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MODELLING HOUSING MARKET CYCLES IN GLOBAL CITIES

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Modelling Housing Market Cycles in Global Cities

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Abstract

In this paper we consider the dynamic features of house prices in metropolises that are characterized by high degree of internationalization. Using a generalized smooth transition model we show that the dynamic symmetry in house price cycles is strongly rejected for the housing markets taken into consideration.

Keywords: house price cycles, dynamic asymmetries, nonlinear models.

JEL Classification: C10, C31, C33.

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1 Introduction

During the last decade housing markets have been characterized by high degree of instability. This has been particularly the case in large metropolitan areas where real estate markets have experienced dramatic swings which resulted in one of the deepest recessions the world has experienced since the great depression in 1930th. Partially motivated by these events, several authors have investigated the cyclical behavior of real estate prices. Housing markets are known to be prone to boom and bust episodes. In a typical expansion phase, transaction volumes are high, average selling times are short, and prices tend to grow fast. In a bust period, transaction volumes are low, average selling times are longer, and price growth moderate or becomes negative.

The empirical literature on housing markets recognizes the vulnerability of the real economy to house price swings, but it is less assertive about the features of cyclical patterns. For example, Muellbauer and Murphy (1997) explore the behavior of house prices in the UK. The authors suggest that transaction costs associated with the housing market cause important nonlinearity in house price dynamics. Further, Seslen (2004) argues that households exhibit rational responses to returns on the upside of the market, but do not respond symmetrically to downturns. On an upswing of the housing cycle households exhibit forward looking behavior 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.

While economic theory suggests that asymmetry may be a characteristic feature of real estate cycles, there have not been many attempts at modeling this phenomenon in an explicit fashion. Traditionally, in empirical literature house price dynamics have been analyzed using error correction mechanisms to investigate short-run deviations from the house fundamental value. 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) analyzes the impact of supply and demand factors on the path of house price adjustments. However, modeling asymmetry would require nonlinear time series models. Econometric models that work under the assumption of symmetry and linearity, in the presence of asymmetry would clearly be misspecified and may lead to spurious inference (see for example Blatt, 1980).

In this paper we investigate the characteristics of housing market cycles in global cities. A global city (or world city) is defined as a city which is of primary importance for the global economic system (Sassen, 2003). The term "global city" has its origins from urban studies and relates to idea that world globalization is facilitated in strategic cities which are instrumental in supporting the operation of the global system of finance and trade. According to Sassen (2003) the process of globalization gave rise to a new geography in which global cities function as places that provide specific knowledge for multinational enterprises to manage globalization. A characteristic feature of world cities is that their housing market dynamics is driven by local and global investment demand, rather than local household earnings. Given the peculiarity of world cities, it is most likely that housing markets in these metropolises have different dynamics than smaller urban settlements.

In this paper we are interested in addressing the following questions. First, what are the characteristics of house price cycles in global cities? Are housing market cycles asymmetric? Also, global cities are interconnected and have shared experience of globalization. An obvious question is therefore: Do world cities have similar housing market cycles? According to economic theory housing markets in large metropolitan areas display significant momentum (Case and Shiller, 1989), are mean reverting (Cutler, Poterba and Summers, 1991), and experience high volatility with respect to the fundamentals (Glaeser and Nathanson, 2015). While house price dynamics at national and regional levels have been widely investigated, research at a more disaggregated level is rare. In this respect, notable exceptions are the work by Cook and Watson (2017) and Alqaralleh and Canepa (2018) where disaggregated data for world cities areas are employed to investigate dynamics of housing markets. Other 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 aggregated at the regional or country level. However, to the best of our knowledge, a comprehensive investigation on the asymmetric adjustment at disaggregated level is still missing in the literature. Simply assuming that the properties of housing market at national or regional level would also describe the features of the housing market world city is counterfactual. Strong demand pressure and inelastic supply leave these metropolises more exposed to bubbles in the housing market than the rest of the country. 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) demonstrates that geographical restrictions constrain the elasticity of supply. The author shows that in cities that lack construction land, the process of urbanization leads to price increases.

Frequent booms and busts in the housing market of world cities open the question of how the series of house prices should be modelled. Accordingly, the second issue we address in this paper is the following: How do we model asymmetric cycles of real estate prices in global cities? As Sichel (1993) points out, an asymmetric cycle is one in which a phase of the cycle is different from the mirror image of the opposite phase. A natural question is therefore: What kind of econometric model would best be able to capture asymmetric adjustments in house prices?

