Modelling House Price Cycles in Large Metropolitan Areas

A thesis submitted for the degree of Doctor of Philosophy

by

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ABSTRACT

The volatility of house prices can raise systemic risks in the housing market due to the vulnerability of the banking and mortgage sectors to such fluctuations. Moreover, the extreme increases in housing markets have been considered a key feature of the last economic crisis and the run-up to it. Such increases, however, came to a sudden halt immediately before the crisis or directly it began. Despite the recent growth of scholarly work on the role of house price behaviour in economic stability, fundamental questions have yet to be answered: for instance: (i) how far do the nonlinear models outperform the linear models? And how does such nonlinearity explain the asymmetry in the cycle; (ii) what are the main characteristics of house price cycles, and how do they differ over time; and (iii) what kind of policy intervention would stop a real estate boom? This thesis, made up of three empirical essays, aims to take a step forward in answering these questions.

The first essay examines whether house prices in large metropolitan areas such as London, New York and Hong Kong follow linear or nonlinear models. The Smooth Transition Autoregressive model was used on a sample of monthly data over the period 1996:1 to 2015:12. The results indicate that linear models are unsuitable for modelling the housing market for the chosen cities. Moreover, strong evidence indicates that real estate prices are largely nonlinear and can well be modelled using a logistic smooth transition model (LSTAR). Estimation results also show different degrees of asymmetry. In particular, the speed of transition between the expansion and contraction of house prices is greater in London than it is in Hong Kong while the speed of transition between boom and bust in New York house prices is the slowest. Further, the forecast results suggest that the LSTAR outdoes the linear model in out-of-sample performance.

The second essay investigates the main features of house price cycles in the same major metropolitan areas by providing a reasonable level of discrimination between the cyclical decomposition techniques available for capturing suitable measurements for house price cycles. Through a sample of large cities in several countries, it is shown that the model-based filter is suitable for capturing the main features of house price cycles and the results confirm that these cycles are centred at

low frequency. Moreover, there is evidence of substantial variation in the duration and amplitude of these cycles both across cities and over time.

The third essay provides evidence that real house prices are significantly affected by financial stability policies. Considering the Hong Kong experience, the results show strong evidence of duration dependences in both the upswing and downswing phases of the cycle. Moreover, the time taken to reach the turning point increases dramatically as the cycle proceeds. The findings also suggest that there is feedback between house price volatility and the policies that affect the housing market. Accordingly, house prices respond with more volatility to any change in the loan to value and lending policy indicators (ignoring the sign of this shock). Finally, the evidence of asymmetry suggests that unanticipated house price increases are more destabilising than unanticipated falls in house prices.

DEDICATED TO …

My Parents, Brothers and Sisters for Their Endless Love, Supports and Encouragements.

The Gentle Soul, Her Kindness and Devotion will always be remembered.

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"And indeed, your Lord is full of bounty for the people, but most of them do not show gratitude." Sorah An-Naml, verse 73.

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DECLARATION OF AUTHORSHIP

I, HUTHAIFA ALQARALLEH, "hereby declare that the thesis is based on my original work, except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Brunel University or other institutions". I confirm that:

1. A paper (*Modelling Asymmetry in Real Estate Cycles in Metropolitan Areas: A Smooth Transition Autoregressive Approach*) was drawn from Chapter 2, written with Dr Alessandra Canepa and presented at: (i) The third International Workshop on Financial Markets and Nonlinear Dynamics (FMND, Paris, June 1-2, 2017); (ii) The 61st World Statistics Congress ISI2017 (Marrakech from 16 to 21 July, 2017).
2. A paper (*Measuring House Price Cycle; Evidence from Metropolitan Areas*) was presented at the 3rd doctoral symposium Brunel University, 5th May 2017.

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1 CHAPTER ONE

1.1 INTRODUCTION

The housing market has been subject to abnormal fluctuations, since some housing markets may react faster or more strongly to a given economic shock than others. Recent advances in research have provided compelling evidence that the bust in house prices, which started in the US and spread to several developed countries, was the primary cause of the last financial crisis (e.g. Bahmani-Oskooee and Ghodsi, 2016; Vincent and Morley, 2012; Borgy *et al.*, 2009). This highlights the role of the housing market on the whole economy, which has led policymakers and researchers alike to pay more attention to the real estate market. For example, in their seminal work, Crowe *et al.* (2013) revealed that real estate booms (busts) have far-reaching effects and neglecting their characteristics can threaten financial and macroeconomic stability.

Given the crucial influence of the housing market to the economy, the empirical literature has sought to provide explanations for the persistence of price changes, volumes and selling times and for the correlations between price and growth. While different research works have deepened our understanding of the macroeconomic factors that affect house price behaviour (e.g. Balcilar *et al.*, 2011; Muellbauer and Murphy, 1997; Hendershott and Abraham, 1992), these works overlook the impact of the high fluctuations of house prices. Empirical evidence shows that the high volatility of house prices contributes a motivating challenge to evaluate house price performance on economic activity (e.g. Égert and Mihaljek, 2007; Capozza *et al.*, 2002; Abraham and Hendershott, 1996). However, this evidence recognises the volatility in the short term, but largely neglects long-term volatility. Very few studies, moreover, have attempted to understand long-term volatility by locating the boom-bust (i.e. cycle activity) in the housing market's sensitivity (e.g. Crowe *et al.*, 2013; Fraser *et al.*, 2008; Himmelberg *et al.*, 2005).

Despite these efforts to understand the role of the housing market in economic stability, most of the literature has assumed that house price cycles are symmetric. In addition, given the crucial role of the asymmetric properties of the house price cycle (highlighted in this thesis), a more comprehensive study would also consider these asymmetric when applying and selecting appropriate housing policies to control (or at least reduce) the consequences of the contraction periods. There is therefore a need for the use of nonlinear methods to accommodate the features of the house price cycle and to address the impact of financial stability policies on the house price cycles (Glaeser *et al.*, 2014; Hansen, 2014; Igan *et al.*, 2011). Additionally, while the current literature has examined and drawn conclusions regarding house price behaviour at country level, house price behaviour in metropolitan areas has yet to be examined. In the seminal work of Glaeser and Nathanson (2017) and Glaeser *et al.* (2014), they highlight that housing prices in the metropolitan area display significant momentum, mean reversion and excess variance relative to fundamentals. Moreover, policymakers and economists tend to view the housing market as a series of interlinking sub-markets. Investigating the issue of regional house prices, therefore, helps to mark changes in asset prices, which have a significant influence on housing affordability and, hence, on economic growth (Glaeser *et al.* 2014; Chen *et al.*, 2011; Abraham and Hendershott, 1996).

To address these limitations, we take advantage of relatively new econometrics methods to model asymmetries in the housing market cycles in large metropolitan areas. Our goal is to deepen knowledge about the features of housing markets such as strong persistence and mean reversion in price appreciation.[1] In addition, we draw motivation from the argument that considering the policy impacts helps to reduce the boom consequences. This work contributes to the empirical literature on the economic cycle in three ways. First, it offers a new way to address the nonlinearity in house price behaviour and, hence, to examine its asymmetry, by considering the appropriate transition function. Second, the evidence of asymmetric cycles permits us to capture the length of each phase of house price cycles and provide more robustness tests to examine the capability of several decomposition techniques over a proposed time series. Finally, it supplies evidence to address the effects of different types of financial and price stability policy on the duration and persistence of volatility in the house price cycle.

[1] In the econometrics context, the importance of a cycle's features have called for several methods to measure and to understand the properties of the cycle, specifically, the NBER method for the classical cycle, non-parametric filters, and a frequency-based model. Despite these efforts, there is still too little evidence on the accurate statistical measurement of cyclical performance.

The contribution of the thesis is structured in three empirical chapters. In the first of these (Chapter Two, below) we adopt the Logistic Smooth Transition Autoregressive (LSTAR) model to examine the capability of nonlinear models to capture the asymmetry in house prices in large metropolitan areas. Chapter Three investigates the statistical properties of the house price cycle through an appropriate decomposition approach. Chapter Four examines the effects of different policies on the volatility of the house price cycle and explores the evidence of duration dependences on this cycle. The contributions and key findings of these chapters are summarised below.

Chapter Two examine the dynamic asymmetry in house price cycles in a sample of metropolitan areas over monthly periods from 1996:1 to 2015:12. This chapter contributes to the present literature in examining, first, whether asymmetric properties can be confirmed in house prices. If they can, then linear house price models, it is implied, are not appropriate tools for cointegration analysis (Bahmani-Oskooee and Ghodsi, 2016; Anderson *et al.*, 2007; Potter, 1995). We perform, also, sequences of the $F - test$ to determine the appropriate transition function and to test if these house prices are asymmetrical or symmetrical distribution. In this case, we find that the asymmetric function is more appropriate. The low speed of the transition between different regimes in house price growth found in the empirical studies validates the application of STAR-type models to address the asymmetry since such models efficiently accommodate the nonlinearity in house prices (Balcilar *et al.,* 2011; Kim and Bhattacharya, 2009; among others). Second, we explore this asymmetry in the house price cycle for the first time at a metropolitan level, which helps to address the question of how far small metropolitan areas differ from large ones. The latter helps, also, to investigate how a varying housing market affects the asymmetry. Last, we compare how *h-step-ahead* forecasts predict performance for the out-of-sample point forecasts of the STAR-type model with classical linear prediction.

The results of this chapter provide several interesting findings. First, house price behaviour can be better explained by using nonlinear models and the estimated model shows a notable asymmetry in the house price cycle. Second, the speed between regimes indicates that the switching between upswing and downswing phases is running smoothly.[2] The positive sign of midpoint between two regimes (regardless of city) indicates also that any shock causes a shift in regimes and increases the speed of transition. These results are supported by the better goodness-of-fit of our model. Finally, comparing *h-step-ahead* forecasts we find that the LSTAR outperforms the linear model in forecasting performance.

This chapter provides a number of important implications for policymakers and practitioners who are interested in understanding and forecasting movements in the housing market. This implication gives a foundation for developing a good policy before price overheating goes too far and demands central bank intervention early in the boom (bust) period. The significance of this chapter lies also in a number of important implications for future practice. Specifically, it investigates the statistical features of house price cycles, which may provide policymakers with early signals on future movements in economic activity and, hence, with better means of policy control. In this regard, the associated characteristics of the cycle based on this asymmetry are currently investigated in Chapter Three.

Chapter Three contributes to the empirical literature in two ways; first, by exploring the best decomposing (filtering) technique to its fluctuations and thus ascertaining the appropriate method of measuring housing cycles. This is necessary since most of the literature in this area is biased towards one procedure or another (e.g. Galati *et al.*, 2016; Claessens *et al.*, 2010; Van den Noord, 2006), which neglects the impact of the nature of the data on developing an ideal filter. We evaluate these techniques by linking the outcomes to the real properties of the cycle. Second, this chapter makes a novel contribution to investigations of the statistical properties of a house price cycle. This type of cycle advances our knowledge concerning the features of the economic cycle with the purpose of drawing policy prescriptions of general relevance and thus reducing the risk of recession.

With respect to the regression analysis, the observed diversity in the cyclical movements (across both cities and time horizons) points to the challenges of modelling such movements. The findings also explain the lack of consensus among the frequency-based filters. However, at this point the Christiano and Fitzgerald filters move ahead of the other family of frequency-based filters, as exposed by the

[2] This result also reveals that the LSTAR model outperforms other types of nonlinear model (see Chapter 2).

periodogram analysis. This chapter also shows that the model-based filter model is suitable for measuring the cycle of house prices and the results confirm that the cycle is centred on the low-medium frequency. Again, we observe a considerable heterogeneity across cities and over time.

The empirical findings in this study provide a new understanding and underscore the degree of commonality in the house price cycle, highlighting the leading role of economic activity. Whatever the cause of the observed formalised facts, these results matter not only for modelling house price cycles, but for policy coordination discussions, since they may reflect the important role of metropolitan areas in the financial system. Indeed, this information can be used to evaluate the policies that affect housing market during different phases in order to reduce the systemic risk generated by house price cycles, which is currently investigated in Chapter Four.

Chapter Four examines the effect of macro-prudential, monetary and lending policy on the duration and volatility of house prices. In specific, the first contribution of this chapter is to examine the duration dependences in the house price cycle that control the effect of various policies through a survival model. This helps not only to investigate the length of the current phase of a cycle, but also to address the power of policies considered to affect this duration. The second contribution is to explain the direction of causality between these policies and the volatility of the house price cycle, which helps risk managers and policy makers (as they continuously adjust the policy) to reflect changes in patterns. Finally, we contribute to the empirical literature by estimating a combination from the $ARIMA(p,d,q)$ model and $EGARCH(m,n)$ model to capture the volatility in the house price cycle, to explore the asymmetry in this volatility and to judge how a borrowing constraint such as loan-to-value (LTV) reduces the volatility of house prices.

Using monthly data for macro-prudential, monetary and lending policy and house prices in the Hong Kong area, the analysis offers three interesting results. First we find strong evidence of duration dependence in both the upswing and downswing phases, while the probability of reaching the turning point increases dramatically over time. Second, Granger causality shows a unidirectional causality running from loan to value and from the loan made to the volatility of house prices. Moreover, a shock in the variables (except for a change in the interest rate) has far-reaching consequences for the volatility of house prices, to which they respond with more volatility regardless of the sign of the shock. Finally, we infer that unanticipated falls in house prices are more strengthening than unanticipated increases in house prices, since the leverage effect is found to be positive. These findings have a number of important implications for policymakers and financial regulators, who want to extend the duration of expansions through applying the loan to value policy instead of reducing the interest rate.

Finally, **Chapter Five** presents the conclusion and summarises the key results of this thesis. It also offers some recommendations concerning policy implications, and identifies the main limitations, together with suggesting some directions for future research that are beyond the scope of this thesis.

2 CHAPTER TWO

Modelling Asymmetry in Real Estate Cycles in Metropolitan Areas: A Smooth Transition Autoregressive Approach

2.1 INTRODUCTION

Over the past decade, the fluctuations in house prices have been regarded as the main culprits for the global subprime crisis in 2008. Moreover, house prices are considered a leading indicator for the whole economy because of the close relationship between the housing cycle and housing market liquidity. Therefore, house prices as economic indicator has attracted widespread analysis, in which the empirical evidence suggest that adjusting house price leads to adjustments in consumption, output and inflation (Stock and Watson, 2014; Gerali *et al.*, 2010; Vargas-Silva, 2008). However, modelling house price is considered a puzzling task most likely due to the great vulnerability of housing markets to regulatory structures, finance systems and market fundamentals. Almost all previous empirical studies on house prices modelling are based on linear specifications (e.g. Égert and Mihaljek, 2007; Capozza *et al.*, 2002).

A growing consensus based on anecdotal and empirical evidence suggests that the behaviour of financial series can be nonlinear. Well known examples of such series include industrial production, GDP and unemployment rates (Sarantis, 2001; Neftci, 1984). Common sense suggests that house prices equally may incorporate some nonlinear properties. Abelson *et al.* (2005) note upturns in house prices foster households' forward-looking behaviour, with only a minor role for equity constraint. Conversely, in contraction phases households are less keen to buy or sell properties because of loss aversion and more pronounced equity constraints, causing shrinkage in the housing market cycle to stick. A seminal work by Kim and Bhattacharya (2009) illustrates the possibility of such nonlinearities as market behaviour fluctuates across the swings of the real estate market contracting and expanding by turns.

