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HOUSING MARKET CYCLES IN LARGE URBAN AREAS

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Housing Market Cycles in Large Urban Areas

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Abstract

This paper examines the asymmetric behaviour of house prices in large metropolitan areas. Using a sample of large cities, in several countries, it is shown that real estate prices cycles are largely nonlinear. It is found that dynamic asymmetries in the housing market cycle can well be modelled using a logistic smooth transition model (LSTAR). Further, it is shown that the LSTAR model has better forecasting properties with respect to a linear autoregressive model.

Keywords: Housing Markets, Asymmetric Cycles, Large Urban Areas, Non-Linear Models.

JEL Classification: C10, C31, C33.

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1. Introduction

Fluctuations in house price and their impact on the financial system have attracted much attention following the recent global financial crisis. Thus far, a well-established literature has maintained that house prices cyclicality is closely related to the behaviour of macroeconomic fundamentals (see for example Edelstein and Tsang, 2007; and Claessens, 2008 among others). However, while cyclicality of housing market is well documented in the literature, little attention has been paid to the asymmetry of housing market cycles.

If by "symmetry" of the housing market cycle we mean that negative shocks have symmetric effects on the absolute values of real estate price series so that a positive shock of equal magnitude would return the stochastic process to its original position, then empirical evidence shows that this degree of symmetry is not evident in the most housing market data. For example, the results in Glaeser and Gyourko (2006) show that for house price series, stochastic processes such a pure random walk fails quite badly in describing the features of house price cycles. Also, a simple data plot for many time series would reveal that housing prices adjust asymmetrically to economic shocks. This widely acknowledged empirical evidence has prompted economists to deliver theoretical models to explain this phenomenon. Asymmetric adjustment in the demand-supply market provides one such explanation. Broadly speaking, in the economic literature, theoretical models used to describe housing market cycles fall within the demand-supply framework, where supply is assumed to be rigid. For example, Abraham and Hendershott (1993) describe an equilibrium price level to which the housing market tends to adjust. The authors divide the determinants of house price appreciation in two groups: one that explains changes in the equilibrium price and another that accounts for the adjustment mechanism in the equilibrium process. Slow adjustment toward the equilibrium can be regarded as an indication of asymmetries in real estate cycles. Muellbauer and Murphy (1997) explore the behaviour of house prices in the UK. The authors suggest that the presence of transaction costs associated with the housing market cause important nonlinearity in house price dynamics.

While economic theory suggests that asymmetry may be a characteristic feature of real estate markets there have not been many attempts at modelling this phenomenon in an explicit fashion. Many empirical works make use of vector autoregressions in which house price series is assumed to be nonstationary and cointegrated with a set of house price determinants. These econometric models assume that, in the long-run, deviations from the demand-supply equilibrium would trigger a market correction of the mispricing. For example, Hendershott and Abraham (1993) estimate a cointegrated model which includes lagged house price changes among other explanatory variables. They found evidence of slow adjustment toward the equilibrium which implies a cyclical adjustment path. Abelson, Joyeux and Milunovich (2005) estimate an asymmetric threshold cointegrated model to investigate nonlinearity in house prices in Australia. Malpezzi (1999) analyses the impact of supply and demand factors on the path of house price adjustments. Vector error correction models and other types of linear models are able to capture many of the characteristics observed in housing market series data. However, asymmetric adjustments across cycles cannot be captured adequately by a linear representation. Modelling asymmetry requires nonlinear time series models. As the majority of empirical works are based upon econometric methods that work under the assumption of symmetry and linearity, in the presence of asymmetry and nonlinearity these models assuming symmetry would clearly be misspecified and may lead to spurious empirical results (see for example Blatt, 1980).

In this paper we consider the real estate market in large urban areas. In general, housing market dynamics are determined by demographic and socio-cultural factors, economic conditions, local jurisdictions and the financial system. However, metropolises have in common high demand pressure in the housing market often coupled with inelastic supply. Also tight land use controls and regulations leave large cities prone to high housing market. It is likely that housing markets in large urban areas, especially major financial centres, have different dynamics than smaller urban settlements. In this respect, few recent studies support this conjecture. For example, Glaeser, Gyourko and Saiz (2008) illustrate that during boom phases house prices in the US grow much more strongly in metro areas with inelastic supply. Saiz (2010) and Hilber and Vermeulen (2010) demonstrate that geographical restrictions constrain the elasticity of supply: in cities that lack construction land, urbanisation leads to price increases.

A fundamental question that has not been adequately addressed in the empirical literature on housing prices is whether home prices in large cities are nonlinear. There is plenty of theoretical discussion on a type of non-rational behaviour that generate bubbles in the housing markets but, to the best of our knowledge, none that consider specifically data at high disaggregate level. For example, Seslen (2004) argues that households exhibit rational responses to returns on the upside of the market but do not respond symmetrically to downturns. Seslen also argues that on an upswing of the housing cycle households exhibit forward looking behaviour and are more likely to trade up, with equity constraint playing a minor role. On the other hand, households are less likely to trade when prices are on the decline causing stickiness on the downside of the housing market cycle. It is likely that this effect that the author describes is much stronger in large metropolitan areas than smaller urban centres.

In this paper the empirical investigation is conducted in three stages. We start our analysis by examining the main features of the real estate market cycles. Questions of interest in the first stage of our research are: What are the main features of large urban areas housing market cycles? Is it actually the case that in large metropolitan areas real estate market expansion phases last longer that contraction periods? Also, what are the characteristic of the amplitude of the cycles? In order to answer these questions, we borrow from methods widely employed in the business cycle literature. In particular, we use the algorithm suggested by Harding and Pagan (2002), which extends the so-called BBQ algorithm developed by Bry and Boschan (1971), to identify the turning points in the log-differences of house price series.

Once that the characteristic of the real estate market cycle has been identified we proceed to the second step of our research and turn our attention to modelling asymmetries in housing market cycles. To this end the logistic smooth transition autoregressive (LSTAR) (see Teräsvirta, Van Dijk, and Medeiros, 2005) is used to capture dynamic asymmetries in the housing market. In the literature a related study is the work by Kim and Bhattacharya (2009) where an exponential smooth transition autoregressive model (ESTAR) to model nonlinearity in the regional hosing market in the United States. Nonlinear models are also used in Crawford and Fratantoni (2003) to forecast house price changes. Regime-switching models such as ESTAR allow the dynamic of house price growth rates to evolve according to a smooth transition between regimes that depends on the sign and magnitude of past realization of house price growth rates (see Chan and Tong, 1986). The low speed of transition between different regimes in house price growth found in empirical studies validates the choice of smooth transition models. A possible shortcoming of this type of nonlinear models is that a symmetric transition function is used to capture oscillations from the conditional mean of the changes in the house price series. Although regime-switching model may efficiently describe nonlinearity in house price growth rates, they may not be suitable to capture dynamic asymmetries in real estate cycles. In this respect, the type of transition function used in this paper allows us to model the smooth transition between states of expansions and contractions which is a characteristic feature of the housing markets while being able to capture the asymmetry in the real estate cycle observed in the analysis of the turning points.