In order to answer the questions above the investigation has been conducted in two stages. In the first step of our investigation we focus on testing for potential asymmetric adjustment in house prices. In particular, the non-parametric Triples test of Randles *et al.* (1980) is used to test for asymmetries in housing market cycles. The advantage with respect to alternative available inference procedures (see for example Sichel, 1993) is that the test statistic has good finite sample properties and it is robust to outliers (see Eubank, LaRiccia and Rosenstein, 1992). The application of the Triples test reveals evidence of asymmetric adjustment in all metropolises under consideration. In particular, the nature of the asymmetry observed indicates prolonged expansions phases in the market along with steeper contractionary periods.

The empirical results in the first step of our investigation can be a useful guide for the specification of the nonlinear model that would best be able to capture the observed features of housing market cycles. Accordingly, in the second step of our investigation, the generalized smooth transition model (GSTAR) suggested in Canepa and Zanetti Chini (2016) is used to estimate house price dynamics for the sample under consideration. The authors propose a STAR-type model where the logistic smooth transition function has two parameters governing the two tails of the sigmoid function in the nonlinear component of the model. The advantage of the proposed parameterization with respect to the ordinary smooth transition models (STAR) is that the resulting specification is able to model the tails of the logistic function independently so that the rate of change in the left tail of the transition function can be different with respect to that of the right tail.

Regime switching models have been used in the literature to capture nonlinearity in the housing market. For example, Kim and Bhattacharya (2009) use a STAR model to investigate for nonlinearity in the regional housing market in the United States. The authors find that West and Northeast regions (and to some extent also the South) are characterized by high speed transition between regimes. Nonlinear models are also used in Crawford and Fratantoni (2003) to forecast house price changes. Regime-switching models such as the STAR 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 validate the choice of smooth transition models. A possible shortcoming of these type of nonlinear models describing the feature of housing markets is that in the model specification a symmetric transition function is used to capture oscillations from the conditional mean of the changes in house price series. Although STAR-type models efficiently describe nonlinearity in house price growth rates, the commonly used transition functions may not be suitable to capture dynamic asymmetries in real estate cycles.

In this paper we argue that what in the related literature has been called "asymmetry" can at most define a qualitative feature of the data, while the modelling issue is still neglected since the logistic transition function which is commonly used to model house price series is symmetric by construction. In other words, STAR-type models used in the related literature are at most able to tackle the question: Do house price series go back to their original regime after a shock and when? However, the primary interest of our investigation is to answer to another, more challenging question: How do we model the fact that the speed of the transition between expansion and contraction phases is different? Also, how can we capture the fact that troughs and peaks are not symmetric? The model proposed by Canepa and

Zanetti Chini (2016) is potentially promising since the type of parametrization of the logistic transition function allows for the expansion and contraction phases to be modelled independently.

The remainder of this paper is organized 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 modelling procedure is briefly discussed before presenting the empirical results. Finally, in Section 5 some concluding remarks are given.

2 Housing Market Cycles in Large Metropolitan Areas

The behavior of housing markets over phases of the business cycle has long been an object of interest in economic literature. From the theoretical point of view economists have explained asymmetric behavior of real estate cycle using demand and supply framework where the supply side is inelastic. For example, Abraham and Hendershott (1996) describe an equilibrium price level to which the housing market tend to adjust. The authors divide the determinant 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. Abelson *et al.* (2005) suggest that during house price increase, households exhibit forward looking behavior, while the equity constraint factor plays only a minor role. On the other hand, households are less willing to buy or sell properties during contraction phases due to loss aversion and more pronounced equity constraints causing stickiness on the downside of the housing market cycle.

Coming to house price dynamics in large metropolitan areas, several authors have argued that in densely populated urban areas rigidity of the supply side plays a major role in housing market cycles. This literature argues that high real construction costs and stricter regulations on new developments introduce unpriced supply restrictions. For example, Capozza *et al.* (2004) show that stricter regulations on new development such as minimum lot size or regulatory-induced delays increase the cost of new housing (both in absolute terms and relative to existing housing) and they reduce the ability of builders to respond quickly to demand shocks. Similarly, Mayer and Somerville (2000) show that construction is less responsive to price shocks in markets with more local regulation. The fact that inelastic housing supply in large metropolitan areas induces high price volatility is broadly consistent with the literature on housing market bubbles. According to this literature bubbles are seen as a temporary increase in optimism about future prices therefore metropolitan areas where housing supply is more inelastic demand shocks have more of an effect on price and less of an effect on new construction. In an influential paper Gleaser *et al.* (2008) present a theoretical model of housing bubbles where it is postulated that housing markets with elastic supply have fewer and shorter bubbles and smaller price increases.

