 400 square metres), medium-middle (141 square metres – 220 square metres) and small-middle (80 square meters – 140 square meters). Thus, six house price indexes (affordable, luxury, middle class (all sizes, large, medium and small sizes)) are analysed in this study, and plotted in Figure 1. The different middle-segments of housing covers the period of 1966:Q1-2012:Q1, while the luxury and the affordable segments start from 1966:Q3 and 1969:Q4 respectively, and ends at 2012:Q1. We observe that all series increase across the sample period, and for the last four (middle class) we notice that the values stabilizes at around the year 2007.

[Insert Figure 1 about here]

In order to account for the main features of the data (i.e. their degree of dependence across time), we start by estimating the fractional differencing parameter d for each series. For this purpose, we employed a parametric approach, using the equations (2) and (3) with z_t = $(1,t)^T$, $t \geq 1$, $(0, 0)^T$ otherwise, i.e., we consider the following model,

$$y_t = \alpha + \beta t + x_t; \qquad (1-L)^d x_t = u_t \tag{5}$$

where y_t is the observed time series (log-price index), α and β are the coefficients corresponding to an intercept and a linear trend respectively, and u_t is supposed to be I(0). However, given the parametric nature of the method employed (Dahlhaus, 1989; Robinson, 1994) we need to specify a model for u_t in (5). We first assume u_t is a white noise disturbance, then we assume autocorrelated errors, and finally, given the quarterly nature of the series examined, we suppose u_t follows a seasonal AR(1) process. In the case of autocorrelated (non-seasonal) errors, we employed the model of Bloomfield (1973), which is basically an approximation to ARMA processes with a reduced number of parameters.

On the other hand, we consider the estimates of d for the three standard cases examined in the literature, i.e., the case of no regressors, i.e. $\alpha = \beta = 0$ in (5), an intercept (α unknown and $\beta = 0$) and an intercept with a linear time trend (α and β unknown in (5)). We report the estimates of d along with the 95% confidence band of the non-rejection values of d using Robinson' s (1994) parametric approach. This method uses model (5) and tests the null hypothesis, $H_0 : d = d_0$, for d_0 equal to any real value. We tried with d_0 = 0, 0.001, …, 2, i.e., from 0 to 2 with 0.001 increments, reporting in parenthesis the subset of non-rejection values of d_0.

Table 1 reports the results for white noise disturbances; Table 2 refers to the case of Bloomfield autocorrelated disturbances, while Table 3 displays the results for quarterly seasonal AR(1) errors. The first thing we observe across the three tables is that the results are very similar in the three cases of no regressors, an intercept, and an intercept with a linear trend. Moreover, the time trend is required in the six series under autocorrelated (Bloomfield) disturbances. However, with white noise or seasonal AR disturbances, the time trend is not statistically significant in some of the series.

[Insert Tables 1 - 3 about here]

Performing some diagnostic tests on the residuals of the selected models, (not reported) the results indicate that the model with Bloomfield disturbances seems to be the most appropriate in all cases, since no additional evidence of serial correlation is present.

Focusing on this model (Table 2) we notice that for all except one series (affordable) the unit root null (i.e. $d = 1$) cannot be rejected. For luxury, the estimated value of d is smaller than 1 ($d = 0.887$), while for the four middle class series, d is above 1. Nevertheless in all these cases the confidence intervals include the value of 1. A different picture emerges for affordable. Here, the estimated value of d is 0.338 and the unit root is rejected in favour of mean reversion ($d < 1$). As a conclusion, in the event of an exogenous shock in the price index of affordable, its effect will be transitory, disappearing in the long run. On the other hand, for the remaining series, the unit root cannot be rejected and shocks are expected to be permanent. Therefore, different policy measures must be adopted in affordable compared with the other cases. In the former, there is no need of strong measures in the event of an exogenous shock since the series will return by itself to its long run projection.

Next we examine the stability of the fractional differencing parameter d across the sample period, and in particular, after the crisis in 2007. We consider recursive estimates of d (and their corresponding 95% intervals), starting with a sample ending at 2006Q4, and then adding successively one observation each time till the end of the sample in 2012Q1. The results are displayed in Figure 2. In general the results are rather stable across the sample period, noting no significant differences across the estimates in each series.