In the final stage we consider whether forecasting using the LSTAR model leads to important improvements over forecasting with an incorrectly specified linear model. In the literature, the issues of the forecasting performance of nonlinear model is still an open question. For example, Balcilar, Gupta and Miller (2015) use a STAR-type model to forecast house price distributions in United States. They found that the use of nonlinear models to forecast house prices typically does not generate improvements in forecast performance, especially at short horizons, to justify the additional costs of nonlinear forecasts. On the other side, Cabrera *et al*. (2011) compare the out-of-sample forecasting performance of international securitized real estate returns using linear and non-linear models. They compare the performance of a number of nonlinear models to the benchmark linear AR model. They conclude that nonlinear models produce better out-of-sample forecasts. Similarly, Miles (2008) using the generalized autoregressive model concludes that the nonlinear specification has superior performance in out-of-sample forecasting especially in housing markets traditionally associated with high home-price volatility.

The remainder of this paper is organised as follows. In Section 2 some theoretical background on housing market cycle asymmetry is introduced. In Section 3 the characteristic of the housing market in large metropolitan areas are investigated. In Section 4 the testing and modelling procedure are briefly discussed before presenting the empirical results. In Section 5 the forecasting properties of the LSTAR are considered. Finally, in Section 6 some concluding remarks are given.

2. Asymmetries in Real Estate Cycles

The dynamic of house prices over phases of the business cycle has long been an object of interest to economists. As Sichel (1993) points out an asymmetric cycle occurs when one phase of the cycle is different from the mirror image of the opposite phase. The literature on housing market cycles is closely related to the real business cycle from which it originated. Early evidence of asymmetry in the business cycle research go back to Burns and Mitchell (1946) where it was found that contractions are steeper, but shorter, than expansions, so that both the average duration and the dynamics of the two phases of the business cycle differ. An important break-through in the analysis of asymmetric adjustment in economic time series is provided by Sichel (1993). In this seminal study, univariate tests of deepness and steepness were developed to examine the possibility of asymmetry in the both the levels and changes of adjustment of time series. Sichel (1993) refers to "steepness" as a type of asymmetry which occurs in the business cycle when troughs are deeper than peaks. In this case recessions and expansions are characterized by the same duration (symmetry along the time axis), but the cycle undergoes a steep fall and a steep recovery, then it peaks at a slower rate and starts falling at a slow, but accelerating, rate; as a result, the distribution of the cyclical component is negatively skewed, with a positive mode (Proietti, 1999). On the other side, deepness considers the possibility that in business cycle peaks and troughs may differ in terms of their respective distances from an underlying trend. Recently, asymmetric behaviour of the business cycle has been analysed in the amplitude-frequency domain and latent factor models have been used to identify the feature of the cycle (see for example Koopman and Lucas, 2005).

Although asymmetries were investigated by early business cycle researchers, the issue has only recently been examined empirically in the housing market context. Holly and Jones (1997) examine asymmetry in aggregate UK house prices and Cook and Holly (2000) consider asymmetry in UK house prices disaggregated according the age, or vintage. Brake (2013) analyses the duration of house price upturns and downturns for 19 OECD countries and found that downturns display duration dependence. In a rare study Cook and Watson

(2017) analyses price adjustment in the London market and find that asymmetric adjustment in house price was particularly evident in the more expensive Inner London region. All these empirical works reveal that asymmetries, well known in the business cycle literature, are also a feature of the housing market. These findings have important implications for the financial stability of the countries involved. This is because as expansions get longer, they are increasingly likely to terminate, signalling a progressively unsustainable departure from fundamental price valuations. Contractions often act as adjustment periods after long expansions: the longer the expansion, the deeper and more painful the subsequent contraction.

Coming to modelling issue, modelling asymmetries in the real estate markets requires special care since, as already mentioned, models that relay on the linear and Gaussian assumptions are incapable of generating asymmetric fluctuations. Evidence of asymmetry may guide empirical investigators toward a particular class of econometric nonlinear specifications able to model asymmetric disturbances. In this respect, the type of nonlinear models used to capture asymmetry need to accommodate for the fact that the phenomenon under investigation behaves differently according to the state of the system defined in terms of a function of a transition variable. Along with the regime switching variable the transition mechanism (that is the way the system moves from one state to another) needs to be specified. Different combinations of transition variables and transition mechanisms produce a variety of nonlinear models that have been used to model the features of the housing market prices. One model often used in the literature to identify housing price expansion and contraction phases is the Markov switching model suggested by Hamilton (1993). In this specification the parameters of the autoregressive data generating process vary according to the states of a latent first-order Markov chain. Empirical studies that follow this approach are Suarez and Ceron (2006), Chowdhury and McLennan (2014) and Miles (2008) among others. Other type of nonlinear models that allow for regime change can be the Threshold Autoregressive Model (TAR), developed by Tsay (1989), or the smooth transition autoregressive (STAR) model developed by Luukkonen, Saikkonen, and Teräsvirta (1988). While TAR and Markov switching models specify a sudden transition between regimes with a discrete jump, the dynamics of the STAR model allows a smooth transition between regimes. Examples of applications to the housing market cycles are Kim and Bhattacharya (2009) and Crawford and Fratantoni (2003) among others.

3. Data and Descriptive Statistics

The data under consideration are related to monthly residential properties prices over the period 1996:1 to 2015:12 for six large metropolitan areas. Namely, New York, Tokyo, Seoul, Hong Kong, Rome and Amman. The data were collected from Bloomberg for all metropolitan areas but Amman for which data were collected from Central Bank of Jordan.