A closely related strand of literature suggests that real estate prices in metropolitan areas exhibit short run persistence and long-run mean reversion (see for example Abraham and Hendershott, 1996; Capozza and Seguin, 1996; Malpezzi, 1999; Meen 2002). In their seminal paper Case and Shiller (1989) find that house prices are correlated, which suggests that residential property markets are inefficient. In a more recent work Case and Shiller (2003) consider house prices in relation to the fundamentals. The authors make a compelling case that house prices exhibit statistically significant short term momentum. Also, Shiller (1990) posits that asymmetries in real estate house price cycles is partially due to backward looking expectations of market participants. In a similar vein, Capozza *et al.* (2004) (see also Dusansky and Koç, 2007) finds that backward-looking expectations are likely to strengthen the momentum effect in booming housing markets.

The presence of high information costs can also result in asymmetric adjustments in the housing markets. In this respect, empirical research has found evidence of a negative correlation between population density and information costs. For example, Clapp *et al.* (1995) find that higher population density increases price transparency in the housing market. When transaction volume increases information costs are lower and, therefore, prices respond more rapidly to macroeconomic shocks. Empirical evidence also suggests that households show stronger behavioral biases when assets are harder to price (Hirshleifer *et al.*, 2013; Kumar, 2009; Capozza *et al.*, 2004). Thus, we expect contraction phases to be shorter in large global cities than countrywide.

To summarize, consensus literature suggests that in densely populated urban areas higher level of real construction costs and stricter regulations increase dynamic asymmetries in housing market cycles. On the other side, greater market transparency should have the opposite effect, so that in these cities the adjustment towards fundamental price level should be more rapid and the momentum effect is expected to be weaker. All in all, dynamic behavior of house prices is strongly dependent on the prevalent signs of these combined effects.

3 Data and Asymmetry Tests

The data under consideration are related to monthly residential properties prices over the period 1996:1 to 2015:12 for five cities. Namely, these are New York, Tokyo, Seoul, Hong Kong and Singapore. The data were collected from Bloomberg.

As far as the sample is concerned global cities have been selected as a representative sample of metropolitan areas that are top ten in the ranking of the Global Power City Index (GPCI) (2018) as world cities[1]. The GPCI index ranks major cities of the world according to their "magnetism," or their

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[1] Note the city of London was at the top of the GPCI index in 2018. However, an extensive investigation on housing market cycles in London is considered in Canepa and Zanetti Chini (2019). Other cities that also scored highly in the ranking are not considered in this work due to data availability. Note also that the GPCI index is published yearly, therefore the ranking of the cities changes over time. However, the cities under consideration have been ranking in the top ten for at least the last five years.

comprehensive power to attract creative people and business enterprises from around the world. More precisely, the GPCI index ranks a number of metropolises according to the degree of their economy, the level of research and development, the degree of cultural interaction, the extend of livability, the quality of the environment, the degree of accessibility, along with other individual indicators. Most of the cities considered in the sample have in common the fact that: *i*) they are headquarters of several multinational corporations, *ii*) they are major financial or manufacturing centres, iii) they are important laboratories of new ideas and innovation hubs in business, economics, and culture, *iv*) they host high quality educational institutions, including renowned universities with international student attendance and world class research facilities, *v*) they feature high degree of diversity in term of language, culture, religion, and ideologies.

3.1 Testing for Asymmetries in the Housing Market Cycles

Detecting asymmetry in the real estate time series is important since linear and Gaussian models are incapable of generating asymmetric fluctuations. Evidence of asymmetry may guide empirical investigators toward a particular class of nonlinear specification able to model asymmetric cycles. Therefore, prior to attempt any model estimation below we investigate the characteristic features of housing market cycles for the cities under consideration.

In this paper we focus on two types of asymmetries which may or not occur simultaneously in the housing market: steepness and deepness. As Sichel (1993) points out, steepness occurs when contractions are steeper than expansions, or viceversa. The second type of asymmetry occurs when troughs are deeper than peaks are tall. Steep cycles in the housing markets may be generated by stiff housing supply. From one side, improving of the economic conditions tend to increase income of households and therefore to boost housing demand. On the other side, when property prices rise above the replacement costs, property developers initiate the construction process based on current property prices. However, the supply of new properties is, by definition, a slow process. By the time new properties are delivered economic conditions may have changed for the worse and prices start to decline. This inertia of supply responsiveness causes asymmetries in the real estate cycles (Davies and Zhu, 2005). Deepness could be generated by a model where endogenous developments in financial markets may amplify the effect of small income shocks through the economy.