[Insert Figure 2 about here]

Moreover, performing Gil-Alana's (2008) approach we do not find evidence of breaks with different fractional differencing parameters in any of the series. Using a similar methodology, we focus exclusively on changes in the deterministic terms. The general model used here is the following;

$$y_t = (\alpha + \beta t) I(t \leq T^*) + (\alpha^* + \beta^* [t - T^*]) I(t > T^*) + x_t; \qquad (1-L)^d x_t = u_t \qquad (6)$$

where $I(x)$ is the indicator function, and T^* is the time of the break. We estimate d for all potential T^* removing the first ten and the last ten observations to avoid extreme cases, choosing the value of d that produces significant coefficients for the deterministic terms with the smallest test statistic in absolute value with Robinson's (1994) method.

The results indicate that there is no break in the case of affordable, and one single break in the remaining series, occurring at 1969Q4 in the case of luxury, and at 2007Q4 for the four middle class series. Results are displayed across Tables 4-6. Table 4 refers to the case of white noise errors; Table 5 to Bloomfield autocorrelated disturbances and Table 6 to seasonal AR(1) errors. The results are consistent in the three cases: α^* and β^* are both statistically insignificant for affordable, implying the existence of a single trend in this series; β is insignificant for Luxury; and β^* is statistically insignificant in the four middle segment series.

[Insert Tables 4 – 6 about here]

Again, we observe that the most significant results are those based on Bloomfield-type disturbances (Table 5). Therefore, we summarize the main results in the table: for two series, the estimated value of d is smaller than 1 and the unit root is rejected in favour of mean reversion ($d < 1$). These series are Affordable and Luxury. For the former, the estimated value of d is 0.388 implying covariance stationary. For the latter, d is equal to 0.781 so the series is nonstationary. In any case, in the two cases, shocks will be transitory, disappearing in the long run, and faster in the case of affordable. For the remaining four series (middle-segment), the estimated value of d is slightly above 1 and the unit root null cannot be rejected implying the permanent nature of the shocks. In these series strong measures must be adopted in the case of negative shocks in order to recover the original trends.

Focusing on the deterministic terms, we observe that for affordable a linear trend is required. For luxury, the trend starts at 1970Q1; and for the four middle-segment series, the trend becomes flat at the end of 2007. The estimated trends are displayed in Figure 3.

[Insert Figures 3 and 4 about here]

A potential interpretation of our results is that the bubble is exploited in the case of the Middle class series in 2007 but this does not happen in the cases of affordable and luxury.

Figure 4 displays the log-series from 2007Q1 till 2012Q1. We observe that in the cases of affordable and luxury, the values continue increasing during this period. However, in case of the middle-segment series, the values start stabilizing. Table 7 displays the price indexes in the two periods along with the growth rate experienced. We see that the highest increases correspond to affordable and luxury (36.28% and 25.06% respectively), much higher than those corresponding to the middle-segment series.

[Insert Table 7 about here]

4. Conclusion

This study adopts a fractional integration model which incorporates breaks and outliers in the analysis of house prices in South Africa. This is a deviation from previous studies on South African house prices based on stationary I(0) or non-stationary I(1) models. Specifically, we present different specifications based on fractional integration, first with no breaks, and then allowing for breaks to describe time series dependence of South African house prices. Our analysis is also conducted with different specifications for the disturbance term. Our results show evidence of long memory ($d > 0$) in all house prices, with orders of integration ranging widely from 0.388 to 1.173 depending on the series under study and the specification of the error term, but with mean-reversion for the affordable and the luxury segments of the housing market. Note that, the price of the affordable segment is controlled by the government, so even though the house price is persistent within this category, in the long-run it tends to revert back to its mean value. At the other end of the market, the mean reversion for the luxury segment is, perhaps, an indication of the smaller number of demanders and suppliers interacting in these markets, resulting in correction of the deviation of the house price from its mean value, but at a slower rate than the affordable segment, since the price is determined freely in the market of the luxury segment. Very high persistence and the lack of mean reversion for the different categories of the middle-segment housing, is likely due to a fall out of large number of economic agents (both on the supply and demand sides) operating in this market, and, hence the difficulty in getting the market cleared up immediately after a shock to the economy. It takes time for buyers and sellers of existing houses to find each other, and also for developers to bring new houses to market after an increase in demand and to work off inventories when demand weakens. Also, as indicated by Inglesi-Lotz and Gupta (forthcoming), the middle-segment of the housing market provides a hedge against inflation, since housing within this segment is not only viewed as a consumption good, but also as an investment opportunity, resulting in a large number of continuous transactions, with agents taking advantages of the hedging opportunities.