As far as the sample selection is concerned, some cities such as Rome, Amman and Tokyo have been selected as representative of bank-based financial systems where banks play a leading role in mobilizing savings, allocating capital, overseeing the investment decisions of corporate managers, and providing risk management vehicles. Other cities such as New York, Hong Kong and Seoul have been selected as a representative sample of metropolitan areas that are major financial centres in market-based system where securities markets share centre stage with banks in getting society's savings to firms, exerting corporate control, and easing risk management. Finally, Amman has been considered as an example of metropolitan areas that experienced great pressure on the demand side of the housing market not so much because of fast economic development, but rather for pressure due to political turmoil in the neighbour countries. Like many other cities in the Middle East, Amman experienced a surge of the refugee population which has an impact on the local property market. The conflict in neighbouring Syria has meant an influx of as many as 1.5 million Syrian refugees since 2011, these in addition to a large influx of Palestinian and Iraqi refugee present also before the Syrian civil war. All in all, the sample represents a good balance of the heterogenous type of financial, political and cultural systems which affect the housing market of large metropolitan areas.

Table 1 reports some descriptive statistics for the data under consideration. From Table 1 it appears that house price volatility in New York was the highest during the period under consideration, whereas Rome presents the most stable prices. Also, the Jarque-Bera (JB) test rejects the null hypothesis of normality for all the series under consideration. The JB test results are corroborated by the skewness and the kurtosis indexes suggesting that house prices are not normally distributed. Finally, the Augmented Dickey Fuller (ADF) test suggests that house price levels follow a random walk process, so that the series of house price changes are stationary. Note that the descriptive statistics are reported for the series in levels, whereas the ADF test relates to the series in first differences.

Table 1. Descriptive Statistics of house prices in the sample.

	Rome	*Tokyo*	*Seoul*	*Amman*	*New York*	*Hong Kong*
Mean	104.6	108.8	75.8	167.2	130.4	105.8
Std. Dev.	10.6	13.4	21.2	14.9	30.4	14.10
Skewness	-0.39	1.33	-0.23	0.45	-0.64	0.56
Kurtosis	2.43	3.95	1.40	1.66	1.81	2.49
JB	8.90**	80.35*	27.54*	25.88*	30.59*	15.03*
ADF	-4.00*	-23.86*	-5.69*	-12.68*	-5.85*	-16.71*

Note: *) **), ***) refer to the 1%, 5%, 10% significance level respectively. “ADF” relates to the Augmented Dickey–Fuller test for unit root and “JB” is the Jarque-Bera test for normality.

3.1. Identifying House Price Cycles

To identify house price cycles, we borrow from the business cycle literature and use the Harding and Pagan (2002) algorithm to detect turning points. The procedure consists in finding a series of local maxima and minima that allow segmenting the series into period of house price expansions and contractions. The algorithm is basically a pattern-recognition program which involves finding points which are higher or lower than a window of surrounding points. Having located the turning points, the duration between these points are measured and a set of censoring rules is then adopted which restricts the minimal lengths of any phase as well as those of complete cycles.

Let Y_t the series of house prices and Δ the first difference operator. Define $y_t = \Delta \log Y_t$, then the turning point of y_t at time *t* is defined as peak if the event

$$\{y_{t-k} < y_t > y_{t+k}\},$$

and a trough if

$$\{y_{t-k} > y_t < y_{t+k}\}, \text{ for } k = 1, \dots, 6.$$

To ensure that we do not identify spurious phases we include the following four censoring criteria: *i*) We eliminate turns within eight months of the beginning/end of the series. *ii*) Peaks or troughs next to the endpoints of the series are eliminated if they are lower/higher than the endpoints. *iii*) Complete cycles of less than 16 months of total duration are also eliminated. *iv*) Each contraction (expansion) phase has a minimum duration of 6 months.

Once that the turning points have been identified the feature of housing market cycles can be investigated. We are particularly interested in the duration of the cycles. Duration for upturns is defined as the distance in months between a trough and a peak, whereas downturn is measured as the distance in months between a peak and the trough.

In Table 2 the results obtained using the algorithm described above are reported. In particular, the second and the fifth column reports the date of peaks and troughs, in columns three and six the duration of expansion and contraction phases in term of number of months is reported. Finally, in the fourth and last columns the percentages of price increase in each phase are reported.

Table 2. Dating of peaks (troughs) in house price cycles.

	Peak	*Duration of contraction (Peak to Trough)*	*Price increase (%)*	*Trough*	*Duration Of Expansion (Trough to Peak)*	*Price decrease (%)*
Tokyo	Sep. 2007	44	0.19	Jan. 2004	97	0.19
	Mar. 2010	11	0.3	Apr. 2009	19	0.38
	Feb. 2014	18	0.11	Aug. 2012	29	0.12
				Aug. 2014	6	0.34
Seoul	Oct. 1997	15	0.12	Jul.1996	7	0.02
	Oct. 2003	59	0.37	Nov.1998	13	0.57
	Sep. 2008	44	0.36	Jan. 2005	15	0.09
	Mar. 2010	12	0.16	Mar. 2009	6	0.23
				Sep. 2013	42	0.06
Rome	Jul.2002	79	0.16	Feb. 2003	7	0.2
	Oct. 2005	32	0.2	Aug. 2006	10	0.1
	Jul.2007	11	0.15	May.2009	22	0.3
	May.2010	12	0.09	Jan. 2012	20	0.29
New York	Aug. 2006	128	0.26	Apr.2009	32	0.14
	Aug. 2010	16	0.14	Mar. 2012	19	0.17
Hong Kong	Aug. 1998	32	0.28	Dec. 2001	40	0.21
	Jan. 2003	13	0.02	Feb. 2005	25	0.21
	Dec. 2007	34	0.15	Aug. 2008	8	0.08
	Apr. 2009	8	0.47	Jul-10	15	0.03
Amman	Dec.1999	41	0.04	Jul.1996	7	0.07
	Apr. 2002	17	0.05	Nov. 2000	11	0.03
	Apr. 2004	17	0.04	Nov. 2002	7	0.03
	Sep. 2008	47	0.11	Oct. 2004	6	0.04
	Oct. 2014	66	0.07	Apr. 2009	7	0.21

Note: The duration of upswing and downswings is expressed in number of months.

Looking at the results in Table 2 the algorithm seems to be quite successful in locating periods in time that have been thought of as picks and troughs in the housing markets, such as the housing market crash that originated the long and deep recession in the US in 2005 and the Asian crisis in 1997. A closer look at Table 2 shows that the peak phase in New York, Rome and Dublin lasted more than 5 years, between 1996 and early 2000 and that the house prices index rose by 0.26%, 0.16% and 0.42% per month, respectively. By contrast, Tokyo suffered a long contraction period between 1996-2004, when the house prices index declined by 0.19% per month due to the Asian financial crisis in 1997. It is interesting to note that the housing market in Hong Kong and New York appear to be more volatile than other large metropolitan areas since price swings are greater than in other large cities in the sample. This seems to agree with our conjecture that market base financial system feature less stable housing market. Another notable fact is that the real house prices for most of cities peaked before the financial crisis (i.e. before the period Aug. 2006 – Sep. 2008). This result confirms the argument in Taylor (2015) (see also Gimeno and Martinez-Carrascal, 2010) that booms in house prices can be used as an early warning of recession for the whole economy.