To investigate possible asymmetries in the housing market cycles the Triples test suggested in Randles *et al.* (1980) has been used. Loosely speaking, the test is based on the principle that if a time series exhibits steepness, then its first differences should exhibit negative skewness. On the other side, if a time series exhibits deepness, then it should exhibit negative skewness relative to mean or trend. Therefore, a test for steepness can be computed by using the series in first difference, whereas a test for deepness can be based on the coefficient of skewness of the house price series in levels. Intuitively, the Triples test counts all possible triples from a sample of size T of a univariate time series. When most of the triples are right-skewed the process is said to be asymmetric (see Randles *et al.*,1980 for more details).

Table 1 reports the calculated test statistics and the relative p-values. In particular, the first row in Table 1 reports the calculated Triples test obtained using the logs of house price series for each city under consideration, whereas the third row reports the same test statistic, but this time calculated using the logs of first differences of the house price series. In both cases, under the null hypothesis the distribution of the house price series is symmetric around the unknown median against the alternative of asymmetry. Therefore, failure to reject the null hypothesis implies symmetry. The asymptotic reference distribution of the test is a standard normal random variable. Note that prior to calculate the test statistics the Hodrick-Prescott filter with smoothing parameter $129,600$ has been used to filter the series of house prices taken in natural logs.

Table 1. Triples test statistic for symmetry (deepness and steepness).

		New York	*Singapore*	*Hong Kong*	*Seoul*	*Tokyo*
Deepness	Triples Stat.	4.069	−1.999	0.046	−1.985	4.104
	p-value	0.000	0.045	0.963	0.047	0.000
Steepness	Triples Stat.	2.226	0.088	−1.784	0.465	−0.063
	p-value	0.026	0.929	0.074	0.642	0.949

Note: The trend is estimated by the HP filter with smoothing parameter $129,600$. Deepness refers to asymmetry in the level of detrended data. Steepness refers to asymmetry in the first-difference of the data. The null hypothesis $\mathcal{H}_0$: symmetry; and the alternative asymmetry. The Triples test statistic, which is asymptotically $N(0,1)$ and the p-values are those of a standard Normal distribution.

From Table 1 it appears that all the cities under consideration feature asymmetric housing price cycles, but they have different characteristics. The city of New York features deep and steep cycles, as in both cases the test statistics reject the null hypothesis. In particular, given the positive signs of the calculated Triples test statistic in New York City housing market peaks are higher than troughs are deep, however it also features rapid house price increase followed by slower declines. On the other side, the cities of Singapore and Seoul feature a deep cycle as the null hypothesis is rejected when the test statistic is calculated using house price changes. In these two cities troughs are deeper than peaks are high, as indicated by the calculated value of the statistic for the series in levels which have negative signs. The city of Tokyo features a deep but not steep cycle, whereas the city of Hong Kong presents a steep cycle with expansion that are longer than contraction phases.

4 Modelling House Price Cycles

4.1 The Econometric Model

Let y_t be a realization of a the house price changes (i.e. $y_t = \Delta y_t$) observed at $t = 1-p$, $1-(p-1), .., -1, 0, 1, T-1, T$. Then, the univariate process $\{y_t\}_t^T$ can be specified using the following model

$$y_t = \phi' z_t + \theta' z_t G(\gamma, h(c_k, s_t)) + \epsilon_t, \qquad \epsilon_t \sim I.I.D.(0, \sigma^2) \tag{1}$$

$$G(\gamma, h(c_k, s_t)) = \left(1 + \exp - \left\{ \prod_{k=1}^{K} h\left(c_k, s_t\right) \right\}\right)^{-1}. \tag{2}$$

In equations (1)-(2) the vectors $z_t = (1, y_{t-1}, \ldots, y_{t-p})'$, $\phi = (\phi_0, \phi_1, \ldots, \phi_p)'$, $\theta = (\theta_0, \theta_1, \ldots, \theta_p)'$ are parameter vectors. The process $\{\epsilon_t\}_t^T$ in (1) is assumed to be a martingale difference sequence with respect to the history of the time series up to time $t-1$, denoted as $\Omega_{t-1} = [y_{1-(p-a)}, y_{t-p}]$, with $E[\epsilon_t|\Omega_{t-1}] = 0$ and $E[\epsilon_t^2|\Omega_{t-1}] = \sigma^2$. The expression $G(\tilde{\gamma}, h(c_k, s_t))$ defines the transition function, which is assumed to be continuously differentiable with respect to the scale parameters $\tilde{\gamma} \in (\gamma_1, \gamma_2)$ and bounded between 0 and 1. Also, $G(\tilde{\gamma}, h(c_k, s_t))$ is continuous in the function $h(c_k, s_t)$ and $h(c_k, s_t)$ is strictly increasing in the transition variable s_t. The transition variable s_t is assumed to be a lagged endogenous variable, that is, $s_t = y_{t-d}$ for a certain integer $d > 0$. The parameters $c_k \in \{1, 2\}$ are the location parameters. Defining $\eta_t = (s_t - c)$ in equation (2) we have