Focusing on changes in the deterministic terms, the results indicate that there is no break in the case of affordable, and one single break in the remaining series, occurring at 1969Q4 in the case of luxury, and at 2007Q4 for the four middle-segment series. The 2007 break date corresponds to the global financial crisis. Mean reversion is obtained in the case of affordable and luxury with their orders of integration strictly below 1, which indicates that shocks are transitory and mean reverting, disappearing in the long run. For the remaining four series, the orders of integration are slightly above 1 and the null of unit root cannot be rejected implying that shocks are permanent and the series are persistent. Focusing on the deterministic terms, we observe that for affordable a linear trend is required. For luxury, the trend starts at 1970Q1; and for the four middle-segment series, the trend becomes flat at the end of 2007. This implies that the bubble is exploded in the case of the middle class series in 2007 but this does not happen in the cases of affordable and luxury. Our results have important policy implications: First, taking first differences of affordable and luxury house prices under the assumption of a unit root could lead to series that are over-differenced and subsequently such a procedure may result in inappropriate policy actions. Second, in the event of a negative shock, strong policy measures will have to be adopted to revert the middle-segment house prices to their original trend whereas affordable and luxury series will not require strong policy measures as they will return to their equilibrium levels over time, Finally and perhaps more importantly, given that South Africa is an inflation targeting country,[6] the persistence property of house prices is of paramount importance, since it is likely to affect the persistence property of the aggregate inflation of the economy, as pointed out by Gupta and Hartley (forthcoming) through their results that house prices lead inflation (and real economic activity). Increase (decrease) in house prices following an increase (decrease) in housing demand, would lead to an increase (decrease) in residential investment, which in turn, would cause aggregate demand to increase (decrease) resulting in inflationary (deflationary) pressures. Now, depending on which segment of the housing market the shock originates from, the behaviour of the inflation in the economy is going to be different: while,

[6] Since the announcement made by the minister of Finance in the February of 2000, the sole objective of the South African Reserve Bank (SARB) has been to achieve and maintain price stability. More specifically, the SARB has now adopted an explicit inflation targeting regime, whereby it aims to keep the Consumer Price Index (CPI) inflation within the target band of 3 percent to 6 percent, using discretionary changes in the Repurchase (Repo) rate as its main policy instrument.

the impact of a house price increase on domestic inflation would be persistent but mean reverting if the shock originates in the luxury and affordable segments, the effect on inflation would be permanent if the shock is observed in the middle-segment, which in any event is likely to be the case, since the dominant proportion of the South African population resides in middle-segment housing. Clearly then, the response of the monetary authority in terms of the adjustment to the policy rate to affect inflation appropriately, is closely tied to which segment of the housing sector the shock in house price surfaces from, with likely changes in the policy rate if house prices changes in the middle-segment.