Table 3 reports the average amplitude and duration of the cycles for each metropolitan area. From Table 3 it appears that in most cities real estate cycles have asymmetric characteristics with expansion phases which last longer than contraction phases. More precisely, the duration of price expansion is between two to five years, whereas contractions last less than two years in average. In term of amplitude, a typical house price cycle feature more pronounced amplitude in expansion phases than contraction.

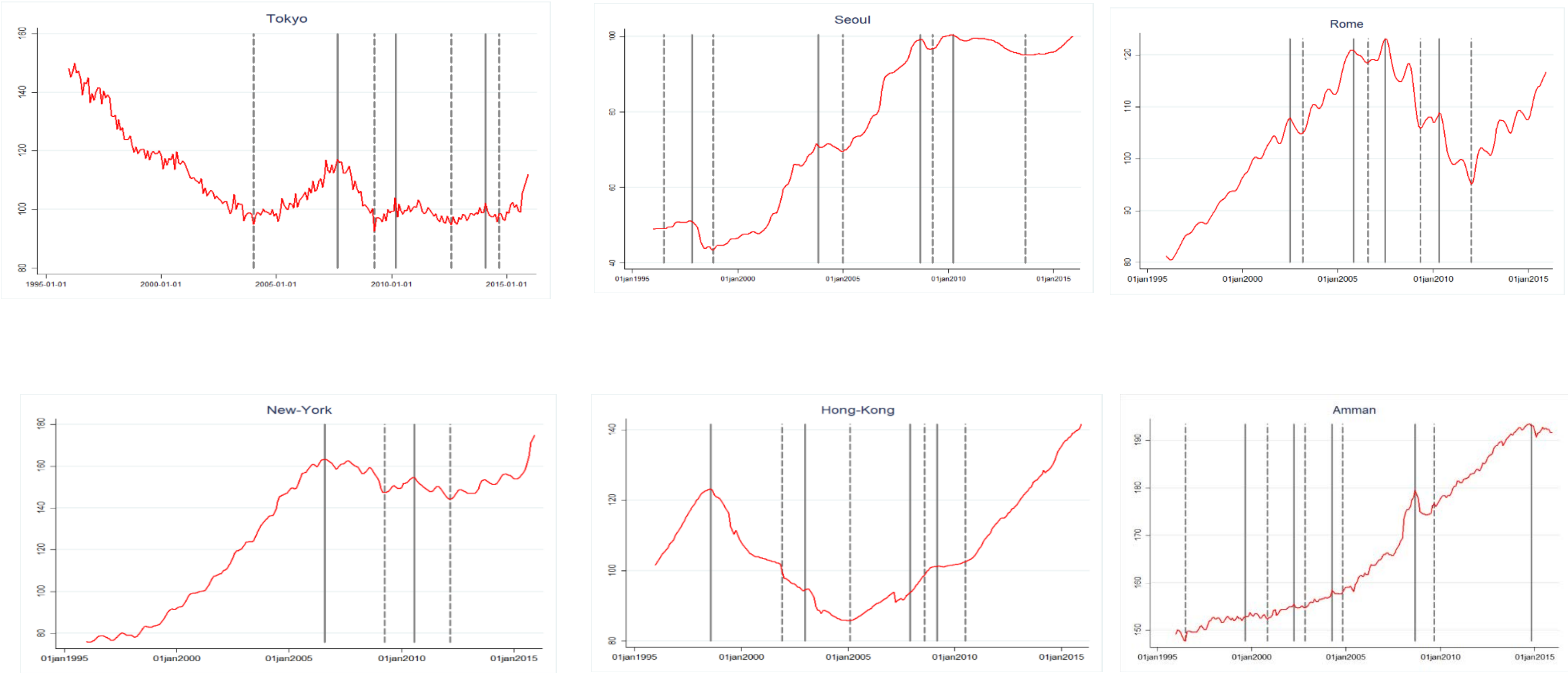
Table 3. Statistics on housing market cycles.

	Contraction		*Expansion*	
	Duration	*Amplitude*	*Duration*	*Amplitude*
Tokyo	37.50	-9.10	22.25	6.07
Singapore	24.75	-11.43	35.00	18.28
Seoul	16.40	-2.43	31.40	8.64
Rome	17.75	-3.64	36.00	6.05
New York	25.50	-3.78	62.67	14.55
Hong Kong	22.00	-5.251	30.20	7.08
Dublin	12.75	-4.04	37.60	13.91
Amman	9.00	-0.48	38.00	2.76

Note: Duration and amplitude refer to the average of the duration and amplitude in number of months.

Figure 1 plots house price changes for the period under considaration along with their peaks and troughs as identified by the Harding and Pagan (2002) alghorithm. Figure 1 clearly reveals that house price cycles have an asymmetric bahavior: in most metropolian areas large, sharp upward movements in house price growth are followed by slow downword drifts. This behavior suggests that non-linear time series models that allow for asymmetric behavior of the cycle may be needed to capture differences in contraction and exapansion pahses of the house price cycle.

Figure 1. House price index with peaks (dashed line) indices and troughs (solid line).



4. The Analysis of Housing Market Cycles

In this section we focus on modelling home price growth rates as a non-linear and state-dependent variable. Below we briefly summarise the econometric model used in the empirical estimation before presenting the estimated results.

4.1. The Econometric model

Let y_t be a realisation of a house prices growth series observed at $t = 1-p, 1-(p-1), \dots, -1, 0, 1, T-1, T$. Then the univariate process $\{y_t\}$ can be specified using the following model

$$y_t = (\phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i})(1 - G(s_t; \gamma, c)) + (\phi_1 + \sum_{i=1}^{p} \phi_i y_{t-i})(G(s_t; \gamma, c)) + \varepsilon_t ,$$
$$= \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + (\beta_0 + \sum_{i=1}^{p} \beta_i y_{t-i}) G(s_t; \gamma, c) + \varepsilon_t , \quad (1)$$

where $\beta_0 = \alpha_0 - \phi_0$, $\beta_i = \alpha_i - \phi_i$, the innovations $\varepsilon_t \sim \mathrm{NIID}(0, \sigma^2)$ and $G(s_t; \gamma, c)$ is the transition function. The transition function $G(s_t; \gamma, c)$ depends on the transition variable s_t, the vector of location parameter c and the slope parameter γ. The regime occurs at time t depending on the type of transition variable s_t. Different choice of transition function leads to different types of regime-switching behaviour.