$$h(\eta_t) = \left\{ \begin{array}{ll} \gamma_1^{-1} \exp\left(\gamma_1 \left|\eta_t\right| - 1\right) & \text{if } \gamma_1 > 0 \\ 0 & \text{if } \gamma_1 = 0 \\ \gamma_1^{-1} \log\left(1 - \gamma_1 \left|\eta_t\right|\right) & \text{if } \gamma_1 < 0 \end{array} \right\}, \tag{3}$$

for $\eta_t \geq 0$ ($\mu > 1/2$) and

$$h(\eta_t) = \left\{ \begin{array}{ll} \gamma_2^{-1} \exp\left(\gamma_2 \left|\eta_t\right| - 1\right) & \text{if } \gamma_2 > 0 \\ 0 & \text{if } \gamma_2 = 0 \\ \gamma_2^{-1} \log\left(1 - \gamma_2 \left|\eta_t\right|\right) & \text{if } \gamma_2 < 0 \end{array} \right\}, \tag{4}$$

for $\eta_t < 0$ ($\mu < 1/2$).

Asymmetric behavior in house price dynamics is introduced in the model by equations (3)-(4). In particular, equation (3) models the higher tail of the probability function, whereas equation (4) models the lower tail of the probability function. The speed of the transition between the expansion and contraction regimes in the housing markets is controlled by the slope parameters $\tilde{\gamma}$. If the vector $\tilde{\gamma} > 0$, the function $h(\eta_{k,t})$ is an exponential rescaling that increases more quickly than a standard logistic function. On the other hand, if $\tilde{\gamma} < 0$, the function $h(\eta_{k,t})$ is a logarithmic rescaling that increases more slowly than a standard logistic function.

Different choices of the transition function $G(\tilde{\gamma}, h(c_k, s_t))$ give rise to different types of regime-switching behaviour. If $k = 1$ in equation (2) the parameters on the right hand side of equation (1) change monotonically as a function of s_t from ϕ to $\phi + \theta$ and the corresponding transition function is given by

$$G\left(\tilde{\gamma}, h\left(\eta_{1,t}\right)\right) = \left(1 + \exp\left\{ \begin{array}{c} -h\left(\eta_{1,t}\right) I_{(\gamma_1 \leq 0, \gamma_2 \leq 0)} + h\left(\eta_{1,t}\right) I_{(\gamma_1 \leq 0, \gamma_2 > 0)} \\ +h\left(\eta_{1,t}\right) I_{(\gamma_1 > 0, \gamma_2 \leq 0)} + h\left(\eta_{1,t}\right) I_{(\gamma_1 > 0, \gamma_2 > 0)} \end{array} \right\}\right)^{-1} \tag{5}$$

with $h(\eta_{1,t})$ given in equations (3)-(4) and $I(\cdot)$ is an indicator function.

The GSTAR nests several well known linear and non-linear models. Before considering the estimation procedure of the GSTAR it is of interest at this point to relate the proposed model to other models available in the literature.

First, the model in (1) with $\gamma_1 = \gamma_2 = \gamma$ in the transition function in equations (3)-(4) implies that the GSTAR model reduces to a one-parameter symmetric logistic STAR model (see Teräsvirta, 1994). However, with respect to the STAR model a clear advantage of the indicator functions in equations (3)-(4) is that slope parameters are not constrained. Positiveness of the slope parameter is an identifying condition which was a crucial assumption in Teräsvirta (1994). Second, the transition function in the GSTAR nests an indicator function $I_{(s_t > c)}$ when $\tilde{\gamma} \rightarrow +\infty$. Therefore, the GSTAR reduces to the model in Tong (1983) when $\tilde{\gamma} \rightarrow +\infty$ and it becomes a straight line around 1/2 for each s_t when $\tilde{\gamma} \rightarrow -\infty$. Finally, the GSTAR model nests a linear AR model when $\tilde{\gamma}$ is a null vector.