Thus far, the well-established literature on the cyclical behaviour of macroeconomic variables has maintained that house prices' nonlinearity is more likely to stem from the asymmetric properties of house price determinants such as GDP, interest rates and bank lending rates possess. Nonlinear models are adopted, for example, in Crawford and Fratantoni (2003) to forecast house price changes. Aye *et al.* (2013), also, forecast house price distributions using a STAR-type model. Kim and Bhattacharya (2009) test for nonlinearity in the regional housing market in the United States through the Smooth Transition Autoregressive (henceforward STAR) model. It is found that the western and north-eastern regions of the country (and also to some extent the South) are characterised by high speed transitions between regimes.

Despite the increasing body of literature, a systematic evaluation of the extent to which a nonlinear model can explain the dynamic of house prices has yet to be provided. Most of the existing studies consider the properties of house prices in the whole country. However, it is likely that house price behaviour in large metropolitan areas follows a different pattern than smaller metropolitan areas. Therefore, the aim of the present paper is to seek empirical evidence of asymmetric behaviour in house prices cycles in these regions.

In order to capture these asymmetries in the housing market, this chapter adopted a regime-switching model namely, the smooth transition model (STAR). This model was adopted for three rationales. First, the model allows a smooth transition between the two regime switch instead of an unexpected changes (Tsay, 1986). Second, the model has the capability to model house price growth rates series that exhibit changes in their dynamic properties over the business cycle as it depends on the sign and magnitude of past realisation of house price growth rates. Finally, the low speed of transition between different regimes in house price growth found in the empirical studies validates the choice of the STAR-family models (e.g. Teräsvirta *et al.*, 2005).

In this chapter, we account for asymmetries in house prices by starting from the realistic assumption that the house prices rate is a stationary, but probably nonlinear.[3] Therefore, we address the following questions: Are downturns in house prices steeper than upturns? Or does the amplitude of the contraction phase in house prices exceed that of expansions? Finally, considering the magnitude of the location parameter, is the shocks to the system are rather persistent?

[3] Following the literature, (e.g. Luukkonen *et al.,* 1988; Granger and Terasvirta, 1993), we assume that the house prices under investigation is stationary.

This chapter provides an opportunity to advance the understanding of house price dynamic in several ways. First, it sheds light on the dynamic of house prices and tests for asymmetric properties using a nonlinear model. Put differently, it examines whether the shrinkage phase in house prices is steeper than the expansion phase. It also documents the amplitude of house prices in such cycles since we model the volatility by investigating the speed of transition between regimes. This allows us to explore whether house price nonlinearities have contributed to a boom in house prices.

Second, extensive body of literature examining house price dynamics concentrate on data from one country as a whole. However, such studies neglect the importance of metropolitan areas, for house price behaviour in large metropolitan regions and in small ones reacts differently to economic shocks. Moreover, neglecting these properties in metropolitan areas may have far-reaching consequences since economists tend to view housing market as a series of interlinking sub-markets. Further, in a smoothly functioning sub-market, an imbalance of demand and supply would eventually self-correct and excess demand should result in an increase in supply (e.g. Glaeser and Nathanson, 2017). Yet there are some essential qualities to housing market that makes it a complex place and, thus, a situation where supply and demand cannot finds a balanced equilibrium position. Consequently, the policies that affect housing market and market regulation (right to buy, stamp duty and loan to value) could have some impact on demand and thus, controlling the market. Accordingly, this chapter considers large metropolitan areas, which may highlight some of the differences within these sub-markets. Therefore, doing this allows us to compare the characteristics and behaviour of housing markets across metropolitan areas both in developed and developing countries.

Finally, this chapter considers forecasting performance of nonlinear models and compare it with a simple autoregressive model. These forecasting can yield informative inference on a house prices series, and that it also may forecast well. The forecasting techniques can be also used as a criterion in evaluating the estimated model, especially regarding a preference between nonlinear and linear models (e.g. Dijk *et al.*, 2002). Therefore, the nature of the house price movements (i.e., either linear or non-linear) will improve the quality of forecasts and vice versa.

Our results provide several insights into the patterns of the house price cycles under consideration. In particular, it is found that the housing prices cycle asymmetry where the regimes of the LSTAR are related to recessions and expansions. Further, the model yield interesting information about how the equilibrium level of house prices has moved over the time. Such asymmetry in house prices have practical implications, in which, a change in house prices proved that the probability of erring to one side (increase or even less rapid decrease) is greater than erring to the other (even faster decrease). We then consider whether forecasting with the proposed nonlinear model leads to more improvement in performance than forecasting with an autoregressive linear model does. Comparing several criteria, it is found that, overall; the proposed nonlinear model performs better than its symmetric counterpart.

The remainder of this chapter falls into four parts. Section 2.2 deals with the literature on house prices. In the Section 2.3, the methodology and specifications of the selected model are introduced, where Section 2.4 discusses the descriptive statistics of the data. Section 2.5 gives the empirical results. Finally, the last section offers some concluding remarks.

2.2 LITERATURE REVIEW

A large body of literature has focused on the close relationship between real estate cycle and the business cycle. From the theoretical point of view, the literature explores the housing market cycles within the demand-supply framework, where supply is assumed to be rigid. On the one hand, improving the economic conditions tends to increase household incomes and therefore to boost housing demand. On the other, once property prices rise above the cost of replacement, property developers initiate the construction process on the basis of current property prices. However, supplying new properties is, by definition, a slow process. By the time a new property is delivered, economic conditions may have changed for the worse and prices start to decline. This inertia in supply responsiveness causes asymmetries in the real estate cycle (Davis and Zhu, 2011).

A seminal work by Abraham and Hendershott (1996) describes an equilibrium price level to which the housing market tends to adjust. The determinants of house price appreciation have been divided into two groups: one explains the changes in the equilibrium price and the other accounts for the adjustment mechanism in the equilibrium process. Asymmetries in real estate cycles can be accounted for by the slowness of the adjustment to the point of equilibrium. Muellbauer and Murphy (1997) examine the behaviour of house prices in the UK. They suggest that the presence of transaction costs connected with the housing market leads to nonlinearity in house price dynamics. In her comprehensive study, Seslen (2004) argues that a household exhibits a rational response to the return on the increasing phase of the market because it shows forward-looking behaviour and is more likely to trade up, while the equity constraint plays a minor role. Households are, however, less likely to trade when prices are in a decline, which leads to stickiness in the downside of the housing market cycle; therefore, prices do not respond symmetrically at such times. Posedel and Vizek (2009), also, show that there is a strong tendency for real house prices to rise in the future if they are rising now.

However, other studies suggest that the changes in determinants do not explain the variations in house prices. In this context, Annett (2005) finds no cointegration relationship between house prices and other demand and supply factors. In addition, Tsatsaronis and Zhu (2004) detect only minor effects of certain variables in their sample of industrialised countries. They suggest that a sharp break in the growth of house prices tends to follow long periods of elevated inflation. Similarly, Mikhed and Zemčík (2009) explore the slow adjustment of house prices toward equilibrium in previous episodes of possible bubbles. They find also that in an asymmetric cycle house prices decrease gradually over an extended period.

Traditionally, in the empirical literature, house price dynamics have been analysed using error correction mechanisms to investigate short-run deviations from the fundamental value. For example, Hendershott and Abraham (1992) estimate a cointegrated model which among other explanatory variables includes lagged house price changes. They find evidence of slow adjustment towards equilibrium, which implies a cyclical adjustment path. Baffoe-Bonnie (1998) examines the impact of a shock on house prices and the housing market which lead to a cyclical movement in real estate. Moreover, this cyclicality occurs in some regions where the average house price is high.

Malpezzi (1999) analyses the impact of supply and demand factors on the path of house price adjustments. Similar influence is observed in the case of Spain, in a study conducted by Martinez Pagés and Maza (2003), in which the Error Correction Model shows a significant effect for income, nominal interest rates and equity returns. Abelson *et al.* (2005) estimate an asymmetric threshold cointegrated model to investigate nonlinearity in Australian house prices. The results provide significant lags in adjustment to equilibrium in the short run. Most of these studies clearly conclude that some locations may be more prone to house price cycles, in particular, to rigid supply conditions delaying the response to demand-side shocks.

Inconsistency among the above studies besides the developed econometrics technique has led to several attempts to adjust the asymmetric cyclical movement of the housing market to the nonlinearity of change in credit cycles. In fact, if one wishes to address asymmetric in financial cycle, these nonlinear models apply (Enders and Siklos, 2001; Balke and Fomby, 1997). Moreover, this type of model has been used to consider the behaviour of such macroeconomics and financial variables as interest rate spread, GDP and the unemployment rate (Sarantis, 2001; Brock and Hommes, 1998; Hsieh, 1991).

Theoretical research has maintained that endogenous developments in financial markets can greatly amplify the effect of small income shocks through the economy. In an influential paper, Bernanke *et al.* (1996) call this amplification mechanism the "financial accelerator" or "credit multiplier". The key idea behind this accelerator is that, under the assumption of a fixed leverage ratio, positive or negative shocks to income have a pro-cyclical effect on the borrowing capacity of households and firms, which in turn affects housing prices. Specifically, positive shocks to household income translate into larger increases in house prices where the prevailing leverage ratio is higher (e.g. New York and London) and smaller in cities where such leverage ratios are lower (e.g. Rome).

Following this argument, Kiyotaki and Moore (1997) state that rising asset prices may set off a lending boom by increasing collateral values. A reversal of fundamentals then increases the loan default rate. Hall *et al.* (1997) suggest that the probability of transition is either time-invariant or depends on the extent of disequilibrium in the system. Moreover, a boom in real house prices is related to an unstable regime and the probability of an unstable regime is less when the equilibrium adjustment value of MS increases. Tsai and Chen (2009) detect the cause of asymmetric volatility in the housing market: that the asymmetric coefficient of conditional variance is highly significant. Furthermore, they detect a negative relationship between lagged innovations and housing return and also find anti-leverage effects in the market.

In a related work by Hott (2011), a theoretical framework that explains the relation between real estate prices and mortgage default is proposed. It is argued that, on the one hand banks contribute to the creation of real estate cycles by providing an increasing level of financial resources for real estate purchases. On the other, banks suffer high losses when the tide changes. An attractive feature of the theoretical framework in Hott (2011) is that the irrational expectations of banks play a crucial role in characterizing bank behaviour. Therefore, the irrational behaviour of banks contributes to the creation of real estate cycles. Tsai *et al.* (2012) explore asymmetric relationships in the US housing and stock markets. They conclude that there is an asymmetric wealth effect between these two markets. In recent work by Bahmani-Oskooee and Ghodsi, (2016), they adopt nonlinear ARDL approach to model the error-correction term in the US. The authors highlight that the changes in the fundamentals have asymmetric effects on house prices.

Few empirical works analyse house prices using smooth transition autoregressive (STAR). A case in point is the paper of Kim and Bhattacharya (2009), in which they show that in three out of four regions the nonlinear model can explain the typical patterns in the behaviour of house price growth. Balcilar *et al.* (2011) test nonlinearity in housing prices and show that the non-linear model always outperforms the linear model in five segments of the South African housing market. Similarly, Aye *et al.* (2013) provide out-of-sample estimates of linear and non-linear models of housing prices in the US Census regions. They observe that the STAR model would outperform a linear model in the long run. Canepa and Chini (2016) propose a novel nonlinear model to capture asymmetries in real estate cycles. Their results indicate that the dynamic symmetry in house price cycles is to be strongly rejected. Moreover, they suggest that the duration of a contraction phase is longer than that of an expansion phase.

All in all, a consensus in the literature proposes that asymmetric cycles are an important feature of house prices. Thus, if real estate markets feature asymmetric patterns of adjustment, models that take account of such nonlinearity may perform better than those which impose symmetric adjustment to rising and falling prices.

Accordingly, following the recent studies on the cyclical analysis of macroeconomic variables, a regime-switching model is used to capture the dynamic asymmetries in housing prices for a large metropolitan area.

2.3 SMOOTH TRANSITION AUTOREGRESSIVE MODEL

The literature suggests that many economic phenomena and time series incorporate nonlinear properties. For these reasons, different nonlinear models have been suggested to explain the changes in behaviour among economic variables from boom to bust (Franses and Van Dijk, 2000; Dijk, et al., 2002). The nonlinearity properties (highlighting in the aforementioned literature) suggest that the nonlinear type models should outperform the linear models. Accordingly, a regime-switching model is used to capture the dynamic asymmetries in housing prices for a large metropolitan area (Boinet et al., 2008). Specifically, we apply the Smooth Transition Autoregressive model (STAR) which has the capacity to generate an asymmetric realisation exhibiting changes in the behaviour of economic variables and allows house prices to switch smoothly between two distinct regimes. Below, we present a nonlinear model which allows for dynamic asymmetric adjustments in housing price cycles.

Let y_t be a realisation of a house prices series 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

$$Y_t = \Phi_1 x_t\big(1 - G(s_t; \gamma, c)\big) + \Phi_2 x_t\big(G(s_t; \gamma, c)\big) + \varepsilon_t\,, \varepsilon_t \sim \mathrm{NIID}(0, \sigma_u^2), \qquad (2.1)$$

where $x_t = (1, \hat{x}_t)^T$, $\hat{x}_t = (y_{t-1}, y_{t-2}, \dots, y_{t-p})^T$, $\Phi_i = (\Phi_{i0}, \Phi_{i1}, \dots , \Phi_{ip})^T, i = 1,2.$

The transition function $G(s_t; \gamma, c)$ is determined by the transition variable s_t, the vector of location parameter c and the slope parameter γ. According to Franses and Van Dijk (2000), the regime occurs at time t depending on the type of transition variable s_t which can be defined by many techniques. For example, this variable is supposed to be a lagged endogenous variable y_{t-d} for a particular integer delay parameter d, exogenous variable $s_t = z_t$, or sometimes linear trend $s_t = t$, in which the changing parameter of the model rises smoothly over the period.

Different types of transition variable lead to a different type of transition function and therefore a different kind of regime-switching behaviour. On the basis of Teräsvirta *et al.* (2005), a common choice for the transition function $G(s_t; \gamma, c)$ is the first order Logistic Smooth Transition function given by

$$G(s_t; \gamma, c) = \left(1 + e^{-\gamma(s_t - c)}\right)^{-1}, \gamma > 0, G(s_t; \gamma, c) \epsilon\ [0,1]. \quad (2.2)$$

The threshold between the two regimes can be interpreted by means of parameter c in Equation 2.2, whereas parameter γ not only controls the smoothness of the change from one regime to the other but also determines the speed of the adjustment to the new regime. Moreover, the change of sign for parameter*s* γ and c determines the increase $(\gamma > 0)$ or decrease $(\gamma < 0)$ in the logistic function value. Meanwhile, the faster transition function is explained by c whereby the greater the value of c, the steeper the transition.