In the light of the results in Section 3 a choice of a transition function that may be suitable to model the asymmetric behaviour of house price cycle is the following

$$G(s_t; \gamma, c) = (1 + e^{-\gamma(y_{t-d} - c)})^{-1} , \text{ with } \gamma > 0 \text{ and } s_t = y_{t-d}, \quad (2)$$

where *d* is the delay parameter which controls the delays in moving between regimes. On the others side, the parameter γ determines the speed of adjustment in switching between regimes.

The model in Eq. (1) with the transition function in Eq. (2) is referred to as Logistic Smooth Transition model in Teräsvirta (2005). The transition function in Eq. (2) has two major features: *i*) it allows for asymmetric cycles of real estate prices, *ii*) it also caters for smooth transition between expansion and contraction regimes. Given that house prices adjust slowly to the economy fundamentals allowing for a smooth transition between phases seems to be reasonable. However, Teräsvirta *et al.* (2005) also suggest the following transition function

$$G(s_t;\gamma,c) = \left(1 + e^{-\gamma(y_{t-d} - c_1)(y_{t-d} - c_2)}\right)^{-1}, \quad c_1 \leq c_2, \gamma > 0,\ G(s_t;\gamma,c) \in [0,1]. \quad (3)$$

Combining Eq. (1) with Eq. (3) results in a model referred to as Exponential Smooth Transition Autoregressive (ESTAR). In contrast to the LSTAR model, the transition function in Eq. (3) is symmetrically *U*-shaped and considering the model in Eq. (1) with the transition function in Eq. (3) would result in a nonlinear specification suitable to model series that feature symmetric housing market cycles. With these two possible models in mind, we therefore frame our problem of modelling housing market cycles as one of choosing the transition function which best describes the features of the housing market cycle described in Section 3. Both models can be estimated by maximin likelihood using standard iterative algorithms.

4.2 Empirical Results

The modelling procedure adopted implies to determine the dynamic structure of the series of house price growth in the first place. In our case, for each house price series the maximal lag order of the AR(*p*) model was chosen by using the Bayesian information criterion and the Portmanteau test for serial correlation. Then, the second step prior to start the estimation procedure is to test if the data support the hypothesis a nonlinear model. A natural way of doing it is to perform a test of linearity and check if the model in Eq. (1) reduces to a linear autoregressive model. This can be done, for example, by using LM principle. However, the distribution of such test would not be identified under the null hypothesis since the parameters γ and c in Eq. (1) are not identified under the null (see Davies, 1977). In their seminal work, Lukkonen *et al.* (1988) solve the identification problem by using a Taylor series approximation to reparametrize the transition function in Eq. (1). Therefore, the function $G(s_t;\gamma,c)$ in Eq. (1) can be replaced by the third-order Taylor series as follows

$$T_3(s_t,\gamma,c) \approx \gamma \left(\frac{\partial G^*(s_t,\gamma,c)}{\partial\gamma}\right) + \frac{\gamma^3}{6}\left(\frac{\partial^3 G^*(s_t,\gamma,c)}{\partial\gamma^3}\right), \quad (4)$$

where $G^*(s_t,\gamma,c)$ is the second derivative with respect to γ. The resulting auxiliary model is than given by

$$y_t = \beta_0 + \beta_{10} + \sum_1^p \beta_{1i} y_{t-i} + \sum_1^p \beta_{2i} y_{t-i} y_{t-d} + \sum_1^p \beta_{3i} y_{t-i} y_{t-d}^2 + \sum_1^p \beta_{4i} y_{t-i} y_{t-d}^3 + \epsilon_t, \quad (5)$$

where β_i are the functions of the parameters γ, c and ϕ_i. The expression in Eq. (5) can be used as the base for the *LM* tests.

Panel A of Table 4 reports the *p*-values of the linearity tests along with the optimal delay parameter for each metropolitan area under consideration. From Table 4 it appears that the null hypothesis of linearity can be rejected for all house price series under consideration. We therefore conclude that a nonlinear STAR type model is better able to capture the features of the time series under consideration than an AR(*p*) model.

Given that the linearity hypothesis is rejected for all the series under consideration, we can now proceed to validate our conjecture that the dynamics of house price changes in the metropolis under consideration can best be modelled using an econometric model which is, by construction, able to capture asymmetric cycles. With this target in mind, we follow Teräsvirta and Anderson (1992) and use the expression Eq. (5) as a base to test a sequence of nested hypotheses which allow us to discriminate model in Eq. (1) with the transition function in Eq. (2) against the model in Eq. (1) with the transition function as specified in Eq. (3). The procedure involves using a sequence of nested *F*-type tests for the coefficients in Eq. (5) which encompasses testing the following hypotheses in turn:

$$H_{01}: \beta_{4i} = 0,$$
$$H_{02}: \beta_{3i} = \beta_{4i} = 0,$$
$$H_{03}: \beta_{2i} = \beta_{3i} = \beta_{4i} = 0.$$

Accordingly, given the optimal delay lag (*d)* established in the previous test of linearity, in Eq. (5) we have three possible sequential outcomes. These outcomes are reported in Panel A of Table 4. First, rejection of $H_{01} : \beta_{41} = 0$ implies selecting the transition function in Eq. (2). If, however, $H_{01} : \beta_{4i} = 0$ is not rejected, we move to the second part of the sequential test which tests if $H_{02} : \beta_{3i} = 0$ given $\beta_{4i} = 0$. Rejection of the hypothesis H_{02} implies the selection of the transition function in Eq. (3). However, if H_{03} is not rejected, we move to the last part of the sequential test which tests: $H_{02} : \beta_{2i} = 0$ given $\beta_{3i} = \beta_{4i} = 0$. Rejection of H_{02} implies the selection of the transition function in Eq. (2) and therefore the LSTAR model. However, according to Kapetanios (2001) strict application of the sequential test may lead to misleading conclusions, since the higher order terms of the Taylor expansion used in deriving these tests are disregarded. The author suggest that the ESTAR model should be used if the *p*-values of the *F*-test resulting from hypothesis H_{02} is smaller than the empirical *p*-value result from testing hypotheses H_{01} and H_{03} and choose the LSTAR model otherwise. Accordingly, on the base of these recommendations in Panel B of Table 4 we follow this criterion and adopt the LSTAR model for all the series under consideration.