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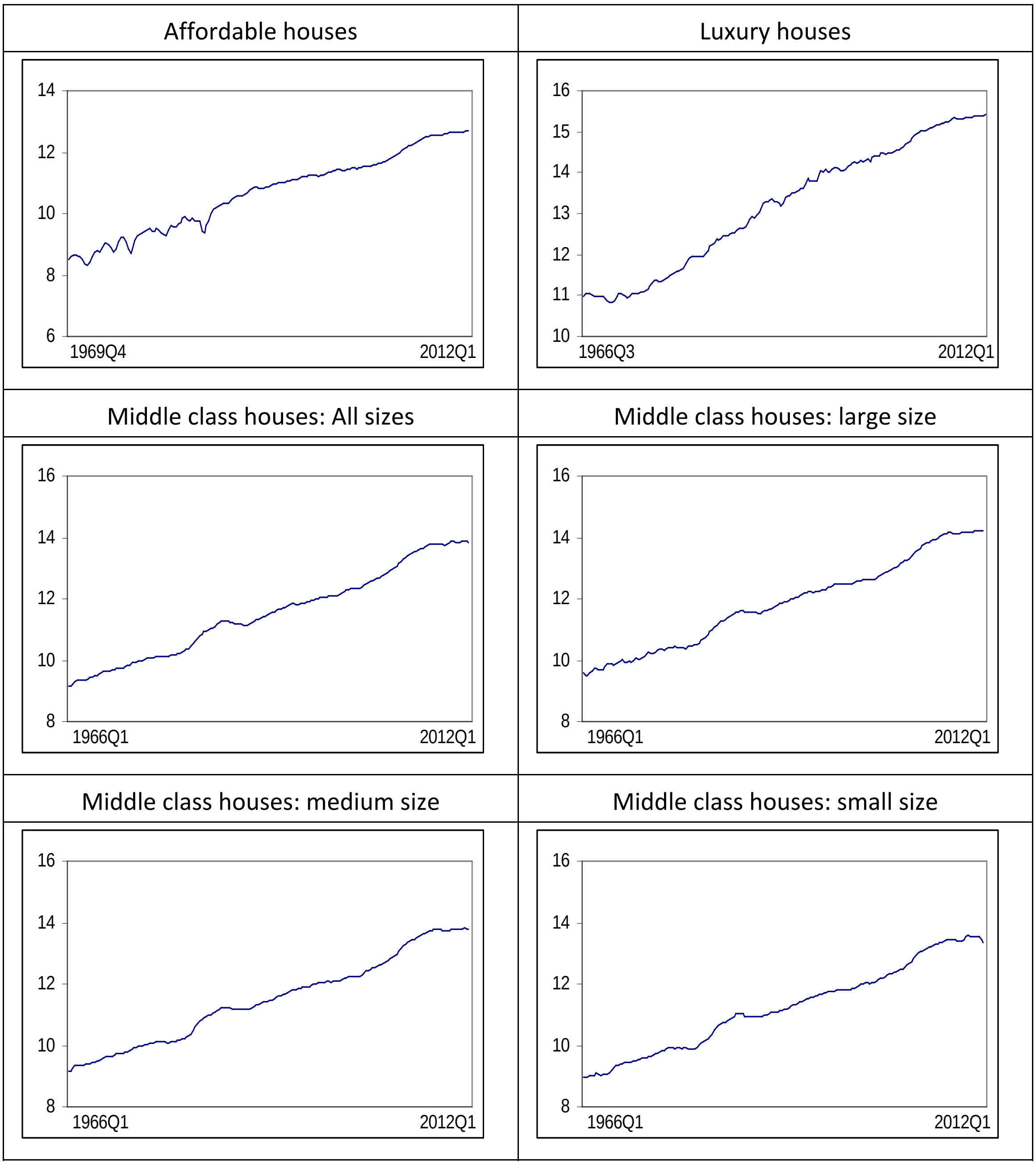