Another well-known model is the Exponential Smooth Transition Autoregressive (ESTAR), in which the transition function is given by

$$G(s_t; \gamma, c) = \left(1 + e^{-\gamma(s_t - c_1)(s_t - c_2)}\right)^{-1}, c_1 \leq c_2, \gamma > 0,\ G(s_t; \gamma, c)\ \epsilon\ [0, 1]. \quad (2.3)$$

In contrast with the LSTAR model, the ESTAR model (Equation 2.3) is symmetrically U-shaped and concentrates only on the size of the transition variable s_t and the parameters c_1, c_2.

The specification of the STAR model and the choice between different types of transition function are discussed with reference to the literature (Teräsvirta *et al.*, 2005; Dijk *et al.*, 2002; Teräsvirta, 1994). This discussion starts by modelling linear Autoregressive (AR) and tests this model against the STAR(p) model. Net, the Lagrange Multiplier is used to select a suitable delay parameter, d, to select the best transition variable. Finally, sequences of nested hypothesis are tested to determine the appropriate type of STAR(p) model. These steps are briefly discussed below.

STEP 1 Linear Autoregressive (AR) Modelling

The first step of modelling STAR(P) is to specify the appropriate order of Autoregressive model AR (p) for a univariate house prices series Y_t, that is

$$Y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t, \tag{2.4}$$

where ϕ_i are the parameters of the AR(p) model.

Prior to that, it is important to verify stationarity of the house price before applying the linearity tests since the house prices data seem to be highly persistent (e.g. KILIC, 2004; Kapatenios *et al.,* 2003). This test can be conveniently reparametrized by combining as Equation (2.1) and Equation (2.2) as

$$\Delta Y_t = \beta x_t + \delta x_t \big(1 - G(s_t; \gamma, c)\big);\ \beta = \phi - 1 \tag{2.5}$$

Equation (2.5) effectively determines the speed of mean reversion which makes economic sense in that many economic models predict that the underlying system tends to display a dampened behaviour towards an attractor when it is far away from it, but that it shows some instability within the locality of that attractor.

The Akaike Information criterion (AIC) (Akaike, 1974) and Schwarz Information criterion (SIC) (Schwarz, 1978) can be used to choose the maximum order of lagged (p) with minimum AIC (SIC) statistics such that the corresponding residuals ϵ_t of lagged P should be white noise.

STEP 2 Prerequisite Modelling

The second stage in modelling STAR(P) is to test the proper order of AR(P) against linearity or nonlinearity. In this context, the test will not be identified if the null hypothesis of linearity is stated as: $H_0: \phi_1 = \phi_2$ with the alternative of: $H_1: \phi_{1,i} \neq \phi_{2,i}$ $\forall$ integer $i \in [0, p]$, because γ and c are unidentified parameters in the transition function (Davies, 1987; 1977). In their seminal works, Luukkonen *et al.* (1988) and Kilic (2004) solve the identification problem by using a Taylor series approximation to replace and reparametrize the transition function in Equation 2.1. Therefore, the linearity can be tested using the Lagrange Multiplier (LM), which is asymptotically χ^2-distributed, under the null hypothesis. In this case, the transition function $G(s_t; \gamma, c)$ in Equation 2.1 can be replaced by the third-order Taylor series as follows

$$T_3(s_t, \gamma, c) \approx \gamma \left(\frac{\partial G^*(s_t,\gamma,c)}{\partial \gamma}\right) + \frac{\gamma^3}{6}\left(\frac{\partial^3 G^*(s_t,\gamma,c)}{\partial \gamma^3}\right). \tag{2.6}$$

The resultant auxiliary model is

$$Y_t = \beta_0 + \beta_{10} + \sum_1^p \beta_{1i} y_{t-i} + \sum_1^p \beta_{2i} y_{t-i} y_{t-d} + \sum_1^p \beta_{3i} y_{t-i} y_{t-d}^2 + \sum_1^p \beta_{4i} y_{t-i} y_{t-d}^3 + \epsilon_t, \tag{2.7}$$

where $G^*(s_t, \gamma, c)$: is the second derivative with respect to (γ) and β_i are the functions of the parameters γ, c and ϕ. $\forall$ integer $0 \leq i \leq p$.

Taken together, the LM statistics under the (new) null hypothesis of linearity, which become $H_0: \beta_{2i} = \beta_{3i} = \beta_{4i}, \ \forall$ integer $i \in [0, p]$, IFF $\gamma = 0$, is given by

$$LM = \frac{(SSR_0 - SSR_1)\ SSR_1}{(3p)(n-4p-1)}, \tag{2.8}$$

where $3p$ and $n - 4p - 1$ are the degrees of freedom of the sum of square residuals given by: $SSR_0 = \sum_{t=1}^n \hat{\varepsilon}_t^2$ and SSR_1 estimated by calculating the auxiliary regression of $\hat{\varepsilon}$ on x_t and $x_t y_{t-d}^j \ \forall j = 1, 2, 3$.

However, this procedure allows only to reject linearity but it is not informative on the type of transition variable. Put differently, this technique does not determine the fixed value of the delay parameter d. Kapetanios *et al. (*2003) suggest that this parameter d be chosen to maximise goodness of fit over $d = \{1;\ 2; \ldots; d_{max}\}$ since there is likely little prior guidance as to the value of the delay parameter. Tsay (1986), also, recommends the LM-test for different values of d such that the optimal choice of d corresponds to the greatest test statistics (where p-value is the smallest). Once the delay parameter is specified, the appropriate transition variable can be determined and this variable is one of the candidates: $\{s_{t-d} : 1 \leq d \leq p\}$. The justification of this operative procedure is to maximise the test power alongside the appropriate transition function.

STEP 3 Choosing Between LSTAR and ESTAR

Once we reject linearity and determine the appropriate transition variables, the final decision is to discriminate between the LSTAR(P) model and the ESTAR(P) model through sequences of the $F-$test. Indeed, the LSTAR model is adopted in the case of asymmetrical distribution, while ESTAR model is preferred in cases of symmetrical adjustment behaviour. Following Dijk *et al.*, (2002), consider the null hypothesis of the form:

$$\begin{array}{lll} H_{01}: & \beta_{4i} = 0 & \text{(i)}, \\ H_{02}: & \beta_{3i} = 0 \text{ and } \beta_{4i} = 0 & \text{(ii)}, \quad \forall \text{ integer } i \in [1, p] \\ H_{03}: & \beta_{2i} = 0 \text{ and } \beta_{3i} = \beta_{4i} = 0 & \text{(iii)}. \end{array}$$

The LSTAR(P) model will be preferred over the ESTAR(P) if we reject Hypotheses (i) and (ii), whereas accepting the null hypothesis (iii) and rejecting(ii) favours ESTAR(P). In contrast, accepting the null hypothesis (ii) and rejecting (iii) support*s* LSTAR(P). Apart from this complicated process, Escribano and Jordán (1999) state that the choice of model can depend on the p-value of the F-test. When it does, the ESTAR(P) will be chosen if the p-value of (ii) is smaller than (i) and (iii). Otherwise LSTAR(P) is the best choice. Kapetanios (2001), also, conclude that such standard information criteria as AIC and BIC have crucial role in this model selection.

STEP 4 Estimation

Once the model has been specified, the nonlinear least square (NLS) can be applied to estimate the parameter of LSTAR(P)in Equation 2.1. The objective is to minimise $Q_T(\theta)$, such that

$$Q_T(\theta) = \hat{\theta} = \sum_{t=1}^{T} (y_t - Y_t)^2, \tag{2.9}$$

where Y_t : is the skeleton of the model given in Equation 2.1.

According to Franses and Van Dijk (2000), Equation 2.9 can be solved through maximum likelihood estimates given that the errors (ε_t) are white noise. Otherwise, NLS can be explained through quasi-maximum likelihood estimates. Furthermore, under certain conditions and with a true parameter (θ_0), the NLS estimates are consistent and asymptotically normally distributed, specifically

$$\sqrt{T}\left(\hat{\theta} - \theta_0\right) \to N(0, C). \tag{2.10}$$

The asymptotic covariance-matrix (C) can be estimated using a Hessian matrix (A_n) and the gradient matrix (B_n), such that

$$C = A_n^{-1} B_n A_n^{-1}. \tag{2.11}$$

$$A_n = -\frac{1}{T}\sum_{t=1}^{T} \nabla^2 q_t(\hat{\theta}) = \frac{1}{T}\sum_{t=1}^{T}(\nabla F(x_t\,; \hat{\theta})\, \nabla F(x_t; \hat{\theta})^t - \nabla^2 F(x_t; \hat{\theta})\hat{\varepsilon}_t). \tag{2.12}$$

such that $q_t(\hat{\theta}) = (y_t - F(x_t; \hat{\theta})^2$ and the outer product of the gradient(B_n) is given by

$$B_n = \frac{1}{T}\sum_{t=1}^{T}(\nabla q_t(\hat{\theta})\, \nabla q_t(\hat{\theta})^t = \frac{1}{T}\sum_{t=1}^{T}(\hat{\varepsilon}_t)^2\, \nabla F(x_t; \hat{\theta})\, \nabla F(x_t; \hat{\theta})^t. \tag{2.13}$$

In principle, many of the conventional nonlinear optimisation procedures can be performed to finish the estimation (Hamilton, 1994; Quandt, 1983). However, the important issue is the choice of the starting value to estimate the parameters, γ and c in particular. According to Schleer (2015); these values can be obtained by applying a two-dimensional grid search to select the smallest estimate for the residuals' variance through replacing the transition function in Equation 2.1 by

$$G(s_t; \gamma, c) = \left(1 + e^{-\gamma \prod_{i=1}^{n} (\frac{(s_t - c_i)}{\omega})}\right)^{-1}, \ \omega = \hat{\sigma}_{s_t}^{n}, \tag{2.14}$$

where $\hat{\sigma}_{s_t}$: is the standard deviation of the transition variables.

This method allows for the values of the transition function to have sufficient variation for each optimal γ and c. An accurate evaluation of γ is a potential concern because many observations in the direct neighbourhood of threshold c are needed for a suitable γ. In fact, if the value of γ is large enough, the STAR model is not far from the threshold model. In their influential paper, Bates and Watts (1988) state that an inaccurate general estimation of γ may give the impression of insignificance when adjudicated by the t-statistic. However, this does not count as evidence against nonlinearity. Besides, sometimes a high value of γ has a minor effect on the transition function and high accuracy in estimating is not necessary. Therefore, the decision should be assessed by diagnostic and misspecification tests, which generalise the corresponding tests for linear models, such as tests of no error autocorrelation, of parameter constancy and of autocorrelation heteroscedasticity.

2.4 DATA AND DESCRIPTIVE STATISTICS

The data under consideration are monthly time series of house price index in nine metropolitan areas over the period 1996:1 to 2015:12, namely: Amman, Hong-Kong, Dublin, London, Rome, Singapore, New York, Seoul and Tokyo.

Regarding the sample selection, some cities, such as London, New York, Singapore and Hong-Kong, are selected to form a representative sample of large metropolitan areas where financial liberalisation and deregulation of the financial markets has recently occurred, leaving the housing markets very much exposed to global financial events. Other cities, such as Rome, Seoul, Tokyo, Dublin and Amman are selected as representative of bank-based economies.

The cities under consideration in this study were also chosen for their relatively strong house price hikes, in which, house prices continue to be the region with the highest average house price. Moreover, the cases reported here illustrate wide discrepancy' between regions.

The surprising situation in New York is that house prices values were 93 percent above their previous peak due to the strong financial performance of rental properties as well as the relatively low yields from competing investments have driven up demand. Further, according to the US Census Bureau,[4] the supply of houses is not rising as fast as the demand, whereas house price increases in Seoul not only reflect increasing demand, but have also resulted from a combination of low interest rates and economic growth.

House prices in London show a significant increase after the sharp fall starting in the 1990s. Furthermore, prices were rising sharply even during the 2001 recession. In point of fact, prices rose above the inflation rate before the 2007 crisis and slowed down and fell after it. Similarly, in Rome the house prices index has shrunk by a total of around 16% in the last ten years. Moreover, this situation may have been aggravated by the number of bad loans and the state of near collapse of the banking system. Unlike Rome, Dublin had a big housing boom but it was followed by the steepest price declines in Europe. Only afterwards did Ireland's strong economic growth push house prices up again. New rules were also applied in Ireland's central

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[4] See for details http://www.jchs.harvard.edu/sites/jchs.harvard.edu/files/jchs_2016_state_of_the_nations_housing_lowres.pdf

bank, aimed at preventing another housing bubble from forming; the loan-to-value ratios on house prices were capped, which slowed their growth again.

Hong Kong's property market is the place where the demand has been driven by a combination of stringent government regulations currency stability; while the land supply, which the government controls, continues to diminish. Similarly, the liquid market and low interest rates in Singapore have played their part in pushing property prices up.

Another interesting case is the effectiveness of a great and powerful economy that is perhaps exemplified in Japan's, ranked third in the world. Surprisingly, although the economy shrank by 6% in 2014 and land prices are still falling, house prices in Tokyo are expected to continue to rise. At the same time, Jordan, as a small and open economy, has been severely affected by the financial crisis and regional socio-political unrest. According to local real estate analysts, Amman's property market slowed sharply in 2008 due to the global crisis, with house prices falling by an estimated 15%. However, in 2011, although the economic growth slowed, the housing market returned almost to the peak levels of 2006 and 2007. A possible explanation for this is that new measures now permit foreigners freely to buy real estate in Jordan.

The descriptive statistics reported in Table 2.1, of the house prices series in the levels indicate that house price volatility in Dublin and London were the highest during the period under consideration, while Rome presents the lowest standard deviation. Comparatively, the higher standard deviation reveals the larger disparity in all the cities under consideration. In addition, the Null Hypothesis of the Jarque-Bera (JB) test for normality was accepted only in London. Thus, the considered series are not normally distributed. Relatively, the skewness and the kurtosis coefficients reveal that all the series under consideration are skewed and fat-tailed.

Furthermore, it is crucial to test the stationarity of the series before testing the linearity since the unit root in the series might result in wrongly rejecting the linear model (e.g. Kilic, 2004; Kapetanios *et al.*, 2003). The calculated ADF test statistics refer to the series in first difference, that is, $\Delta y_t = y_t - y_{t-1}$. The results indicate that the null of nonstationary of house price series is clearly rejected at all levels of significance. For this reason, we proceed to apply the linearity tests and the STAR models.

Table 2.1 Descriptive Statistics

	Rome	Tokyo	Seoul	Dublin	Amman	New York	London	Hong Kong	Singapore
Mean	104.652	108.806	75.808	451.439	167.298	130.410	296.837	105.861	106.228
Std. Dev.	10.627	13.446	21.213	147.150	14.991	30.455	114.412	14.100	38.942
Skewness	-0.379	1.337	-0.230	-0.450	0.452	-0.646	0.013	0.561	0.652
Kurtosis	2.433	3.957	1.402	1.689	1.664	1.816	2.322	2.499	1.888
JB	8.908**	80.349*	27.538*	25.172*	25.882*	30.587*	4.589*	15.034*	29.230*
ADF	-4.005*	-23.864*	-5.699*	-11.850*	-12.684*	-5.854*	-9.282*	-16.715*	-13.875*

Significant Codes: *: 1%, **:5%. ***: 10%. ADF: Augmented Dickey–Fuller test. JB: Jarque-Bera normality test. The 1% and 5% Critical Value for ADF are: -3.464 and -2.881 respectively.