Panel B of Table 4 reports the estimated coefficients of the LSTAR model. For easy of interpretation in Table 4 the estimated autoregressive parameters for the expansion and contraction regimes in Eq. (1)-(2) are reported separately. In Panel B for each urban area the models have been estimated using the optimal delay parameter *d* reported in Panel A.

Looking at the estimated coefficients it appears that in most cities house price persistence is higher in expansion than contraction phases, since most of the estimated parameters in the higher regime are greater in modulus that the corresponding parameters in contraction phases. Coming now to the estimated parameters γ , it appears that they are statistically significant for all estimated models. The speed of adjustment between regimes is higher for some cities than others, however the relatively small estimates of the parameter γ suggests that the value of the logistic function changes slowly from zero to unity around the location parameter *c*. This implies that models such us the TAR or Markov regime switching models, where γ is infinity and there is a sudden switch between regimes are not suitable to capture the housing market dynamic. This result contrasts with much of the previous literature where these types of models are used to describe housing market behaviour. Another significant finding is that the estimated location parameters c shows the different level of sensibility to the magnitude of exogenous shocks. Namely, New York, Rome and Seoul are the most sensitive to the market shocks. One the other side, Tokyo, Hong Honk and Amman seems to be less responsive to shocks than other cities.

Table 4. Estimation results.

	Rome *AR(p)* = 9*	*Tokyo* *AR(p)* = 7*	*Seoul* *AR(p)* = 6*	*Amman* *AR(p)* = 5*	*New York* *AR(p)* = 4*	*Hong Kong* *AR(p)* = 3*
Panel A: Linearity test						
Optimal delay parameter (*d*)	7 (0.006)	4 (0.048)	1 (0.000)	5 (0.001)	1 (0.000)	3 (0.000)
LM test for model selection						
$H_{04}: \beta_{4i=0}$	0.007*	0.105	0.000*	0.034	0.000*	0.231
$H_{03}: \beta_{3i=0}$	0.151	0.644	0.261	0.088	0.001	0.008
$H_{02}: \beta_{2i=0}$	0.175	0.025*	0.002	0.006*	0.000	0.001*
Panel B: Estimated Parameter						
Lower Regime						
θ_0	0.127**	-5.91	0.095	-0.062	-0.267	3.806**
	(-0.059)	(-5.858)	(-0.086)	(-0.066)	(-0.169)	(-1.606)
θ_1	-0`.052**	-1.477**	-0.099	0.585*	0.245**	-0.477*
	(-0.024)	(-0.627)	(-0.151)	(-0.164)	(-0.102)	(-0.186)
θ_2	0.018	-0.706	0.195*	0.516*	0.226**	-0.493**
	(-0.071)	(-0.851)	(-0.072)	(-0.104)	(-0.118)	(-0.217)
θ_3	0.346**	1.283**	0.008	0.488*	0.353*	-1.291*
	(-0.169)	(-0.621)	(-0.100)	(-0.114)	(-0.099)	(-0.348)
Higher Regime						
β_0	-0.862**	5.774	1.024*	0.389*	1.359*	4.649*
	(-0.432)	(-5.866)	(-0.265)	(-0.123)	(-0.314)	(-1.676)
β_1	-0.874	1.067*	-0.116	-0.728*	-0.425*	0.36
	(-0.788)	(-0.631)	(-0.197)	(-0.205)	(-0.198)	(-0.223)
β_2	-1.249**	0.776**	-0.064	-0.688*	-0.212	0.31
	(-0.561)	(-0.378)	(-0.202)	(-0.192)	(-0.204)	(-0.256)
β_3	-1.642**	-1.300**	-0.850*	-0.654*	-0.326*	1.233*
	(-0.943)	(-0.623)	(-0.186)	(-0.178)	(-0.120)	(-0.373)
Smooth Transition Parameter						
c	1.014*	-0.5152*	0.531*	-0.276*	0.462**	-0.595**
	(-0.16)	(-0.048)	(-0.101)	(-0.081)	(-0.226)	(-0.201)
γ	8.753***	4.251**	6.562**	1.76*	2.942**	2.266**
	(-4.598)	(-1.852)	(-2.887)	(-0.785)	(-1.462)	(-0.906)
Panel C: *p*-values for Misspecification Tests						
$AR(4)$ Test	0.675	0.147	0.191	0.244	0.443	0.196
No Rem. Nonlinearity	0.598	0.2	0.419	0.157	0.225	0.411