As far as the estimation of the GSTAR model is concerned, estimation is performed by concentrating the sum of square residuals function with respect to the vectors θ and ϕ, that is minimizing:

$$SSR = \sum_{t=1}^{T} (y_t - \hat{\psi}' x_t')^2, \tag{6}$$

where

$$\hat{\psi} = [\hat{\phi}, \hat{\theta}] = \left(\sum_{t=1}^{T} x_t'(\tilde{\gamma}, c) x_t(\gamma, c) \right)^{-1} \left(\sum_{t=1}^{T} x_t'(\tilde{\gamma}, c) y_t \right),$$

and

$$x_t(\hat{\gamma}, \hat{c}) = \left[z_t z_t' G\left(\hat{\gamma}, h\left(\hat{c}, s_t\right)\right) \right].$$

Note that under the assumption that the vectors $\tilde{\gamma}$ and c are known and fixed, the GSTAR model is linear in the vectors θ and ϕ. Therefore, the nonlinear least square minimization problem reduces to a minimization on three (or four) parameters and can be solved via a grid search over γ_1, γ_2 and c. In our application, both γ_1 and γ_2 are chosen between a minimum value of -10 and a maximum of 10 with an increase rate of 0.5; whereas the grid for the parameter c is the set the values computed for the range of the 10^{th} and 90^{th} percentile of s_t with the increase rate computed as the difference of the two percentiles at the boundary divided by an arbitrarily high integer.

Before the estimated GSTAR model can be accepted as adequate, it should be subjected to misspefication tests. Some important hypotheses which should be tested are: *i*) the hypothesis that there is no residual correlation, *ii*) the hypothesis that there is no remaining nonlinearity and *iii*) the hypothesis of parameter constancy (See Canepa and Zanetti Chini, 2016 for more details).

4.2 Estimation results

The modelling procedure adopted involves determining 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 has been 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 of nonlinearty. A natural way of doing it is to perform a test of linearity and check if the model in equation (5) reduces to a linear autoregressive model. This can be done by using LM principle, however, the distribution of such test would not be identified under the null hypothesis since the parameters $\tilde{\gamma}$ and c in equation (5) are not identified under the null. The identification problem can be solved by using a Taylor series approximation to reparametrize the transition function in equation (5).

Table 2 reports the linearity tests, the estimation results and the misspecification tests. On the basis of the empirical p-values reported at the top panel of Table 2 the null hypothesis of nonlinearity can be rejected for all cities at 5% or 10% significance level, thus confirming our conjecture that a nonlinear specification needs to be used to model the house price series at hand.

With respect to the transition function from equations (3)-(4) it is clear that the choice of the number of location parameters k affects the type of asymmetric behavior characterized by the model. The nature of the asymmetry observed in Section 3 indicates prolonged upswings in the housing markets to pronounced cyclical peaks along with sharper contractionary periods. Evidence of asymmetry in Table 1 therefore points toward the GSTAR model which can be estimated using the expression in equation (5) with $k = 1$. On the other hand, choosing $k = 2$ in (5), would result in an exponential form of the transition function suitable to model a symmetric cycle where contraction and recovery phases have similar dynamics.

In the middle panel of Table 2 the estimated parameters and the relative standard errors are reported. From Table 2 it appears that house price changes are persistent since most of the estimated autoregressive coefficients, ϕ_i and θ_i (for $i = 1, ..., 3$), are significantly different from zero. This result is consistent with the findings in Capozza *et al.* (2004) where evidence of backward-looking expectations in the housing market is found (see also Dusansky and Koc, 2007).

The estimated parameters γ_1 and γ_2 indicate the speed of the transition between expansion and contraction regimes, respectively. These coefficients are also significantly different from zero. With regard to the signs of these coefficients it is observed that the parameter γ_1 is negative in most cases, whereas γ_2 is in most cases positive. This indicates that the speed of the transition from one regime to the other regime increases during periods of house price busts at a rate that is greater than one which would be consistent with a standard logistic curve, but increases during the periods of house price expansions at a rate which is slower than one that would be consistent with a standard logistic function. Note that the magnitude of the estimated γ_1 and γ_2 is consistent with the results of the Triples test in Table 1. From Table 2 it appears that the estimated parameter $|\gamma_1| > |\gamma_2|$ in the case of Singapore, Seoul and Tokyo, whereas the opposite is true for the city of New York. Therefore, the former group of metropolises features a strong deep and mildly steep cycle. On the other side, the housing market in New York City presents more the feature of a cycle which is strongly steep and moderately deep. Finally, considering the city of Hong Kong the estimated parameters $|\gamma_2| < |\gamma_1|$, however the coefficient for γ_2 is not statistically significant, thus indicating that steepness is a predominant feature of the housing market cycle in this city. Note that the relatively small estimates of γ_1 and γ_2 indicate that other types of nonlinear models in the class of regime switching, such as the Markov switching or the TAR models, are no suitable to capture housing market dynamics since these models assume a sudden transition between one regime and the other (i.e. in these models $\gamma_1 = \gamma_2 \longrightarrow \infty$ by assumption). Coming now to the parameter c, this indicates the halfway point between the expansion and contraction phases of the housing markets. In all cases, the values of c is statistically significant at the 5% level. Another significant finding is that the estimated location parameters c shows the different level of sensibility to the magnitude of exogenous shocks. Namely, Singapore and Hong Kong are more sensitive to the market shocks then other metropolises.