2.5 EMPIRICAL RESULTS

This section reflects the steps of modelling asymmetry, as described in Section 2.3.

Identifying AR Model

The first step involves choosing the optimal lag order p of the linear model and tests this order against any misspecification. Table 2.2 presents the estimated parameters for the $AR(p)$ models for the data under consideration and the selection criteria used.

From Table 2.2 it emerges that different metropolitan areas present different levels of persistence, perhaps reflecting different market conditions and local housing policies. For example, both the AIC and BIC statistics indicate that the $AR\ (3)$ model is suitable for modelling house prices for London, Hong Kong and Singapore. In contrast, Rome and Tokyo need the highest number of lags in order to make the residuals white noise, thus revealing a higher level of persistence in these markets. As far as the other large metropolitan areas are concerned, the lag order is included in these two boundaries.

The adopted AR (p) is tested against any misspecification problem since the autocorrelation in the residual has far-reaching consequences on the autoregressive estimated AR models. A common strategy to detect autocorrelation is the Portmanteau test of Ljung and Box (1978). As presented in Table 2.6 of Appendix 1, the null hypotheses of no residual autocorrelations up to lag h, where $h = P + i\ ;\ i = 1, 2\ ,3$ is accepted which indicates that there is no autocorrelation in the supposed lag. The same outcome is found from the Breusch-Godfrey test for serial correlation (Breusch and Pagan, 1979). Panel B supports the evidence that AR (p) is well specified, since the null hypothesis of no serial dependence autocorrelation is accepted.

Table 2.2 Estimated Parameter of AR (P) Model

	Rome	Tokyo	Seoul	Dublin	Amman	New York	London	Hong Kong	Singapore
C	0.16	-0.11	7.66*	2.02*	0.18**	0.10**	1.99**	0.16***	10.37**
	(0.11)	(0.18)	(1.91)	(0.85)	(0.05)	(0.04)	(0.60)	(0.11)	(4.72)
Y_{t-1}	1.69*	-0.52*	1.96*	0.15**	0.22*	1.96*	0.22**	-0.19**	1.10*
	(0.06)	(0.07)	(0.06)	(0.07)	(0.07)	(0.02)	(0.06)	(0.06)	(0.06)
Y_{t-2}	-1.03*	-0.18**	-1.19*	0.11**	-0.12**	-1.19*	0.18**	-0.13**	0.17**
	(0.13)	(0.07)	(0.14)	(0.06)	(0.05)	(0.09)	(0.06)	(0.06)	(0.09)
Y_{t-3}	0.23**	0.01	0.13**	0.04	-0.02	0.24**	0.29**	-0.15**	-0.27**
	(0.14)	(0.07)	(0.06)	(0.07)	(0.07)	(0.15)	(0.06)	(0.06)	(0.06)
Y_{t-4}	-0.19	0.13***	0.14	0.16**	0. 23**	0.02**			
	(0.15)	(0.08)	(0.16)	(0.07)	(0.07)	(0.01)			
Y_{t-5}	0.10**	0.17**	0.12**	0.03**	0. 21**				
	(0.05)	(0.07)	(0.08)	(0.01)	(0.07)				
Y_{t-6}	0.19	0.34*	-0.16**						
	(0.15)	(0.08)	(0.06)						
Y_{t-7}	-0.18	0.21**							
	(0.15)	(0.08)							
Y_{t-8}	-0.09	0. 11**							
	(0.13)	(0.04)							
Y_{t-9}	0.15**								
	(0.07)								
D-W	1.97	1.97	1.89	2.00	2.00	1.98	1.95	2.06	2.00
AIC	-34.53	1072.94	204.25	1600.97	432.12	508.76	1197.19	1082.86	1076.95
BIC	3.72	1107.70	232.06	1625.30	456.46	529.62	1214.58	1100.24	1094.33

Significant Codes: *: 1%, **:5%. ***: 10%. AIC: Akaike criterion information. SIC: Schwarz criterion information. D.W., Durbin-Watson. Standard error in parentheses.

Non- Linearity test and Choosing between LSTAR and ESTAR

Once we define the linear $AR(P)$, the Lagrange Multiplier (LM) is used to verify the presence of Linearity against Smooth Transition Autoregressive $STAR\ (P)$ for each delay parameter d. Table 2.3 provide the results.

As shown in Panel A of Table 2.3, we reject the linearity in all cases since the P −value is less than 5% and, hence, we accept the nonlinearity. Moreover, the table provides an optimum delay parameter for each city, and so the optimal choice of transition variables. [5] these delay parameters are constrained to be $1 \leq d \leq P$. Given P and the value of d that minimizes the p-value as explained before. Note that the lag length, P and the delay parameter, d are not the same. This is because P represents the lag length of the autoregressive process that is required to remove any autocorrelation.

Table 2.3 Testing Linearity against a Nonlinear Model

	Rome	Tokyo	Seoul	Dublin	Amman	New York	London	Hong Kong	Singapore
					Panel A: Testing Linearity against STAR				
	0.432	0.634	0.000*	0.231	0.007	0.000*	0.005*	0.046	0.300
	0.009	0.694	0.004	0.000*	0.112	0.000	0.045	0.000	0.042*
	0.050	0.440	0.000	0.011	0.002	0.000	0.079	0.000*	0.045
	0.115	0.048*	0.047	0.169	0.503	0.001			
	0.028	0.640	0.013	0.240	0.001*				
	0.068	0.789	0.009						
	0.006*	0.373							
	0.065	0.273							
	0.430								
					Panel B: Choosing Between LSTAR and ESTAR				
H	S_{t-7}	S_{t-4}	S_{t-1}	S_{t-2}	S_{t-5}	S_{t-1}	S_{t-1}	S_{t-3}	S_{t-2}
1	0.007	0.105	0.000	0.810	0.034	0.000	0.076	0.231	0.296
2	0.151	0.644	0.261	0.058	0.088	0.001	0.336	0.008	0.082
3	0.175	0.025	0.002	0.003	0.006	0.000	0.004	0.001	0.069
	LSTAR	LSTAR	LSTAR	LSTAR	LSTAR	LSTAR	LSTAR	LSTAR	LSTAR

The table provides the P-values of Lagrange Multiplier (LM) test. The Bold-Italic values indicate the lowest p-value. Hi: The P-values of nested F-test, i= 2, 3, 4.

[5] Dijk *et al.* (2002) state that: "The appropriate value of the delay parameter d cannot be uniquely determined from the test results. For that reason, we estimate LSTAR models with and different delay parameters defer the choice of the delay parameter until the evaluation stage".

As shown in panel B of Table 2.3, the linearity is rejected most strongly at $d = 1$. Therefore, the variable s_{t-1} can be the best option for New York, London and Seoul since it has the lowest P-value of all the delays shown. In the cases of Dublin and Singapore, the linearity test is rejected mostly at $d = 2$; hence the variable s_{t-2} may be the best possibility. Rome, Tokyo and Amman have the highest quantity, in which the linearity is rejected at $d = 7, 5$ and 4 respectively and, thus, $s_{t-7}, s_{t-5}, s_{t-4}$ can be used.

2.5.1 Estimated Parameter of LSTAR Model

Table 2.4 reports the estimated coefficients of the nonlinear LSTAR (p) model. What is interesting about these outcomes is that, first, most of the parameters are statistically significant, especially the speed of transition between two regimes γ, which is always positive and statistically significant. The relatively small magnitude of the estimated parameters γ suggests a slower transition between two regimes, which endorses the choice of the LSTAR model instead of a TAR or MS nonlinear model.[6] Finally, the midpoint between the expansion and the contraction phase c is statically significant and positive for all cities (except Tokyo and Amman). The latter pair indicates that a different value of house price shock caused a notable shift in regime for each city.

There are also differences in the ratios of the periods of expansion and contraction, which is measured by the speed of switching between regimes. More specifically, in Rome the rate of transition between regimes was the highest ($\gamma = 8.8$) while Amman had the lowest value ($\gamma = 1.8$). Another significant finding is that the vector of the location parameter c, which was also used to measure the response to the shocks, shows the different responses at the time in each city. The results indicate that Singapore and London were the most sensitive to the changes in the market. By contrast, the effect in both Tokyo and Amman took longer than it did in the other cities.

Turning to the other estimated coefficients, the results reveal a number of interesting dissimilarities between regimes. In particular, the estimated parameters for the lower regime of the linear part of the model (reported in Panel A of Table 2.4)

[6] See Teräsvirta *et al.* (2005) for more information.

show positive and negative signs for Rome, Tokyo and Seoul. However, the estimated parameters are positive for Dublin, New York, Amman, London and Singapore. Panel B of Table 2.4 also highlights dissimilarities in the estimated parameters of the higher regime. Specifically, London and Hong Kong were positively affected by the time shocks. By contrast, Rome, Seoul, Amman and New York had negative persistence.

Table 2.4 Estimated Parameter of LSTAR Model

Coefficient	Rome	Tokyo	Seoul	Dublin	Amman	New York	London	Hong Kong	Singapore
Panel A: Lower Regime									
ϕ0	0.127**	-5.91	0.095	1.467*	-0.062	-0.267	0.709*	3.806**	0.179
	(0.059)	(5.858)	(0.086)	(0.477)	(0.066)	(0.169)	(0.226)	(1.606)	(0.145)
ϕ1	-0`.052**	-1.477**	-0.099	0.201*	0.585*	0.245**	0.144**	-0.477*	0.268*
	(0.024)	(0.627)	(0.151)	(0.066)	(0.164)	(0.102)	(0.066)	(0.186)	(0.068)
ϕ2	0.018	-0.706	0.195*	0.076	0.516*	0.226**	0.196*	-0.493**	0.134**
	(0.071)	(0.851)	(0.072)	(0.064)	(0.104)	(0.118)	(0.069)	(0.217)	(0.062)
ϕ3	0.346**	1.283**	0.008	0.04	0.488*	0.353*	0.346*	-1.291*	0.031
	(0.169)	(0.621)	(0.100)	(0.064)	(0.114)	(0.099)	(0.083)	(0.348)	(0.061)
Panel B: Higher Regime									
ϕ0	-0.862**	5.774	1.024*	42.07*	0.389*	1.359*	-12.469	4.649*	10.513*
	(0.432)	(5.866)	(0.265)	(7.480)	(0.123)	(0.314)	(7.776)	(1.676)	(6.529)
ϕ1	-0.874	1.067*	-0.116	-26.878*	-0.728*	-0.425*	0.797*	0.36	-11.904*
	(0.788)	(0.631)	(0.197)	(4.057)	(0.205)	(0.198)	(0.230)	(0.223)	(1.611)
ϕ2	-1.249**	0.776**	-0.064	12.461**	-0.688*	-0.212	0.089	0.31	14.235**
	(0.561)	(0.378)	(0.202)	(5.959)	(0.192)	(0.204)	(0.186)	(0.256)	(8.635)
ϕ3	-1.642**	-1.300**	-0.850*	29.026*	-0.654*	-0.326*	0.873	1.233*	-13.841*
	(0.943)	(0.623)	(0.186)	(12.690)	(0.178)	(0.200)	(0.686)	(0.373)	(4.088)
Panel C: Smooth Transition Parameter									
C	1.014*	-5.152*	0.531*	2.163*	-0.276*	0.462**	6.644*	-0.595**	8.866*
	(0.160)	(0.482)	(0.100)	(0.782)	(0.080)	(0.226)	(0.578)	(0.201)	(0.935)
γ	8.753***	4.251**	6.562**	3.743*	1.76*	2.942**	5.397*	2.266**	3.382*
	(4.598)	(1.852)	(2.887)	(1.085)	(0.785)	(1.462)	(1.475)	(0.906)	(1.125)

Significant codes: *: 1%, **:5%. ***: 10%. Standard error between parentheses, ϕ_i: LSTAR Parameter.

On a visual inspection, the estimated transition function in Figure 2.1 is plotted against the transition variable $G(s_t; \gamma, c)$ in Equation 2.2. From Figure 2.1, it appears that for New York and London 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. For Dublin, Figure 2.1 reveals that the observations are spread smoothly between the two regimes. The transition functions plotted in Figure 2.1 show clearly the impact of the negative effect of 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. By contrast, Rome, Singapore and Seoul are clear examples of the divergence between the values of the Transition Parameter.

To evaluate the goodness of the estimated model, misspecification tests are applied. These tests include the LM test for serial independence, a test of No Remaining Nonlinearity, the ARCH-LM tests tor heteroscedasticity and the LM-tests for parameter constancy. Table 2.7 in Appendix 2 reports the p-value of the mentioned tests. These results verify that the estimated models do not have any misspecification problems. To be specific, Panel A of Table 2.7 shows that the null hypothesis of no autocorrelation was accepted against the q-order autoregressive for all estimated models. In the same way, the test for no remaining nonlinearity does not reject the null hypothesis for the estimated models as shown in Panel B. Similarly, panel C provide the LM tests based on a third-order Taylor approximation to test for parameter constancy. Again, the null hypothesis was accepted for all the estimated models. Finally, the results of the ARCH-LM tests (see Panel D), which validate the null hypothesis that there is no ARCH effect present, are accepted.