Figure 1: Log-transformed time series

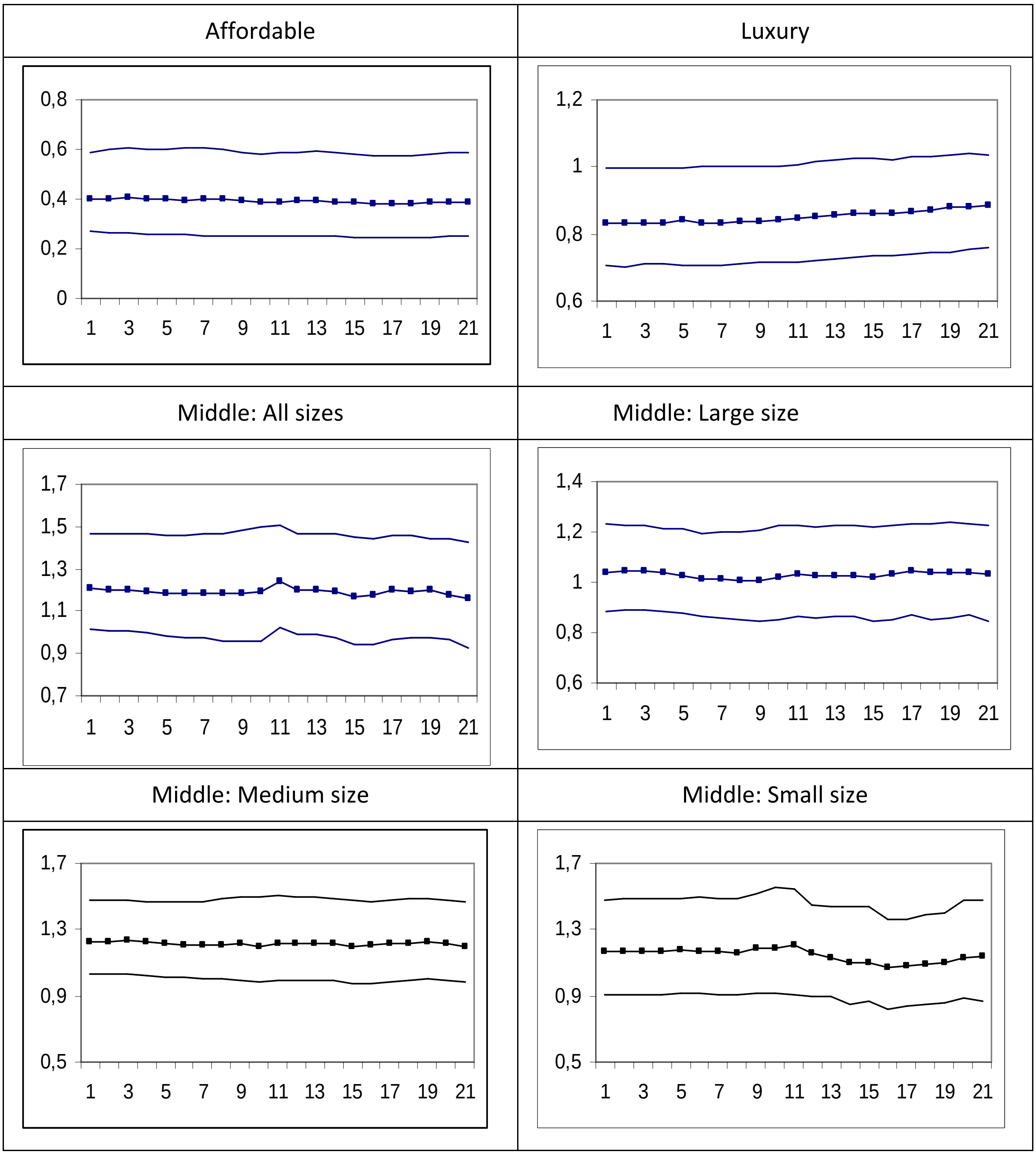

Figure 2: Recursive estimates of *d* with data ending at 2006Q4, and adding one observation each time