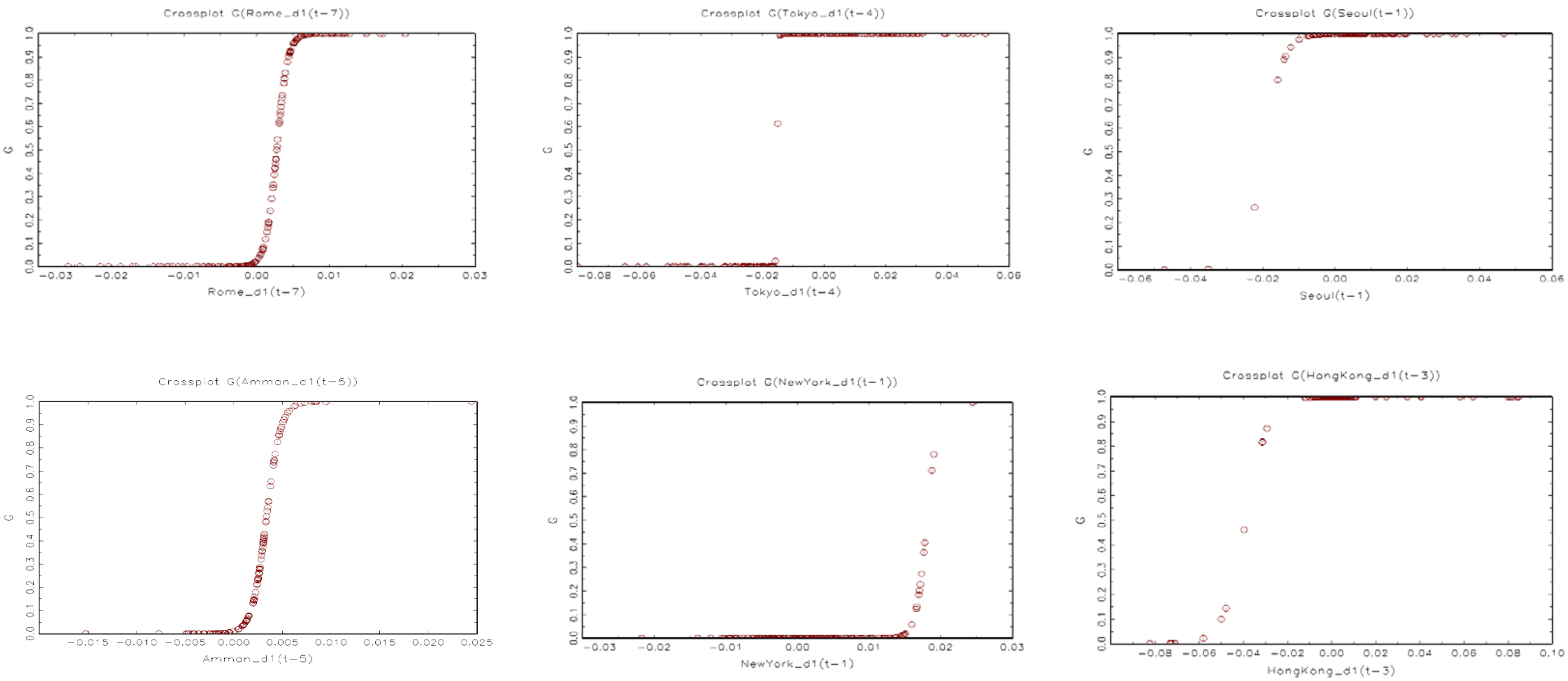
Panel A reports the linearity tests. Note that the selection of the optimal lag, AR(*p*)*, was made using the AIC statistic. The numbers in parentheses refer to the lowest *p*-value of the test in Eq. 5. Panel B reports the estimated parameters. Standard errors of the estimated parameters are given in parentheses. Panel C reports misspecification tests. *) **) and ***) relate to 1%, 5% and 10% significance level, respectively.

Once that the model has been estimated the goodness of fit can be evaluated using misspecification tests. The diagnostic statistics considered here are the LM test for serial independence for the hypothesis that there is no serial correlation against the *q*-order autoregression (for $q = 4$) and the test for no remaining nonlinearity.

The *p*-values of the tests are reported at the bottom panel of Table 4. Looking at the misspecification tests it emerges that the autocorrelation tests do not reject the null hypothesis of no autocorrelation against the *q*-order autoregression for all estimated models. There is also no evidence of remaining nonlinearity given that the tests do not reject the null hypotheses for the estimated models. Overall, the results in Table 4 suggest that the estimated models do not suffer from misspecification problems.

The estimated transition functions in Figure 2 are plotted against the transition variable $G(s_t; \gamma, c)$ in Eq. (2). From Figure 2 it appears that for New York about two-thirds of the observations are located in the lower part of the graph, corresponding to the segment between 0 and 0.5 of the vertical axis, while the rest correspond to the upper regime. The opposite is found in the case of Hong Kong since about 80% of the observations are located in the segment between 0.8 and 1. The transition functions plotted in Figure 2 clearly show the impact of the negative effect of the parameter c in the cases of Amman and Tokyo. However, Amman makes a smooth transition because the speed of this transition corresponds with the impact of the shocks measured by c.

Figure 2. Estimated transition function for the house price series.



5. Forecasting Housing Prices

A rolling forecast experiment is implemented in order to investigate the forecasting ability of the LSTAR model. With this target in mind the house price series are split in two subsamples: a pre-forecast period (for $t = 1, \ldots, T_{s-1}$) from which the model is estimated and a forecast period $t = T_s, \ldots, T$ with $T_s = t + h$. Then h-step-ahead forecasts are computed and compared with the pre-forecast period. The forecast period under consideration is $h = \{1, 3, 6, 12\}$ months. For each city we compare a linear AR(p) model and the LSTAR model in their out-of-sample point forecasts. The out-of-sample forecast comparisons do not rely on a single criterion; for robustness we compared the results of using four different measures. These comprised the Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE). The performance measures are calculated as follows

$$ME = \frac{\sum_{t=1}^{T} E_t}{N}.$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} {E_t}^2}{N}}.$$

$$MAE = \frac{\sum_{t=1}^{T} |E_t|}{N}.$$

$$MPE = \frac{\sum_{t=1}^{T} E_t}{\sum_{t=1}^{T} Y_t}.$$

$$MAPE = \frac{\sum_{t=1}^{T} |E_t|}{\sum_{t=1}^{T} |Y_t|}.$$

Table 5 reports the results of the forecasting exercise. In columns 1 and 2 the forecasting the forecast error measures and the horizon are reported, respectively, whereas in columns 3-14 the forecasting results are reported. From the top panel of Table 5 it is clear that according to the ME, RMSE and MAE criteria the LSTAR model performs better than its symmetric counterpart does. However, the results according to the MPE and MAPE are mixed.

Table 5. Forecasting: point predictive performances.

		Rome		*Tokyo*		*Seoul*		*Amman*		*New York*		*Hong-Kong*	
Error measure	*Horizon*	*AR*	*LSTAR*	*AR*	*LSTAR*	*AR*	*LSTAR*	*AR*	*LSTAR*	*AR*	*LSTAR*	*AR*	*LSTAR*
ME	1	0.02	0.00	0.88	0.00	0.05	0.00	0.00	0.00	0.58	0.00	0.03	0.00
	3	0.17	0.00	0.91	0.00	0.06	0.00	0.00	0.00	0.71	0.00	0.09	0.00
	6	0.21	0.03	1.12	0.00	0.07	0.02	-0.05	0.14	0.87	0.00	0.12	0.00
	12	0.14	0.07	0.76	0.00	0.05	0.03	-0.18	0.06	0.61	0.00	0.78	0.00
RMSE	1	0.57	0.00	3.43	0.00	0.50	0.00	0.30	0.00	0.78	0.00	1.85	0.00
	3	0.21	0.01	2.19	0.36	0.36	0.06	0.58	0.36	0.70	0.45	2.28	0.12
	6	1.79	0.02	2.24	0.26	0.40	0.10	0.11	0.27	0.61	0.44	1.06	0.17
	12	2.12	0.02	3.34	0.18	1.55	0.12	0.85	0.29	0.58	0.53	3.01	0.29
MAE	1	0.73	0.00	0.57	0.00	0.56	0.00	0.54	0.00	0.32	0.00	1.51	0.00
	3	0.15	0.01	1.68	0.31	0.23	0.05	0.39	0.32	0.48	0.43	1.29	0.10
	6	0.42	0.02	1.85	0.18	0.32	0.08	0.56	0.15	0.49	0.39	2.61	0.14
	12	0.55	0.02	1.69	0.10	0.50	0.10	0.73	0.23	0.53	0.41	1.83	0.24
MPE	1	0.06	0.00	0.53	0.00	0.42	0.00	0.39	0.00	0.42	0.00	0.48	0.00
	3	0.80	-0.14	0.58	0.61	0.05	-3.46	0.43	0.98	0.85	-0.22	0.51	-0.83
	6	0.66	0.20	0.52	0.12	0.61	2.29	0.44	0.25	0.78	-0.38	0.53	-0.96
	12	0.57	0.53	0.44	0.14	0.51	-0.14	0.42	1.50	0.44	-0.36	0.47	2.60
MAPE	1	0.69	0.00	0.52	0.00	0.56	0.00	0.00	0.00	0.00	0.00	0.56	0.00
	3	0.63	0.11	0.67	0.88	0.34	0.16	0.71	0.98	1.51	0.50	0.93	0.26
	6	0.45	0.20	0.44	0.74	0.43	0.22	0.43	0.58	0.44	0.66	0.74	1.25
	12	0.79	0.17	0.65	0.48	0.51	0.31	0.44	1.96	0.44	0.59	0.74	3.27