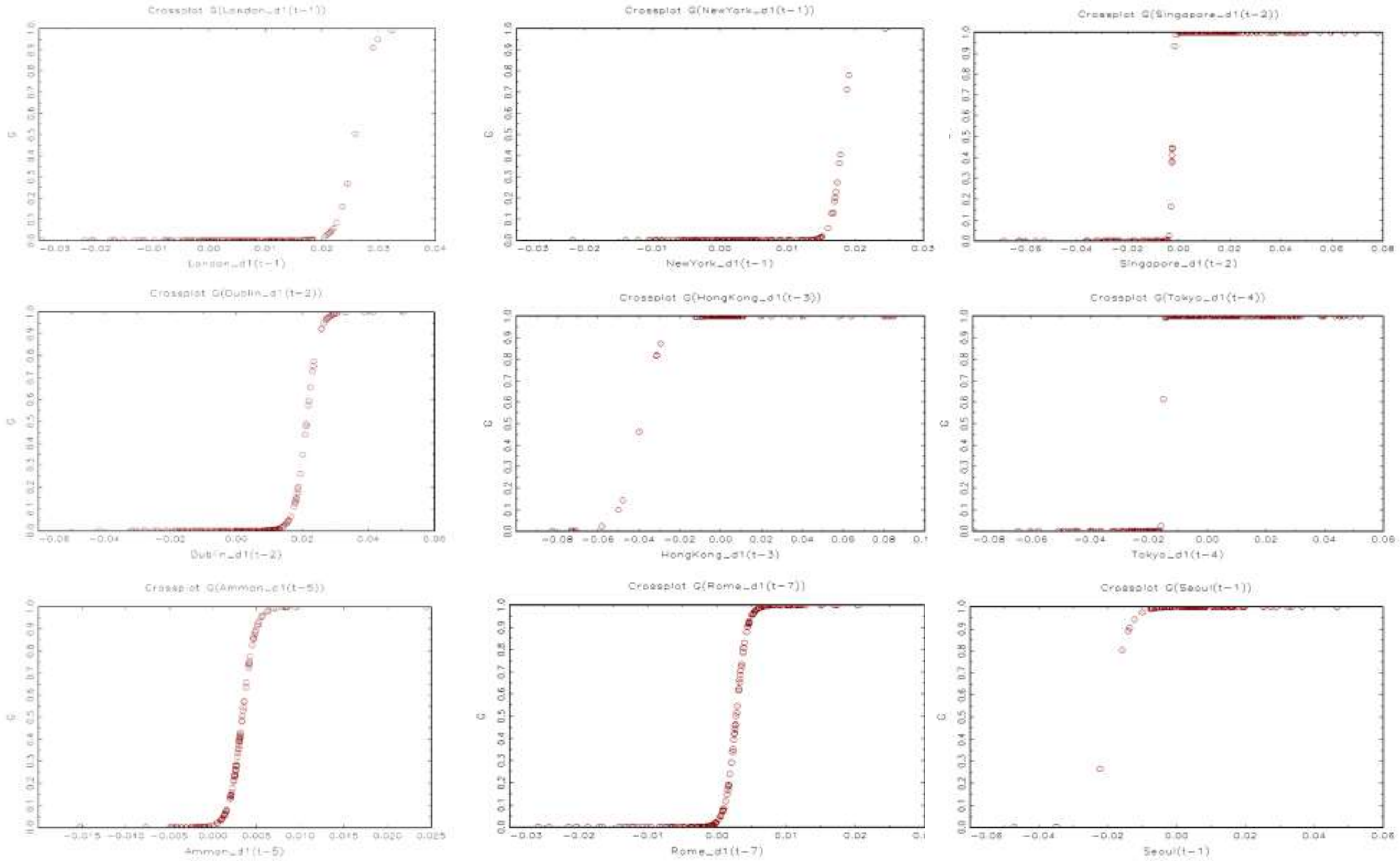

Figure 2.1: Transition Function versus transition variables

2.5.2 Forecast Accuracy

Forecasting the movement of house prices helps to provide early information on economic activity in the future and leads to better policy control. In terms of econometrics, the performance of the forecasting can also be used as a selection criterion to evaluate the estimated model, above all in choosing between a nonlinear model and a linear one (Dijk *et al.*, 2002). Therefore, the nature of the movement of house prices (i.e., whether linear or non-linear) will improve the performance of the forecasts and vice versa.

In order to investigate the forecasting ability of the LSTAR model a rolling forecast experiment was implemented. To this end, the house price series for each metropolitan area was split two subsamples: a pre-forecast period from which the model was estimated and a forecast period. Then h-step-ahead forecasts were computed and compared with the pre-forecast period. The forecast period under consideration is $\mathrm{h} = \{1,3,6,12\}$. For each metropolitan area we compared a linear $AR(p)$ model and the LSTAR model in their out-of-sample point forecast. 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 idea behind these measures was to test which model produced the smallest amount of error in the forecasting (Canepa and Chini, 2016; Crawford and Fratantoni, 2003; Rescher, 1998). The performance measures were calculated as follows

$$ME = \frac{\sum_{t=1}^{T} E_t}{N}. \tag{2.5}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T} {E_t}^2}{N}}. \tag{2.66}$$

$$MAE = \frac{\sum_{t=1}^{T} |E_t|}{N}. \tag{2.17}$$

$$MPE = \frac{\sum_{t=1}^{T} E_t}{\sum_{t=1}^{T} Y_t}. \tag{2.78}$$

$$MAPE = \frac{\sum_{t=1}^{T} |E_t|}{\sum_{t=1}^{T} |Y_t|}. \tag{2.19}$$

The results obtained from these measures are reported in Table 2.5, the forecast error and horizon provided in columns 1 and 2. It can be seen from the results that the LSTAR model has superior forecasting properties to those of the AR model, according to ME, RMSE and MAE criteria. However, the results according to the MPE and MAPE are mixed. In detail, $AR(P)$ performed better than the LSTAR model in some horizons of forecast in Tokyo, Amman and Hong-Kong. Overall, these results indicate that the LSTAR(P) outperformed the AR(p) model in forecasting performance. Therefore, these results support the contention that house prices incorporate nonlinear properties.

2.6 CONCLUSION

This chapter examines asymmetries in the house price cycle by concentrating on metropolitan areas as leading indicators of a whole economy for a sample containing monthly data over the period 1996:1 to 2015:12.

The estimation of a nonlinear model was built on the assumption that if the series was not operating in a linear way then a Smooth Transition Autoregressive (STAR) model was required. The STAR model is particularly suitable for allowing smooth transitions between regimes rather than unexpected jumps. We also compared the forecasting performance of this model with the linear model.

Applying nested tests indicated that different orders of lags were needed for the linear model AR(p). Consequently, the linear hypothesis was rejected and we found strong evidence indicating that house prices incorporate nonlinear properties. Furthermore, tests show that the LSTAR model prevailed over the ESTAR model. Moreover, the results of using LSTAR showed different degrees of asymmetry in the cities since the estimated parameters γ and c were significant. The results regarding forecast accuracy support the idea that house prices incorporate nonlinear properties. In the present research, the results indicated that the LSTAR model outperformed the rival AR (p) in forecasting performance. Finally, the misspecification tests indicated that the estimated model has no misspecification problems. These results suggest that the linear model will generate inaccurate estimates not only for house prices, but also the economy, since house prices lead real economic activity.

These findings suggest several courses of action that might be followed, specifically, it provides a number of important implications for policymakers and practitioners who are interested in understanding and forecasting movements in the housing market. This implication gives a foundation for developing a good policy before price overheating goes too far and demands central bank intervention early in the boom (bust) period. The significance of this chapter lies also in a number of important implications for future practice. Specifically, it investigates the statistical features of house price cycles, which may provide policymakers with early signals on future movements in economic activity and, hence, with better means of policy control.

Table 2.5 Forecasting: point predictive performances

		Rome		Tokyo		Seoul		Dublin		Amman		New York		London		Hong-Kong		Singapore	
error measure	horizon	AR	LSTAR	AR	LSTAR	AR	LSTAR	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	-0.02	0.00	0.00	0.00	0.58	0.00	0.02	0.00	0.03	0.00	0.26	0.00
	3	0.17	0.00	0.91	0.00	0.06	0.00	-0.02	0.00	0.00	0.00	0.71	0.00	0.03	0.00	0.09	0.00	0.41	0.00
	6	0.21	0.03	1.12	0.00	0.07	0.02	-0.02	0.00	-0.05	0.14	0.87	0.00	0.05	0.00	0.12	0.00	0.59	0.00
	12	0.14	0.07	0.76	0.00	0.05	0.03	-0.01	-0.09	-0.18	0.06	0.61	0.00	0.04	-1.15	0.78	0.00	0.21	0.00
RMSE	1	0.57	0.00	3.43	0.00	0.50	0.00	3.00	0.00	0.30	0.00	0.78	0.00	2.62	0.00	1.85	0.00	3.09	0.00
	3	0.21	0.01	2.19	0.36	0.36	0.06	6.69	0.28	0.58	0.36	0.70	0.45	2.90	3.87	2.28	0.12	2.31	0.22
	6	1.79	0.02	2.24	0.26	0.40	0.10	5.61	0.30	0.11	0.27	0.61	0.44	2.06	3.50	1.06	0.17	5.98	0.17
	12	2.12	0.02	3.34	0.18	1.55	0.12	4.97	0.24	0.85	0.29	0.58	0.53	4.97	3.27	3.01	0.29	3.05	0.14
MAE	1	0.73	0.00	0.57	0.00	0.56	0.00	3.73	0.00	0.54	0.00	0.32	0.00	0.43	0.00	1.51	0.00	5.22	0.00
	3	0.15	0.01	1.68	0.31	0.23	0.05	4.93	0.26	0.39	0.32	0.48	0.43	1.92	3.64	1.29	0.10	1.78	0.19
	6	0.42	0.02	1.85	0.18	0.32	0.08	2.01	0.27	0.56	0.15	0.49	0.39	0.74	3.27	2.61	0.14	6.71	0.14
	12	0.55	0.02	1.69	0.10	0.50	0.10	3.49	0.17	0.73	0.23	0.53	0.41	0.66	2.97	1.83	0.24	6.51	0.10
MPE	1	0.06	0.00	0.53	0.00	0.42	0.00	0.41	0.00	0.39	0.00	0.42	0.00	0.44	0.00	0.48	0.00	0.43	0.00
	3	0.80	-0.14	0.58	0.61	0.05	-3.46	1.71	-1.18	0.43	0.98	0.85	-0.22	0.31	-0.19	0.51	-0.83	0.57	0.58
	6	0.66	0.20	0.52	0.12	0.61	2.29	0.75	-1.46	0.44	0.25	0.78	-0.38	0.56	-0.17	0.53	-0.96	0.53	0.70
	12	0.57	0.53	0.44	0.14	0.51	-0.14	0.69	-4.39	0.42	1.50	0.44	-0.36	0.52	-0.31	0.47	2.60	0.71	-0.39
MAPE	1	0.69	0.00	0.52	0.00	0.56	0.00	0.61	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.56	0.00	0.01	0.00
	3	0.63	0.11	0.67	0.88	0.34	0.16	1.97	0.10	0.71	0.98	1.51	0.50	2.10	0.46	0.93	0.26	0.69	0.85
	6	0.45	0.20	0.44	0.74	0.43	0.22	0.66	0.11	0.43	0.58	0.44	0.66	1.37	0.42	0.74	1.25	0.50	1.02
	12	0.79	0.17	0.65	0.48	0.51	0.31	0.51	0.07	0.44	1.96	0.44	0.59	1.04	0.46	0.74	3.27	1.42	0.74

2.7 Appendices

Appendix 1

Table 2.6 Misspecification Tests For AR(p)

lag(p+i)	Rome	Tokyo	Seoul	Dublin	Amman	New York	London	Hong Kong	Singapore
Panel A: Portmanteau Tests for Autocorrelations for Fitted AR(p) model									
p+1	2.068	3.961	5.287	2.097	0.224	1.748	0.731	2.303	0.538
	[0.356]	[0.138]	[0.071]	[0.351]	[0.894]	[0.417]	[0.694]	[0.316]	[0.764]
p+2	2.132	5.009	5.288	2.412	0.812	1.816	0.899	3.429	3.859
	[0.546]	[0.171]	[0.152]	[0.491]	[0.847]	[0.612]	[0.826]	[0.330]	[0.277]
p+3	2.401	6.075	6.579	2.562	4.129	2.141	1.210	4.098	4.178
	[0.662]	[0.194]	[0.160]	[0.634]	[0.389]	[0.710]	[0.876]	[0.393]	[0.383]
Panel B: Breusch-Godfrey Serial Correlation LM Test for Fitted AR(p) model									
Chi-Square	0.434	0.057	0.074	0.534	0.549	0.094	0.670	0.401	0.134
RESID(-1)	-0.583	-0.979	-0.570	-0.945	1.608	1.978	-0.130	-2.087	-0.364
	(0.426)	(0.436)	(0.632)	(3.074)	(2.179)	(1.504)	(0.663)	(2.921)	(0.625)
	[0.179]	[0.031]	[0.372]	[0.760]	[0.464]	[0.195]	[0.845]	[0.478]	[0.564]
RESID(-2)	0.202	0.103	0.684	0.409	1.340	0.555	-0.014	0.871	-1.202
	(0.411)	(0.426)	(0.353)	(1.965)	(1.861)	(0.685)	(0.579)	(1.707)	(0.559)
	[0.626]	[0.811]	[0.059]	[0.836]	[0.475]	[0.422]	[0.981]	[0.612]	[0.036]
RESID(-3)	-0.273	0.594	0.229	0.445	1.099	0.011	-0.528	-0.956	-0.380
	(0.370)	(0.422)	(0.349)	(1.222)	(0.816)	(0.531)	(0.551)	(0.871)	(0.500)
	[0.465]	[0.167]	[0.516]	[0.718]	[0.185]	[0.983]	[0.343]	[0.278]	[0.451]

Panel A: The values in the square brackets are the p-values of the Ljung and Box test. The test is valid only for lags larger than the AR lag order. Panel B: the test is explained the Chi-Square for lag 3. RESID (i): indicates the LM statistics for the residuals for each lag.

Appendix 2

Table 2.7 Misspecification tests For LSTAR (p)

	Rome	Tokyo	South Korea	Dublin	Amman	New York	London	Hong Kong	Singapore
Panel A: Test of No Error Autocorrelation									
lag 1	0.238	0.166	0.978	0.608	0.824	0.295	0.166	0.122	0.481
lag 2	0.360	0.024	0.999	0.719	0.906	0.390	0.345	0.150	0.714
lag 3	0.529	0.056	0.097	0.608	0.035	0.368	0.539	0.150	0.859
lag 4	0.672	0.089	0.091	0.711	0.044	0.443	0.699	0.196	0.743
lag 5	0.675	0.135	0.112	0.621	0.060	0.603	0.700	0.265	0.293
lag 6	0.756	0.130	0.165	0.713	0.093	0.551	0.045	0.257	0.425
lag 7	0.600	0.121	0.085	0.778	0.132	0.550	0.075	0.308	0.246
lag 8	0.657	0.083	0.094	0.576	0.192	0.660	0.080	0.286	0.127
Panel B: Test of No Remaining Nonlinearity									
	0.598	0.200	0.419	0.497	0.157	0.225	0.766	0.411	0.097
Panel C: Parameter Constancy Test									
transition function									
H1	0.362	0.228	0.096	0.812	0.381	0.138	0.267	0.220	0.257
H2	0.083	0.136	0.086	0.970	0.572	0.081	0.499	0.175	0.160
H3	0.093	0.229	0.066	0.531	0.394	0.057	0.295	0.057	0.279
Panel D: ARCH-LM TEST									
p-Value(F):	0.206	0.259	0.061	0.494	0.957	0.197	0.072	0.075	0.353
p-Value(Chi^2):	0.230	0.284	0.075	0.494	0.960	0.220	0.063	0.091	0.377

The values in the table are the p-value for each test.

3 CHAPTER THREE

Measuring House Price Cycle; Evidence from Metropolitan Areas

3.1 INTRODUCTION

Effective economic policies are linked to the present information regarding the state of the economy. Policymakers and researchers suggest that the relevant information about economic status must not only be extracted through a good economic indicator but should also be investigated using robust and rigorous statistical methods (e.g. Taylor, 2015; Borio, 2014; Hiebert *et al.*, 2014). Difficulties arise, however, when an attempt is made to assess such status, especially, with noisy data that may create mixed signals about the overall state of the economy. Therefore, scientists seek to set up models that can provide a true and clear reflection of current economic developments including economic growth and large variation. Moreover, economists argue that an economic time series contains features that interact with one another, such as seasonal components, trends and cycles. However, the interaction between components cannot be observed directly from the data. Consequently, an econometric model is needed to be able to manage the noisy data.