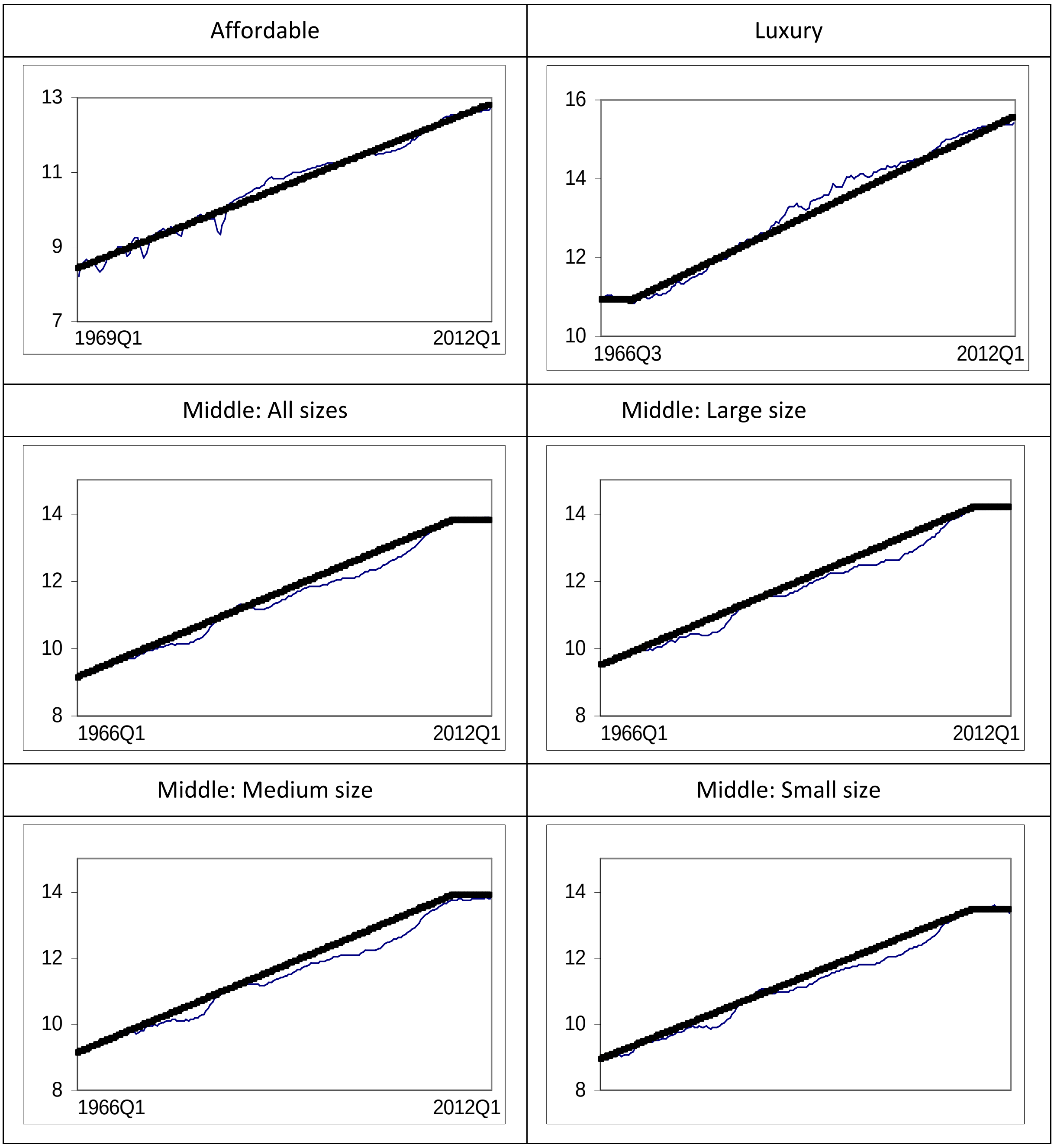

Figure 3: Log-series and the estimated time trends from 2007Q1

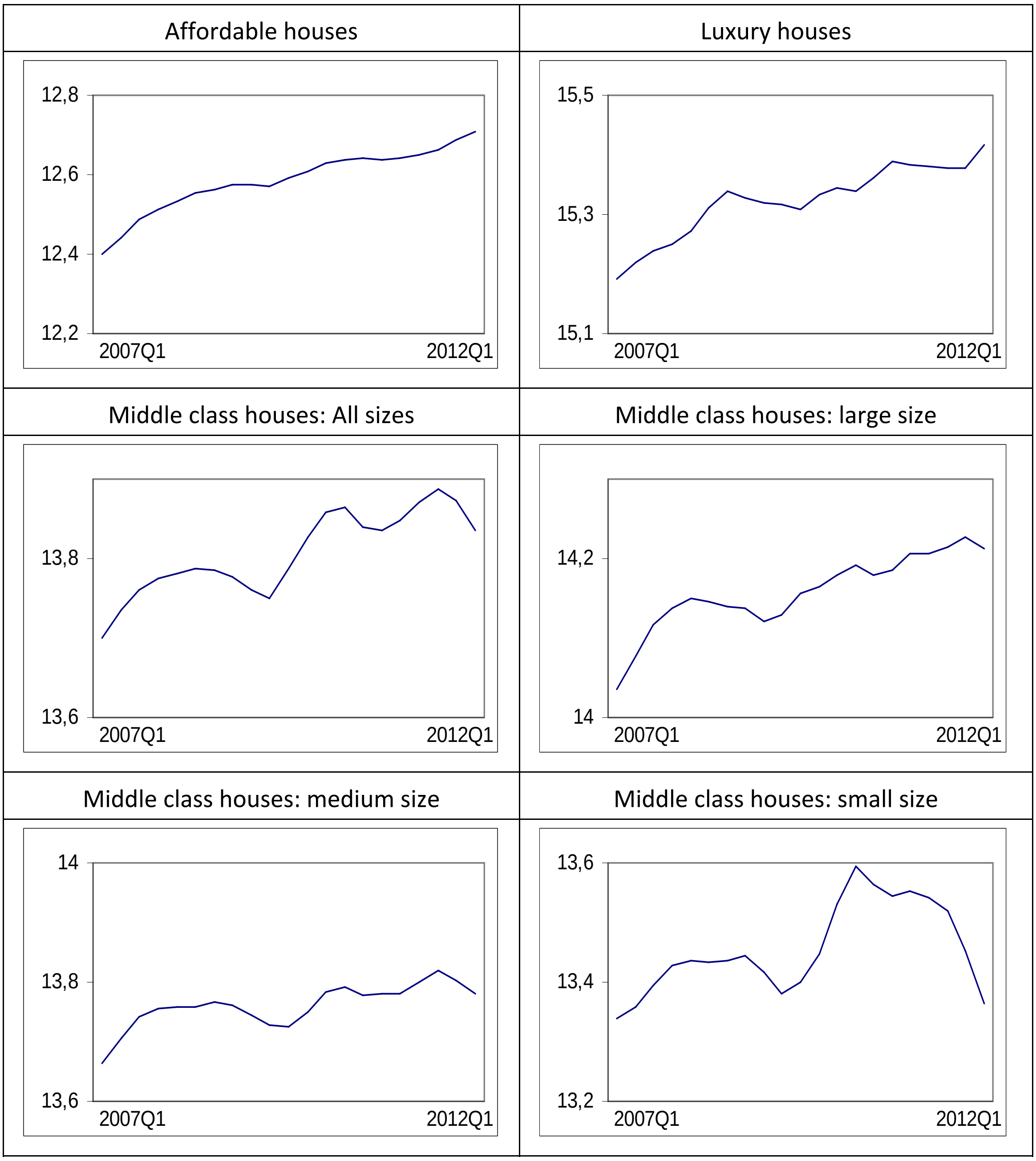

Figure 4: Log-transformed time series

Table 1: Estimates of *d* and 95% confidence interval: White noise disturbances

Series: Original	No regressors	An intercept	A linear time trend
Affordable	1.333 (1.229, 1.482)	1.333 (1.223, 1.449)	**1.347** **(1.244, 1.496)**
Luxury	1.151 (1.088, 1.255)	1.162 (1.091, 1.265)	**1.184** **(1.105, 1.293)**
Middle: All sizes	1.261 (1.161, 1.391)	1.233 (1.152, 1.374)	**1.261** **(1.174, 1.395)**
Middle: Large size	1.526 (1.406, 1.791)	**1.499** **(1.362, 1.736)**	1.521 (1.382, 1.742)
Middle: Medium size	1.277 (1.166, 1.412)	1.252 (1.152, 1.393)	**1.283** **(1.172, 1.427)**
Middle: Small size	1.070 (0.973, 1.261)	1.068 (0.961, 1.234)	**1.081** **(0.978, 1.263)**

Note: bold indicates the cases where the deterministic components (intercept and time trend) are statistically significant at the 5% level.

Table 2: Estimates of *d* and 95% confidence interval: Bloomfield disturbances

Series: Log-transform	No regressors	An intercept	A linear time trend
Affordable	0.930 (0.764, 1.148)	0.689 (0.651, 0.753)	**0.388** **(0.249, 0.585)**
Luxury	0.928 (0.769, 1.136)	0.928 (0.865, 1.037)	**0.887** **(0.758, 1.036)**