Table 2. Estimated parameters for the GSTAR model and diagnostic tests.

	New York	*Singapore*	*Honk Kong*	*Seoul*	*Tokyo*
			Linearity Tests (p-values)		
	0.080	0.081	0.016	0.088	0.063
			Estimated Parameters		
ϕ_0	0.124 (10.169)	0.0266 (0.044)	-0.647^* (0.087)	0.086^* (0.010)	0.074^* (0.046)
ϕ_1	2.059^* (0.033)	0.718^* (0.044)	0.527^* (0.027)	1.807^* (0.016)	0.466^* (0.014)
ϕ_2	-1.594^{**} (0.091)	0.231^* (0.017)	-0.085^* (0.025)	-1.209^* (0.026)	0.482^* (0.013)
ϕ_3	0.468^* (0.081)	-0.151^* (0.014)	-0.885 (1.541)	0.332^* (0.014)	–
θ_0	0.600^{**} (0.29)	-1.419 (1.852)	3.114 (3.240)	0.794 (0.682)	1.253 (2.395)
θ_1	0.668^* (0.063)	0.376 (0.279)	0.026^* (0.066)	0.100 (0.112)	0.283^* (0.095)
θ_2	0.964 (0.119)	0.054 (0.105)	0.203^{**} (0.103)	-0.617 (0.595)	-0.239^{**} (0.093)
θ_3	-0.526^* (0.097)	-0.449 (0.391)	-0.150^{**} (0.556)	0.419 (0.408)	–
γ_1	-0.500^* (0.290)	-7.500^{**} (4.855)	5.900^{**} (1.522)	-7.500^* (0.181)	-3.150^* (0.769)
γ_2	1.750^* (0.064)	3.000 (4.247)	-1.750 (1.577)	1.194^* (0.221)	1.027^* (0.027)
c	4.800^* (0.119)	8.127^{**} (4.470)	8.025^* (0.593)	4.107^{**} (0.261)	5.016^{**} (0.927)
			Diagnostic Tests (p-values)		
LM test for No Error Correlation					
$q = 4$	0.944	0.420	0.999	0.594	0.337
LM Test for no Remaining Asymmetry					
	0.999	0.981	0.996	0.995	1.000
LM Test Parameter Constancy					
$\mathcal{H}_1$	0.999	1.000	1.000	0.974	0.999
$\mathcal{H}_2$	0.998	1.000	0.985	0.989	0.999
$\mathcal{H}_3$	0.999	0.999	0.992	0.997	0.921

The table reports the linearity tests in the top panel. The estimated parameters are reported in the middle panel and p-values for the misspecification tests are given in the bottom panel. The diagnostic statistics are: $i)$ the LM and the F tests for the hypothesis that there is no serial correlation against the q-order autoregression, $ii)$ the LM test for the hypothesis that there is no remaining asymmetry, $iii)$ the LM test for parameter constancy. Note: * and ** indicate significance level at 5% and 10%, respectively.

Once that the model has been estimated, the goodness of fit can be evaluated using the misspecification tests. The diagnostic statistics considered here are: $i)$ the LM test and the F-test for the hypotheses that there is no serial correlation against the forth order autoregression (for $q = 4$), $ii)$ the LM test the hypothesis that there is no remaining asymmetry, $iii)$ the LM test for parameter constancy. The p-values of the tests are reported in the bottom panel of Table 2. Looking at the results of the misspecification tests it emerges that both tests do not reject the null hypotheses of no autocorrelation against q-order autoregression for all estimated models. There is also no evidence of remaining asymmetry given that the LM test does not reject the null hypothesis for the estimated models. Similarly, the LM test of parameter constancy also does not reject the null hypothesis at the 5% significant level for all the estimated models. Overall, the results in Table 2 suggest that the estimated models do not suffer from misspecification problems.