The cycle of any economic time series is particularly important because it measures the fluctuations of economic activity as well as the stability of the economy. However, the trends and cycles interact and influence each other (e.g. Alessi and Detken, 2011; Adrian and Shin, 2010; Valle e Azevedo *et al.*, 2006). For this reason, many theories have called for a better definition of cycles. In this respect, a debate has arisen whether a particular series, such as the price series, are "pro- or counter-cyclical" (Koopman and Lucas, 2005; Harding and Pagan, 2002). However, current studies of cyclical behaviour still concern how one should isolate the cyclical component of an economic time series.

In the light of development econometrics, several methods to measure the economic cycle have been proposed. These methods include variations of the dating turning points (e.g. Claessens *et al.*, 2012; Burns and Mitchell, 1946). At the same time, a few attempts have been carried out using the frequency-based filters method (e.g. Aikman *et al.*, 2015; Stock and Watson, 2014). With the aim of reaching more robust conclusions, Hiebert *et al.* (2014) and Igan *et al.* (2011), among other studies, have applied both approaches. A few studies have also extracted cycles by means of the unobserved components time series model (e.g. Marczak and Gómez, 2017; Galati *et al.,* 2016; Creal *et al.,* 2010).

Despite this relatively rich background of past and contemporary work, there is much in this area that needs to be done. In particular, the debate, relate the uncertainty that surrounds the best approximation (ideal filter) for investigating the behaviour of economic cycles. Further uncertainty in this case concerns the indicators that define cyclical movements. In this context, Galati *et al.*, (2016) suggest that consensus on which variables to include in the analysis is subject to the data limitations of financial variables. In addition, hundreds of economic variables might be used as indicators for cyclical behaviours (Hiebert *et al.,* 2014; Chu, 2014; Stock and Watson, 2003). Nevertheless, most of the literature focuses on investigating the business and financial cycle and, to the best of our knowledge, only very few previous studies have dealt with the house price cycle.

Altogether, one can welcome the revival of attention paid to filtering and de-trending methods for the financial and economic indicators related to recent research, not only in business and financial cycles but also in other types of cycles. This chapter is to bridge the gap to reduce the above confusion by empirically studying the economic cycles and fluctuations. The present study concentrates on a critical type of economic cycle, that is, the house price cycle. In this context, the chapter addresses the following questions: i) How does the action of filtering as an approach vary across real macroeconomic time series? ii) What are the characteristics of house price cycles, and how do they differ over time? iii) Does the house price cycle have different features from business cycles?

This chapter extends and complements the existing literature on house price cycles in several ways. First, in the literature on turning points and economic cycles, scholars investigate cyclical behaviour by concentrating on one procedure (e.g. Galati *et al.*, 2016; Claessens *et al.,* 2010; Van den Noord, 2006). However, the debate about the nature of data has gained fresh prominence, with many arguing that such data affect the realisation of an ideal filter. This work attempts to fill this gap in the literature. In particular, the analysis seeks to compare different methods of decomposing and measuring the fluctuations in the cycle. For this purpose, we have considered several techniques of time series decomposition to reach a suitable form of cycle measurement. In addition, to assess the quality of the filtering techniques, we plot their periodogram as an estimate of the actual spectra. For robustness, the results of the proposed approaches are linked with the properties of an authentic cycle. This linking provides an opportunity to examine the differences between the measuring cycle approaches that are proposed in the literature.

Second, a number of published studies have investigated the boom-bust of house prices in the sensitivity of the housing market (Crowe *et al.*, 2013; Fraser *et al.*, 2008). However, these studies do not capture the volatility in the house price cycle when they considered the performance of the housing market during different phases. Some statistical characteristics of cycles in house prices have been discussed in the context of work on financial cycles (Igan *et al.*, 2011; Claessens *et al.*, 2010; Van den Noord, 2006). Despite this effort, far too little attention has been paid to performance of the house price cycle. To best of our knowledge, this is the first study that seeks to shed light on the statistical properties of the house price cycle. In this study, we contribute to the literature by analysing the characteristics of the house price cycle, especially, the duration of its expansions and contractions. In fact, the increased information about the duration and the amplitude of the house price cycle helps policymakers and optimises the policy decisions, thus reducing the risk of recession.

Finally, this chapter advances the knowledge concerning the properties of large metropolitan areas. This study documents the magnitude and characteristics of a house price cycle to shed new light on the importance of submarket at metropolitan areas level. Indeed, these could be used by the whole economy to give early warning of booms (busts) in house prices, and hence, may help to investigate the house price properties of a whole country.

The empirical analysis in this chapter offers several interesting results. First, there are differences in the cycle's characteristics between cities and over time, especially in term of fluctuation and excess area. Second, according to the periodogram analysis, the C-F filters outperform the other family of frequency-based filters. Third, according to the model-based filter model, the frequency and the variance of the model-based filters are significantly estimated. The notation emerging from the latter is that the cycle is centred on low-frequency components. Additionally, the cyclical components are near the estimated central frequency. Furthermore, considerable heterogeneity is observed not only across cities but also over time. Finally, in the case of assessing the capability of parametric and non-parametric filters, we find that the UCM are more appropriate for measuring the cycle in house prices.

In section 3.2, we continue our paper by analysing the relevant literature on the cycle technique. In section 3.3 the methodology and the specification of the procedure that was used are detailed, whereas section 3.4 discuss some data issue and the features of the classical cycle. The research results are presented in section 3.5. We conclude with a summary of the main findings.

3.2 A BRIEF OVERVIEW OF THE PREVIOUS LITERATURE

The behaviour of economic cycles has roots in the interaction between the macro economy and systematic boom-bust patterns. The literature emphasizes the role of financial stress as an early warning of recession (e.g. Marczak and Gómez, 2017; Berg and Pattillo, 1999; Kaminsky *et al.*, 1998). However, difficulties arise when one seeks the best indicator to measure the stress in economics and hence identify the economic cycle.

Several lines of empirical reseach suggest that hundreds of economic time series might be considered to measure business and financial cycles. According to Hiebert *et al.* (2014), a financial cycle should be investigated through cycles of goods and services such as credit related to the financial cycle being studied. In practice, the deviation of the credit-to-GDP ratio was found to be a good early warning indicator for the 2008 banking crisis (Hiebert *et al.*, 2014; Stock and Watson, 2014; Borio *et al.*, 2014). Yet any consensus on which variables to include in the analysis is subject to data limitations (Galati *et al.*, 2016; Stock and Watson, 2003).

To date, the literature on understanding cycle behaviour has been mostly restricted to limited comparisons of early warning indicators of financial stress and the way in which the dynamics of credit and asset markets are connected to macroeconomic activity. However, the aftermath of the last financial crisis draws attention on the importance of cyclical activity for the whole economy. Therefore, there has been renewed interest in investigating the statistical properties of cycles. In this context, the literature has taken three basic approaches, namely, turning point analysis, frequency-based filters, and unobserved component time series models.

The study of the turning point analysis approach dates back to its origins in traditional cycle-dating methods, particularly dating the peaks and troughs to identify business cycles. Seminal studies in this area have been conducted in the literature (see e.g. Claessens *et al.*, 2012; 2010), in which the authors examine the interactions between the financial and business cycles. They find that the cycles in housing and equity markets tend to be longer and are highly synchronised. Moreover, house price recessions that are associated with financial disruption episodes tend to be the longer and deeper ones.

The second approach measures the statistical properties of these cycles using frequency-based filters (such as the Hodrick-Prescott and bandpass filters). Indeed this strand of research is commonly used to analyse the financial cycle. Aikman *et al.* (2015) in their study investigate the relationship between the business and credit cycles. They estimate the spectral density using the bandpass filter of Christiano and Fitzgerald (2003). The results suggest that the amplitude and length of the financial cycle exceeds the length of the business cycle. In addition, booms in the cycle are closely connected with banking crises.

Few studies, however, have attempted to reach more robust conclusions by characterising the economic cycle with bandpass filters and the turning point approach combined. In their influential papers Stremmel (2015) and Drehmann *et al.* (2012) use the C-F filter to filter the component of each series and then investigate the turning points. Their main finding is that financial crises are associated with the peaks of the financial cycle. Furthermore, they show marked increases in the length and amplitude of the financial cycle. Finally, they highlight the importance of measuring the financial cycle in the context of macro-prudential policy. Similarly, Igan *et al.* (2011) suggest that, in the long term, the house price cycle usually leads the business and credit cycles. However, Schüler *et al.* (2015) argue that, according to the asymmetries of indicator cycles, substantial fluctuations are found in the financial cycles at shorter intervals.

In recent years, a few authors have begun to extract cycles through the unobserved components time series model. This model, like the above filter approaches, decomposes a series into a long-term trend and a short (medium) term cycle. However, this approach allows for the accuracy of the estimated trend and cycle to undergo diagnostic testing. Additionally, unlike non-parametric filters, this model requires no pre-assumptions about the length of the cycle.

An early example of research is the study conducted by Koopman and Lucas (2005), in which they examine the credit and business cycles. They argue that co-cyclicality is stronger between defaults and spreads, on the one hand, and between spreads and GDP, on the other. Furthermore, the spreads expose a positive and negative co-cyclicality with GDP and failure rates, respectively. The work by Galati *et al.* (2016) also attempts to identify the financial cycle concerning the behaviour of individual financial variables, namely, house prices, credit and the credit-to-GDP ratio. They find that the financial cycle tends to be longer than the business cycle and the amplitude is higher too.[7] Moreover, they find evidence of similarity in many cases; the financial cycle has the same cycle length, persistence, spectrum and cross-auto covariance function as the business cycle.

To date, far too little attention has been paid to the performance of house price cycles and only a few authors have attempted to describe the characteristics and behaviour of cycles in house prices. Van den Noord (2006) examined whether real house prices were nearing a peak. He found that an increase in interest rates would result in the probability of a peak. More recent attention has focused only on the use of house prices as measures of the financial cycle, as discussed (e.g. Galati *et al.*, 2016; Igan *et al.*, 2011; Claessens *et al.*, 2010).

All this evidence suggests the need for further empirical studies to compare the capability of the approaches to measuring cycles and to address the characteristic of the house price cycle. The motivation in this work is to give priority to the type of data that allows us to discriminate between proposed decomposition techniques.

3.3 EMPIRICAL METHODOLOGY

The study of cyclical behaviour is essentially carried out via time series decomposition. In this context, each time series is treated as a compound of three elements, namely, trend-cycle components, seasonal components and irregular

[7] These results refer to a complete cycle (i.e. from peak to peak or from trough to trough)

components. A researcher on cyclical behaviour should be aware of the impact of the secular trend or irregular components (e.g. Zarnowitz and Ozyildirim, 2006; Christiano and Fitzgerald, 2003; Baxter and King, 1999).

A variety of techniques is used in the way a series is decomposed to assess cyclical movements. One of the most insightful remains the Fourier decomposition, which views the signal as a linear combination of purely harmonic components, each having a time-invariant amplitude and a well-defined frequency. However, they are not easily implemented with short-length series and are not broached in this paper.

A selective filtering operation over an infinite continuous signal is defined by specifying the range of individual frequencies that should be extracted and those that should be removed. In the case of finite-length samples, it is impossible to design a filter that preserves all frequencies in a given range and completely removes those outside it (the so called ideal filter).

Recently, most research in the field of financial and business cycles considers three aspects; first, the turning point analysis which is used by the National Bureau of Economics Research (NBER);[8] second, the frequency-based filters approach; and finally, the model-based filter approach. However, debate and uncertainty continue about the best strategies for decomposing this component since the cycles and trends may interact and influence each other.

Part of the aim of this chapter is to reduce the sources of uncertainty over the different approaches to cycle estimation and to compare them. Below we give a brief overview of the recent procedure for measuring cycles.

3.3.1 Frequency-Based Filters Approach

A considerable amount of literature has grown around the theme of isolating the cyclical pattern of a particular series. In each case, a researcher has used criteria to select a frequency domain interpretation of the time series. The strategies to enhance the understanding of cycle movement involve the frequency-based filter technique. What we know about such filter techniques is largely based on empirical studies. Such frequency-selective filters as the Hodrick-Prescott (henceforward H-P) filter (Hodrick and Prescott, 1997), the Baxter-King (henceforth B-K) filter (Baxter and

[8] We refer to this methodology to investigate the classical features of the house price cycle in order to compare the results of different decomposition techniques.

King, 1999) and the Christiano and Fitzgerald (hereafter C-F) filter (Christiano and Fitzgerald, 2003) have been widely used.

The H-P filter has been used extensively to obtain a low-frequency smoothed-curve time series in studies of the business cycle. Thus, it is more sensitive to long-term than short-term variations. As stated by Hodrick and Prescott (1997) the time series can be viewed as a sum of cyclical, seasonal and growth components. Therefore, the H-P filter tends to decompose the original series $y_t = \log(Y_t)$ into cycle (c_t) and trend (τ_t) components such that the distance is minimised.[9]

Let $y_t = \tau_t + c_t$ be the house prices series. The target is to decompose this series such that

$$min\ [\sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=1}^{T}((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2], \quad (3.1)$$

where the smoothing parameter, λ, presents the trade-off between the two goals.

In Equation 3.1, the first part controls for the goodness of fit, while the second part is the second difference of the summed squares of the trend components. Since $T \rightarrow \infty$, the solution of Equation 3.1 can be found explicitly in the frequency domain, as follows

$$\mathrm{H}(L) = \frac{\lambda L^{-2}(1-L)^4}{1+\lambda L^{-2}(1-L)^4}\ . \quad (3.2)$$

The degree of smoothness is positively correlated with the values of λ since this parameter penalises variation in the trend components. Thus, the optimal value calculated for this variable are given by ($\lambda = \frac{\sigma_\tau^2}{\sigma_c^2}$), where $\sigma_\tau^2, \sigma_c^2$ are the standard deviation of the trend and of the cyclical components, respectively. The cyclical component of the H-P filter in Equation 3.2 has a particularly simple Fourier transform with cut-off frequency ($\omega = \frac{\pi}{16}$) or ($\omega = \frac{\pi}{32}$) of the form[10]

$$\tilde{\mathrm{C}} = \frac{4\lambda(1-\cos(\omega))^2}{1+4\lambda(1-\cos(\omega))^2}\,. \quad (3.3)$$

[9] The authors assumed that the data are seasonally adjusted; this component has already been removed.
[10] See King and Rebelo (1993) for the derivation.

Thus, the cyclical component of the H-P filter places zero weight on the zero frequency. In the case of very large λ, the first difference in the trend components must be arbitrarily near some constant, say β. However, Hodrick and Prescott (1997) suggest that $\lambda = 1600;\ 400$ is reasonable value for quarterly and annual data, respectively. In the case of monthly data, Kaiser and Maravall (2002) suggest that $\lambda = 6400$ may be preferred because this value is associated with the cycle definition of Burns and Mitchell (1946).