Middle: All sizes	0.945 (0.797, 1.141)	1.149 (0.980, 1.408)	**1.160** **(0.927, 1.422)**
Middle: Large size	0.936 (0.782, 1.140)	1.049 (0.945, 1.238)	**1.032** **(0.847, 1.229)**
Middle: Medium size	0.947 (0.792, 1.152)	1.185 (1.010, 1.449)	**1.193** **(0.981, 1.470)**
Middle: Small size	0.929 (0.782, 1.131)	1.105 (0.918, 1.441)	**1.134** **(0.869, 1.479)**

Note: bold indicates the cases where the deterministic components (intercept and time trend) are statistically significant at the 5% level.

Table 3: Estimates of *d* and 95% confidence interval: Seasonal AR disturbances

Series: Original	No regressors	An intercept	A linear time trend
Affordable	1.738 (1.622, 1.907)	**1.742** **(1.631, 1.915)**	1.737 (1.637, 1.909)
Luxury	1.295 (1.222, 1.407)	1.288 (1.217, 1.399)	**1.307** **(1.237, 1.407)**
Middle: All sizes	2.251 (1.966, 2.583)	**2.325** **(2.051, 2.653)**	2.329 (2.055, 2.658)
Middle: Large size	1.763 (1.677, 1.898)	**1.785** **(1.682, 1.915)**	1.789 (1.684, 1.921)
Middle: Medium size	1.975 (1.791, 1.923)	**2.023** **(1.842, 2.297)**	2.023 (1.845, 2.294)
Middle: Small size	1.903 (1.723, 2.135)	**1.922** **(1.743, 2.156)**	1.923 (1.744, 2.155)

Note: bold indicates the cases where the deterministic components (intercept and time trend) are statistically significant at the 5% level.