Note: The table compares, for each city, a linear AR(p) model and the LSTAR model in their out-of-sample point forecast performance. The forecast measures are: i) Mean Error (ME), ii) Root Mean Squared Error (RMSE), iii) Mean Absolute Error (MAE), iv) Mean Percentage Error (MPE) and v) Absolute Percentage Error (MAPE). The forecast horizon are 1,3,6, and 12 month ahead.

5.1 Discussion

What do we learn from this application? First, the LSTAR model well characterizes the dynamic asymmetry of all the metropolises under consideration. This result highlights the fact that the behaviour of housing market in high density urban areas may have different dynamics with respect to lower population density urban areas. In metropolises high real construction costs such land cost and stricter regulations on new developments introduce unpriced supply restrictions. In this respect our results are in line with the model in Capozza *et al*. (2004) where it is found that higher real income, higher level of real construction costs and tight regulation increase asymmetries in the housing market cycles. On the other side, markets with a higher level of transactions have lower information costs; thus, prices adjust more quickly to their long-run equilibrium value. Transaction frequency also affects reservation prices in search models of the housing market (Wheaton 1990). This implies that price correction in large metropolitan areas is faster than urban areas with lower transaction volume per unit area. Therefore, the transmission of an exogenous shock to the housing market is faster with respect to less densely populated urban areas. This is why nonlinearity occurs.

Second, the practical implication of the LSTAR handling house price series is that housing market in large cities are more prone to bubbles than lower density areas. Tight housing supply and strong demand pressure in high population density urban areas gives rise to deviation from the market fundamental price which are then abruptly corrected. In an influential paper Gleaser *et al*. (2008) suggest a theoretical model where irrational bubbles cause a temporary increase in optimism about future prices so that demand shock have more of an effect on price and less on new construction. Their model predicts that places with more elastic housing supply have fewer and shorter bubbles, with smaller price increases. Consensus literature suggests that supply inelasticity is a crucial determinant of the duration of a bubble (see for example Abraham and Hendershott, 1993). It is generally agreed that when housing supply is elastic positive economic shocks prompt new construction house prices rise, which causes the bubble to quickly unravel.

Third, there is an extensive literature on how regional house prices interact through the "ripple effect" and how they converge or diverge over time (see for example Holmes and Grimes, 2008; Cook, 2006). The "ripple effect" or "price diffusion effect" is the phenomenon where a shock in a given housing market is spread out to the rest of the territory over time. More precisely, ripple effect on house prices is shown as a co-movement (rise or fall) in real estate prices which affect in the same direction other region's prices. Spatial diffusion can occur in contiguous geographical areas, but not necessarily, it may also affect discontinuous spatial territory with similar socio-economic conditions. Among other empirical works, evidence of the price diffusion effect is given in Tsai (2018) for the US, Cook and Watson (2016) for the UK, Taltavull *et al*. (2017) for Spain. Good prudential policy requires action before the overbuilding goes too far and necessitates authorities' intervention. An investigation of a selection of 18 financial crisis from post-war period in several countries carried out by Reinhart and Rogoff (2009) has found that housing markets tend to undergo a significant expansion prior to each of the financial crises. A good understanding of the time-series properties of metropolises that are at the centre of a country economic activity may inform policy makers on the course of action to take before it gets too late.

6. Conclusion

In this paper we investigate the time series properties of a sample of metropolises. We start our analysis by investigating the duration and amplitude of house price cycles. The results show that all the cities considered in the sample present the features of an asymmetric cycle, with expansion lasting longer than contraction phases and trough that are deeper than peaks. Another notable fact is that real estate markets present synchronized turning points, for example, most housing markets peaked before the financial crisis that started 2006 in the United States. This result is important since it implies that a shock in housing market may signal cyclical turning point for the whole economy. In the second step of our empirical investigation we model house price dynamics using the LSTAR model. The advantage of this type of nonlinear model with respect to other models in the same class is that the LSTAR model is able to capture both asymmetries in house price cycles and the smooth transition between regimes. The estimation results are encouraging since it is shown that the LSTAR model is able to capture the features of house price series and it has good forecasting properties.

The present paper extends the existing literature in several ways. First, it provides an examination of asymmetrical behaviour in house prices in the large urban areas. We believe this is the first study to approach dynamic asymmetries in the housing market at this level of aggregation. Related studies that investigate the turning points such as Cook (2006), Holly and Jones (1997) and Cook and Holly (2000) consider asymmetry in house prices disaggregated at regional or country level. It is reasonable to expect real estate prices in large metropolitan areas to have distinctive dynamic patterns with respect to smaller urban settlements. Second, most empirical works in economics are based upon the assumptions of symmetry and linearity. Therefore, in the presence of nonlinearity, econometric models assuming symmetry are not correctly specified and may lead to spurious results. Finally, asymmetrical behaviour may inform alternative economic theories of the housing market. Many theoretical models assume that asymmetries play an important role over the various phases of the housing cycles. These models suggest that price dynamics might differ across expansion and contraction phases of the market therefore nonlinear modelling of house price cycles should improve our understanding of how the real estate market operates.

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