The H-P filter is constructed to extract the unit root (i.e. a stochastic trend that moves smoothly over time). In addition, this filter has the capacity to remove long cycle components (low frequencies). However, the researchers observe a poor estimate near the end point and highlight a phase shift in the series. Therefore, this H-P filter seems to be ideal as a high-pass filter.[11] Alternatively, the family of bandpass filters[12] has been introduced in the literature to remove the long cycle components (low frequencies) as well as the short ones (high-frequencies) (Christiano and Fitzgerald, 2003; Baxter and King, 1999).

Baxter and King (1999) propose a business cycle filter that takes out both slow-moving trends and very high frequency ones. Their empirical investigations related to the work of Burns and Mitchell (1946) who define the duration of the cycle as between 18 and 96 months. The authors propose several conditions for accepting this filter and ensuring that this method is operational. First, the identified range of periodicities should be extracted. Second, the filter should not introduce phase shift. Third, the method is an optimal approximation to the ideal bandpass filter. Thus, an estimated bandpass essentially results in a stationary time series even when applied to trending data. Fourth, the filter should able to remove quadratic deterministic trends from a time series, and hence, the filters' response will be exactly zero at the zero frequency. Fifth, there is no connection between the sample period length and the method of yielding business-cycle components.

The B-K filter relies mainly on the use of a symmetric finite odd-order moving average of the form $M = 2K + 1$ which produces a new series given by

[11] The term 'ideal filter' refers to a filter that preserves all frequencies in a given range and completely removes those outside it.

[12] A bandpass filter refers to a filter that passes signals within a certain "band" or "spread" of frequencies without distorting the input signal or introducing extra noise.

$$\nu_t = \sum_{n=-K}^{K} (a_i y_{t-n}) = a_0 y_t + \sum_{n=1}^{K} (y_{t-n} + y_{t+n}). \tag{3.4}$$

For the set of M weights, a_n is obtained by truncating the ideal filter coefficients at M under the frequency response constraint $H_0 = \Delta t \sum_{-N/2}^{(N-1)/2} (a_n)$ of the correct amplitude at the cut-off frequency $\omega = 0$, that is, $H\ (0) = 1$ for low-pass filters and $H(0) = 0$ for high-pass and bandpass filters. The coefficients of the filters are driven by the following optimization problem

$$min \int_{-(2\Delta t)^{-1}}^{(2\Delta t)^{-1}} \left(\sum_{n=-K}^{K} ((a_n)^{BK} - (a_n)^{ideal})\, (e)^{-2i\Pi n\omega\Delta t}\right)^2 d\omega \;\; s.t{:}\; \sum_{n=-K}^{K} (a_n)^{BK} \frac{H(0)}{\Delta t}, \tag{3.5}$$

where $i = \sqrt{-1}$ and $(a_n)^{ideal}$ refers to the case in which the filters allow a specified frequency range of interest to pass through. $(a_n)^{BK}$ stands for the objective value calculated through the B-K filter.

The solution of Equation 3.5 reveals that the same constant quantity shifts in all ideal coefficients, given by

$$(a_j)^{BK} = (a_j)^{ideal} + \frac{H(0) - \sum_{n=-K}^{K} (a_n)^{ideal}}{M\Delta t}. \tag{3.6}$$

According to Baxter and King (1999), the lag operator is $\alpha(L) = \sum_{n=-K}^{K} (\alpha_n L^n)$ and besides, mathematics simplification tools lead to

$$\alpha(L) = (1 - L)(1 - L^{-1})\ \psi(L), \tag{3.7}$$

where $\psi(L)$ is symmetric moving average with $K - 1$ leads and lags.

As shown in Equation 3.7, the B-K filter can render the stationarity of the series that contain up to two unit roots. In addition, the filter produces properties of symmetry since there is no shift phase present. Moreover, the moving average does not depend on the number of observation N. In this context, since $M < N$ the filter is unresponsive to linear deterministic trends, which in turn implies that the filter performance does not depend on more data being available. The filtering in the time domain involves the loss of K data values from the beginning and the same values from the end of the series. However, the authors tend to put $K \geq 12$ for the cycle of $(18, 96)$ months. The key problem with this explanation is that the performance of the B-K filter depends on an increase in the value of the moving average M, which leads to a decrease in the available data.

The issue of dropped observations has received critical attention in the literature. In their seminal work, Christiano and Fitzgerald (2003) consider the following optimization problem

$$\min_{\{\alpha_j\}} \int_{-(2\Delta t)^{-1}}^{(2\Delta t)^{-1}} \left(\sum_{\{j\}}\left((\alpha_j) - (\alpha_j)^{ideal}\right)(e)^{-2i\Pi_j\omega\Delta t}\right)^2 \left(U^{exact}(\omega)\right)^2 d\omega. \qquad (3.8)$$

Equivalently, the filter is supposed to written as the discrepancy between the effectively filtered data and the ideally filtered ($\omega_j{}^{\mathrm{ideal}}$) that is

$$\min\ \left(\omega_j - \omega_j{}^{\mathrm{ideal}}\right)^2 = \int_{-(2\Delta t)^{-1}}^{(2\Delta t)^{-1}} \left(\mathrm{H}(\omega) - \mathrm{H}^{\mathrm{ideal}}(\omega)\right)^2 \left(\mathrm{U}^{\mathrm{exact}}(\omega)\right)^2 d\omega. \quad (3.9)$$

The spectral density of the original series $U^{exact}(\omega)$ is assumed to be known. This case sheds light on the set of indexes {j} which lead to different types of filter. To be specific, they are constant symmetric if $j = -K, \dots, K$, constant asymmetric if $j = -K, \dots, K'$ or general time-varying if $j = -(n-j), \dots, j-1$. Thus, the explicit solutions are obtained through different powers of the spectral density shapes, i.e. $\left(U^{exact}(\omega)\right)^2 \propto \omega^{-2}$. Clearly, this procedure is optimal when the series is a case of the random walk process and the coefficient can be found explicitly by truncating the ideal filter and then adjusting only the (α_{-K}) and (α_K). In this way, if we consider j to be the ideal coefficient, $\hat{\alpha} = \frac{\alpha_0}{2}$ and $\alpha_{\{0,j\}} = \alpha_0 + \alpha_1 + \dots + \alpha_j$, then the filtering operation could be written as

$$\begin{bmatrix} \omega_1^{CF} \\ \omega_2^{CF} \\ \vdots \\ \vdots \\ \vdots \\ \omega_{N-1}^{CF} \\ \omega_N^{CF} \end{bmatrix} = \begin{bmatrix} \hat{\alpha} & \alpha_1 & \alpha_2 & & \alpha_{N-3} & \alpha_{N-2} & \alpha_{N-1} \\ \hat{\alpha}-\alpha_1 & \alpha_0 & \alpha_1 & \cdots & \alpha_{N-4} & \alpha_{N-3} & \hat{\alpha}-\alpha_{\{0,N-3\}} \\ \hat{\alpha}-\alpha_{\{0,1\}} & \alpha_1 & \alpha_0 & & \alpha_{N-5} & \alpha_{N-4} & \hat{\alpha}-\alpha_{\{0,N-4\}} \\ \vdots & & & \ddots & & & \vdots \\ \hat{\alpha}-\alpha_{\{0,N-4\}} & \alpha_{N-4} & \alpha_{N-4} & & \alpha_0 & \alpha_1 & \hat{\alpha}-\alpha_{\{0,1\}} \\ \hat{\alpha}-\alpha_{\{0,N-3\}} & \alpha_{N-3} & \alpha_{N-4} & \cdots & \alpha_1 & \alpha_0 & \hat{\alpha}-\alpha_1 \\ \alpha_{N-1} & \alpha_{N-2} & \alpha_{N-3} & & \alpha_2 & \alpha_1 & \hat{\alpha} \end{bmatrix} \times \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ u_{N-1} \\ u_N \end{bmatrix}. \quad (3.10)$$

To sum up, empirical evidence shows that both the B-K filter and the C-F filter are proficient at removing low and high frequencies. A serious weakness of these filters, however, is that the B-K filter loses $(2K)$ observation based on the moving average order K which reduces the data available for analysis and the only solution provided is to reduce this K. However, this decrease will affect the performance of the filter. This losing observation problem is addressed by the C-F filter. Nonetheless, the issue supposed to be raised by rising with C-F filter is that this filter drops the symmetry and stationarity conditions on the filter coefficients since this procedure produced N different filters which lead to the inconstancy during the time.

Recently, an alternative model-based filter approach has been proposed by Harvey and Trimbur (2003). In this case, the filter is defined implicitly through the unobserved components method. In addition, this type of filtering adapts automatically to the ends of the sample and finds mean square errors. The following sub-sections elaborate on this procedure.

3.3.2 Model-Based Filter Approach

The key aspect of model-based filters or Unobserved Component Model (UCM), unlike the previous approach, is that they estimate the cycle frequency through estimating an unobserved component model with the maximum likelihood method. This model is useful for modelling fat tailed data because it uses a parameter driven through the Kalman filter (Durbin and Koopman, 2012; Harvey and Trimbur, 2003). Additionally, researchers can use diagnostics to evaluate the validity and accuracy of the model.

Following the seminal work of Harvey and Trimbur (2003), this model decomposes an economic time series $y_t = \log Y_t$ into three unobserved components, specifically, the long-term trend ($\tau_{i,t}$), the short- to medium-term cyclical dynamics in the series i at time t ($\psi_{i,t}$) and a normally distributed residuals stand, ($\epsilon_{i,t}$), that is

$$y_{i,t} = \tau_{i,t} + \psi_{i,t} + \epsilon_{i,t}, \quad \epsilon_{i,t} \sim i.i.d\ N\left(0, \sigma_{\epsilon,i}^2\right). \tag{3.11}$$

The cycle associated with one variable is apparently unrelated to the cycle of the other variables. This also applies to the trend and the residual components. However, the covariance between the disturbances driving a particular component is typically non-zero and indicates a dependence structure among the dynamic characteristics of all components.

The crucial challenges in this decomposition are, first, to choose the smoothness of the trend $(\tau_{i,t})$. Put differently, how can we measure the fluctuations in the trend components compared with the fluctuation in the cyclical ones? According to Harvey *et al.* (1997), the smoothness of the trend depends on the differencing order (m). The following are the criteria for selecting the degree of smoothness

$$\begin{aligned} \tau_{i,t+1}^{(m)} &= \tau_{i,t}^{(m)} + \tau_{i,t}^{(m-1)} \\ \tau_{i,t+1}^{(m-1)} &= \tau_{i,t}^{(m-1)} + \tau_{i,t}^{(m-2)} \\ &\vdots \\ \tau_{i,t+1}^{(1)} &= \tau_{i,t}^{(1)} + \xi_{i,t} \end{aligned} \quad ; \ \xi_{i,t} \sim \mathrm{i.i.d}\ N(0, \sigma_{\xi,i}^2). \tag{3.12}$$

where $\xi_{i,t}$ stand for the irregular components.

In the frequency domain, the resulting trend is positively related to the m. In this case, a higher value for m entails that the low-pass gain function will have a sharper cut-off.[13] The additional critical challenge is to specify the relevant stochastic process for the cycle ($\psi_{i,t}$). A cyclical component in the time series can be specified as an autoregressive model with complex coefficient roots. Below is shown the standard approach of Harvey (1990); the cyclical components are specified as[14]

$$\begin{pmatrix} \psi_{i,t+1} \\ \psi_{i,t+1}^* \end{pmatrix} = \varphi_i \begin{bmatrix} \cos(\lambda_i) & \sin(\lambda_i) \\ -\sin(\lambda_i) & \cos(\lambda_i) \end{bmatrix} \begin{pmatrix} \psi_{i,t} \\ \psi_{i,t}^* \end{pmatrix} + \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{i,t}^* \end{pmatrix}, \mathrm{s.t} \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{i,t}^* \end{pmatrix} \sim \mathrm{i.i.d}\ N\left(0, \sigma_{i,\varepsilon}^2\right). \tag{3.13}$$

The parameter φ_i denotes the damping, i.e. the spread around the estimated central frequency λ_i which is measured in radians.[15] All trend, cycle and residual disturbances are mutually and serially uncorrelated, at all times and lags, but separately they may be correlated with a corresponding item of the other two variables.

The UCM can be formulated in the general state space form (see Durbin and Koopman, 2012; Harvey, 1990)

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[13] Further, the series assumed to be stationary if m=0. In addition, it has a random walk if m=1. However, most macro and financial variables are supposed to use m=2 as optimum choices.

[14] The cyclical component is specified as an autoregressive of order 2 with complex root.

[15] The cycle should model as a stationary stochastic process so the damping should be $(0 < \varphi < 1)$.

$$y_t = A_t\alpha_t + \varepsilon_t\ , \tag{3.14}$$

$$\alpha_{t+1} = B_t\alpha_t + \mu_t\ . \tag{3.15}$$

Equation 3.14 is stated as the observation equation with state vector α_t, and Equation 3.15 is called the state-equation. The two matrices A_t, B_t contain the objective parameters. Once the model is represented in state space form, the Kalman filter and the related state space methods can be applied. The unknown static parameters are estimated by the maximum likelihood method.[16] Given these estimates, the prediction residuals are obtained for diagnostic checking and model evaluation from the Kalman filter. In addition, the smoothed estimates of the unobserved trend, cycle and residuals components are obtained from a smoothing method (Durbin and Koopman, 2012).

Together, there is ongoing debate surrounded the capability of the aforementioned filtering approach. It can be seen that obtaining the appropriate filter demands picking a finite range of frequencies with infinite resolution, which requires an infinite number of data. However, with limited data availability, the ideal filter cannot be realised straightforwardly. A more comprehensive study would include all the types of filter. This procedure helps to compromise the cyclical properties investigated through the filters compared with the classical cycle defined by NBER. The next section of this chapter examines the performance of the different filters on authentic data.

3.4 DATA AND DESCRIPTIVE STATISTICS

The data under consideration consist of a monthly time series of the house price index over the period 1996:1 to 2015:12 for a sample of nine metropolitan areas. The potential of using city-level data is that they reflect the importance of particular cities (with highest average prices) as an early warning for the boom (bust) in house prices for the whole economy. Because of the limited data availability, the sample was carefully chosen to represent the different structure of economies around the world. This sample includes Tokyo, Singapore, Seoul, Amman, Hong Kong, Dublin, London, Rome, and New York. Data for this study were collected using Bloomberg.

[16] Numerical maximization requires the Kalman filter to compute the log likelihood function

It is also worthy to note that we use the global house prices index as there is no difference among other house prices indices.

Since house prices show deviations over short periods and dramatic mean reversion over long periods, the cases reported here illustrate volatility from one region to others in the sample. This simple statistical analysis illustrated here is used to report the movement's features in house prices between the turning points. To identify the behaviour of a classical cycle's, this study applies the turning point procedure to date the peaks and troughs in the log-level of aggregate economic activity (Harding and Pagan, 2002; Bry and Boschan, 1971).[17] This algorithm recognises local maxima (minima) to disentangle the expansion (contraction) phase of a time series.