Table 4: Results with breaks in the deterministic terms and white noise disturbances

Series	Break date	α (t-val.)	β (t-val.)	α^* (t-val.)	β^* (t-val.)	d (95% C.I.)
Affordable	XXX	8.1005 (115.92)	0.0451 (1.743)	XXX	XXX	1.382 (1.081, 1.831)
Luxury	1969Q4	10.9066 (271.95)	XXX	10.5200 (111.54)	0.0270 (4.857)	1.124 (0.998, 1.316)
Middle: All sizes	2007Q4	9.1081 (596.75)	0.0245 (1.849)	13.2324 (5.947)	XXX	1.714 (1.564, 1.919)
Middle: Large size	2007Q4	9.4454 (340.42)	0.0293 (3.912)	14.3859 (11.412)	XXX	1.279 (1.177, 1.427)
Middle: Medium size	2007Q4	9.0927 (587.66)	0.0298 (2.272)	14.1141 (6.399)	XXX	1.699 (1.559, 1.894)
Middle: Small size	2007Q4	8.9065 (392.15)	0.0288 (2.043)	13.7670 (5.796)	XXX	1.538 (1.407, 1.704)

Note: XXX indicates statistical insignificance.

Table 5: Results with breaks in the deterministic terms and autocorrelated (Bloomfield) disturbances

Series	Break date	α (t-val.)	β (t-val.)	α^* (t-val.)	β^* (t-val.)	d (95% C.I.)
Affordable	XXX	8.3880 (235.28)	0.0260 (70.316)	XXX	XXX	0.388 (0.249, 0.585)
Luxury	1969Q4	10.9355 (261.96)	XXX	10.5059 (167.79)	0.0276 (22.68)	0.781 (0.664, 0.929)
Middle: All sizes	2007Q4	9.1078 (439.78)	0.0278 (9.905)	13.7966 (219.17)	XXX	1.121 (0.933, 1.360)
Middle: Large size	2007Q4	9.4567 (313.56)	0.0279 (10.130)	14.1572 (30.564)	XXX	1.036 (0.884, 1.202)
Middle: Medium size	2007Q4	9.0953 (453.29)	0.0284 (8.226)	13.8692 (23.903)	XXX	1.173 (0.997, 1.411)
Middle: Small size	2007Q4	8.9047 (317.16)	0.0270 (9.082)	13.4627 (26.861)	XXX	1.068 (0.833, 1.397)

Note: XXX indicates statistical insignificance.

Table 6: Results with breaks in the deterministic terms and seasonal AR disturbances

Series	Break date	α (t-val.)	β (t-val.)	α^* (t-val.)	β^* (t-val.)	d (95% C.I.)
Affordable	XXX	9.4429 (343.74)	0.0267 (2.431)	XXX	XXX	1.330 (1.103, 1.764)
Luxury	1969Q4	10.9039 (273.71)	XXX	10.5179 (98.408)	0.0272 (4.040)	1.165 (1.059, 1.318)
Middle: All sizes	2007Q4	9.1022 (596.34)	0.0238 (1.708)	13.1381 (5.593)	XXX	1.751 (1.614, 1.923)
Middle: Large size	2007Q4	9.4425 (343.45)	0.0301 (3.350)	14.5151 (9.608)	XXX	1.328 (1.216, 1.481)
Middle: Medium size	2007Q4	9.1075 (589.22)	0.0291 (2.074)	14.0169 (5.933)	XXX	1.749 (1.623, 1.917)
Middle: Small size	2007Q4	8.9096 (393.97)	0.0286 (1.856)	13.7318 (5.295)	XXX	1.538 (1.407, 1.704)

Note: XXX indicates statistical insignificance.

Table 7: Growth rates in price indexes from 2007Q1 till 2012Q1

Series	2007Q1	2012Q1	Growth rate
Affordable	242959	331126	36.28%
Luxury	3961101	4953866	25.06%
Middle: All sizes	891540	1019411	14.34%
Middle: Large size	1245479	1487260	19.41%
Middle: Medium size	858212	966943	12.66%
Middle: Small size	621709	636544	2.38%