4.3 Discussion

Before concluding this section a question is in order: What do we learn from the GSTAR model about housing market dynamics in world cities? Looking at the results in Table 2, it is clear that the type of logistic transition function commonly adopted in STAR models may be suitable to estimate house price dynamic at higher level of aggregation (e.g. country or regional level), but may not be the best specification to capture asymmetric oscillations from the conditional mean of house price in global cities. This is because house prices in these metropolises are subject to strong exogenous shocks that make the stochastic processes highly nonlinear. Being the sigmoid in the transition equation a logistic function the LSTAR is model reflexively symmetric. Hence, the resulting model may be able reproduce steepness but not deepness which we found to be an important feature of the data at hand. In this respect, using a class of models indexed by two shape parameters that influence the symmetry and heaviness of the tails of the fitted transition equation may be more suitable to fit the non-central regions of the probability function and therefore better capture the asymmetries found in the previous section.

In the business cycle literature, which is closely related to the application in this paper, asymmetric behavior over the business cycle has long been object of interest in applied and theoretical works. Asymmetric behavior has been observed in many macroeconomic series, it is therefore not surprising that several variations of the STAR model have been suggested in the literature. For example, Sollis, Leybourne and Newbold (1999) suggest raising the transition function of the STAR to an exponential. Alternatively, Sollis, Leybourne and Newbold (2002) propose to add a parameter inside the transition function in order to control the asymmetry of both tails of the transition function. The suggested procedures successfully address the issue of dynamic asymmetry in several classical macroeconomic series. However, Zanetti Chini (2018) shows that neither of these solutions is free from challanges: in the Sollis *et al.* (2002) model, the transition function can be non-smooth; whereas the Sollis *et al.* (1999) parametrization conveys a smooth transition, but the effect of increasing the asymmetry parameter often translates to no more than a shift effect in the same transition function if it is not properly restricted. This shift could translate into an almost symmetric predictive density. On the other side, the logarithmic (exponential) rescaling of the GSTAR model preserve the smoothness of the transition function, by construction. No restrictions are required to determine the model identification and estimation, therefore, the specification allows us to model the two states (or possibly more, if multiple transition functions are required) in the density function of the process.

5 Conclusion

This paper investigates potential asymmetrical adjustment of house prices in cities which score highly in the ranking of the Global Power City Index (2018). The index evaluates major cities in the world according to their comprehensive power to attract people, capital, and enterprises from around the world. Global cities play a crucial role in supporting global finance, trade and enhancing knowledge transfer. A peculiarity of world cities real estate markets is that house price dynamics are driven by local and global investment demand, which often makes homes rather unaffordable to average local income earners. Strong pressure on the demand side and inelastic supply make these cities vulnerable to housing market bubbles. It is probably not a coincidence that most of the metropolises under consideration in this paper also score highly in the UBS Global Real Estate Bubble Index (see UBS Global Real Estate, 2018) which estimates the probability of a bubble bursting in a given metropolis at a given point in time.

To model house price dynamics we use a generalized logistic function which is able to parametrize the asymmetry in the transition equation of house price series, thus capturing the dynamic asymmetry in the conditional mean of house price series. Our findings reveal several insights into the patterns of the housing markets under consideration. In particular, the results obtained show extensive evidence of asymmetry to exist with deep and steep housing cycles frequently detected. The fact that house prices exhibit widespread evidence of asymmetry has important implications, for several reasons. First, observing a deep cycle implies that the housing market may overheat during expansion phases with high peaks in house prices being observed or may struggle with severe housing market busts which would trigger financial instability in the economic system. Therefore, knowing the characteristic features of the cycle may inform policy makers on economic policy targeted at stabilizing the housing market and hence preserve financial stability in the country. Second, given that dynamic asymmetry has been detected in all the cities under consideration econometric models that tend to be symmetrical in nature fail to capture fundamental features of the data, with important consequence on the reliability of the estimated parameters. Third, there is an extensive literature that reports the existence of a ripple effect of house price dynamic in major metropolitan areas on neighbor areas (see, for example, Cook and Holly, 2000 and the references therein). Therefore, being able to forecast movements in the housing market of large cities may plays a critical role for policy makers and their willingness to 'lean against the wind'. Finally, empirical evidence suggesting that housing market feature deep and steep cycles may support the construction of theoretical models able to explain why this empirical evidence is so persistent.

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