This procedure defines cyclical behaviour as sequences of contractions and expansions in the level series and the results deal with the characteristics of the short-term cycle. This position is taken by the ''classical cycle'' approach and can be analysed with (without) trend adjustments (Morley and Piger, 2012; Zarnowitz and Ozyildirim, 2006). Following Bry and Boschan (1971), the turning point of the series $y_t = \Delta \log Y_t$ at time t is defined as

$$\text{Peak at} \quad \mathrm{t} = \{\mathrm{y_{t-k}} < \mathrm{y_t} > \mathrm{y_{t+k}}\}. \tag{3.16}$$

$$\text{Trough at} \quad \mathrm{t} = \{\mathrm{y_{t-k}} > \mathrm{y_t} < \mathrm{y_{t+k}}\},\ \forall\, \mathrm{k} = 1, \ldots, 5. \tag{3.17}$$

Following the seminal work in this context, we adopt the business cycle methods of Burns and Mitchell (1946) in the housing market context to investigate the house price cycle; that is, we use the official dates of the start and end of recessions to separate the house price series into expansions and contractions (see e.g. Claessens *et al.*, 2012; 2010). With monthly data, a complete cycle takes at least 15 months.[18] In addition, each contraction (expansion) phase has a minimum duration of 6 months. Moreover, the selected turning point is chosen so that they alternate. In other words, a peak (trough) must be higher (lower) than the previous one.

[17] This rule is still widely used in the Euro Area Business Cycle Dating Committees and the NBER.
[18] A complete cycle occupies the distance between two proposed consecutive peaks (troughs).

Table 3.1 Dating of peaks (troughs) in real house prices

	peak	Duration of upswing	Price increase (%)	trough	Duration of downswing	Price decrease (%)
Tokyo	Sep. 2007	44	0.19	Jan. 2004	97	0.19
	Mar. 2010	11	0.30	Apr. 2009	19	0.38
	Feb. 2014	18	0.11	Aug. 2012	29	0.12
				Aug. 2014	6	0.34
Singapore	Mar. 1997	15	0.19	Nov. 1998	20	1.00
	Apr. 2000	17	0.99	Dec. 2003	44	0.27
	Feb. 2008	50	0.51	Feb.2009	12	0.61
	Jan.2014	59	0.44			
Seoul	Oct. 1997	15	0.12	July 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	July 2002	79	0.16	Feb. 2003	7	0.20
	Oct. 2005	32	0.20	Aug. 2006	10	0.10
	July 2007	11	0.15	May 2009	22	0.30
	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
	Nov. 2004	107	0.45	Apr. 2005	5	0.11
London	Feb. 2008	34	0.33	Apr. 2009	14	0.59
	July 2010	15	0.40	Dec.2010	5	0.11
	Aug. 1998	32	0.28	Dec. 2001	40	0.21
	Jan. 2003	13	0.02	Feb. 2005	25	0.21
Hong-Kong	Dec. 2007	34	0.15	Aug. 2008	8	0.08
	Apr. 2009	8	0.47	July 2010	15	0.03
	July 2004	103	0.42	Feb. 2005	7	0.16
	Aug. 2007	30	0.34	Mar. 2009	19	0.56
Dublin	Apr. 2010	13	0.24	Dec. 2011	20	0.14
	July 2014	31	0.24	Dec. 2014	5	0.13
	Dec.1999	41	0.04	July 1996	7	0.07
	Apr. 2002	17	0.05	Nov. 2000	11	0.03
Amman	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

Duration is expressed in months.

The results in Table 3.1 report the date at which the peaks (troughs) of the house price cycle occur. A visual exploration of these results confirms that house price cycles varied significantly in the period under review and behaved very differently across regions. For example, the peak phase for New York, London, Rome and Dublin continued for more than 5 years, between 1996 and early 2000 and the house prices index rose by 0.26%,0.45%,0.16% and 0.42% per month, respectively. By contrast, the case of Tokyo shows a long period of downswings during the period 1996-2004, where the house prices index declined by 0.19% per month due to the Asian crisis in 1997.

A closer inspection of Table 3.1shows that the upswing (downswing) had a greater impact on house prices in Singapore than anywhere else in the sample. In addition, it is interesting to note that the rest of the sample experienced switching between ups and downs in 1996-2005. Another remarkable outcome is that the real house prices in most of cases peaked before the financial crisis (i.e. before the period Aug. 2006 – Sep. 2008). The signs of these results are in line with our expectation that the boom in house prices in the metropolitan areas provided clear evidence that house prices can be used as an early warning for the whole economy. These results are in agreement with those obtained by Taylor (2015) and Gimeno and Martinez-Carrascal (2010). When the crisis hit, house prices were in no long-term decline and the contractions during the crisis periods lasted no more than three years. Moreover, most of them have experienced continued upswings since the trough in early 2009.

A second simple set of non-parametric statistical analyses is applied to capture two main features of the cyclical phases, namely, duration and amplitude. Harding and Pagan (2002) state that the duration of expansion (contraction) refers to the number of months between one peak (trough) and the next in a completed cycle. In the same procedure, the amplitude relates to a change in the series of interest from a peak (trough) to the next trough (peak).

Following the work by Engel *et al.* (2005) and Morley and Piger, (2012), suppose the dates of turning point produce M expansions and contractions. The average duration of expansions (D^E) and contractions (D^C) are given by

$$\mathrm{D}^{\mathrm{E}} = \frac{1}{\mathrm{M}}\sum_{\mathrm{i}=1}^{\mathrm{M}} \mathrm{D}_{\mathrm{i}}^{\mathrm{E}} \quad ; \quad \mathrm{D}^{\mathrm{C}} = \frac{1}{\mathrm{M}}\sum_{\mathrm{i}=1}^{\mathrm{M}} \mathrm{D}_{\mathrm{i}}^{\mathrm{C}}. \tag{3.18}$$

In addition, the total gain (loss) in house prices over the phase can be estimated through cumulative movement, which is given by

$$\mathrm{C.M} = \sum_{\mathrm{j=1}}^{\mathrm{D}} (\mathrm{y_j} - \mathrm{y_0}) - \frac{\mathrm{A}}{2}. \qquad (3.19)$$

where D and A refer to the duration and amplitude of expansion (contraction), respectively.

Combining the duration, amplitude and cumulative movement, we can calculate the total rise (fall) in house prices output

$$excess\ area = \frac{C.M - AD}{AD},\ s.t;\ AD = \frac{D * A}{2}. \qquad (3.20)$$

The results of the average duration and amplitude are presented in Table 3.2 below, which illustrates the features of house price movements between the identified turning points. For each region, Table 3.2 splits the data into expansion and contraction phases. In addition, for each phase, the results are presented for the average duration of the phase (in months), the average amplitude of the phase (in total and rate per month) and movement in prices (in percentage changes).

A relatively similar pattern to those of the business and financial cycles[19] emerges for the typical house price cycle during contractions, although the typical house prices cycle has a shorter upturn phase. It is encouraging to note in Tokyo that the duration of contractions is longer than that of expansions. A possible explanation for this may be that the series of events in last two decades that has affected the growth of the housing market sector as well as the whole economy (for example, the global financial meltdown, the Great Tohoku Earthquake and the economic slowdown in China, Japan's largest export market) exacerbated the situation.[20] Another significant finding is that the evidence of asymmetry in house price cycles, where the upturn phases are longer than the decline phases.[21] The latter is a well-known feature of most of the asymmetric cycles in economic activity. The impression of these results is possibly that the cyclical differences may relate to differences in the structure of the financial systems and housing markets of countries

[19] More details about the features of these cycles can be found in the literature (Berg and Pattillo, 1999; Kaminsky *et al.*, 1998; Goldfajn and Valdés, 1998).

[20] More details about the property price can be found via http://www.globalpropertyguide.com/

[21] The same results are found by Hiebert *et al.* (2014), Drehmann *et al.* (2012) and Claessens *et al.* (2012).

such as different owner-occupation rates, shares of mortgage debt and the pervasiveness of variable rate mortgages.[22]

From Table 3.2 it also appears that there are notable differences in the cycle's characteristics across cities. For instance, the duration of both the upturn and downturn in Tokyo, Singapore, New York and Hong Kong are greater than in other cities. In other words, house prices in these cities appear to be fluctuate less than in other housing markets. Regarding the duration across all regions, the duration of price expansions is about two to five years. However, contractions seem to last less than two years on average. In addition, Table 3.2 reveals that the average cycle (peak-to-peak) takes about five to seven years. Similarly, regarding the amplitude, the house prices bust in Singapore and Tokyo was deeper than the other cities. In contrast, during the expansion phase, house prices in London, New York, Singapore and Dublin were higher than elsewhere in the sample. Another important finding is that downswing (upswing) in this study qualifies as "major" since the cumulative real price decline (increase) is at least 15%.

Table 3.2 Classical House Prices Cycle Characteristics

	Contraction				Expansion			
	Duration	Amplitude	Cumulative	Excess-area	Duration	Amplitude	Cumulative	Excess-area
Tokyo	37.500	-9.106	-272.562	0.596	22.250	6.072	69.465	0.028
Singapore	24.750	-11.434	-155.408	0.098	35.000	18.283	420.845	0.315
Seoul	16.400	-2.429	-22.612	0.135	31.400	8.643	189.815	0.399
Rome	17.750	-3.636	-36.118	0.119	36.000	6.052	161.864	0.486
New York	25.500	-3.798	-38.197	-0.211	62.667	14.552	658.423	0.444
London	8.000	-3.118	-20.751	0.664	53.750	20.951	841.841	0.495
Hong Kong	22.000	-5.251	-80.913	0.401	30.200	7.077	186.055	0.741
Dublin	12.750	-4.041	-35.287	0.370	37.600	13.912	400.689	0.532
Amman	9.000	-0.485	-2.558	0.172	38.000	2.764	65.128	0.240

Duration and amplitude refer to the average of the duration and amplitude of the cyclical component by city.

Amplitude, cumulative and excess area are expressed in percentages.

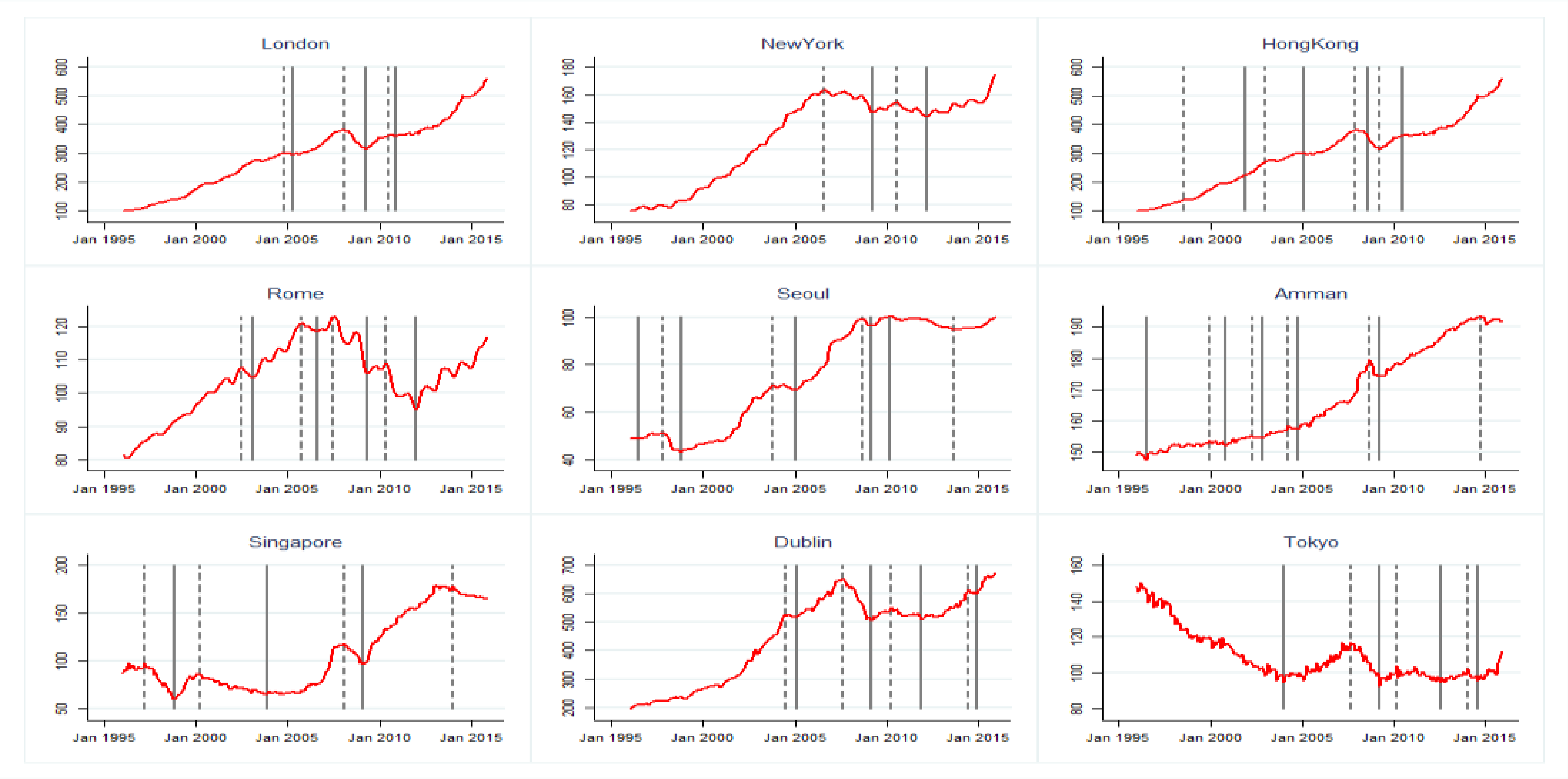
Going on toward the excess area, we consider the growth (decline) in house prices during an expansion (contraction). Interestingly, there are differences in the

[22] The literature suggests that an asymmetric cycle occurred when the expansion phase lasted twice as long as the contraction phase due to the financial structure of the country (Taylor, 2015; Igan *et al.*, 2011).

ratios of the excess area. For instance, a close relationship between the expansion period and the rise in output is obtained in all cases. One unanticipated finding within the sample (except in the case of New York) is that the contraction period has no negative impact on the total gain in house prices. An explanation for this may lie in the liquidity of the housing market and new policies and measures permitting foreigners to buy real estate freely in these cities (Knoll, Schularick and Steger, 2015).[23]

[23] More details about property prices can be found via *http://www.globalpropertyguide.com/*

Figure 3.1 House price index with peaks (troughs) indices



The dashed line shows the peak date while the solid line shows the trough date.

3.5 EMPIRICAL RESULTS

The results in the previous section indicate quite different features of the house price cycle across both time and region. This section, therefore, examines the capacity of the filtering technique (discussed in Section 3.3) to capture these features. Each filter is evaluated in terms of its ability to display the necessary characteristics. In this context, the necessary characteristics are: i) the ability to isolate the frequency of the cycle component without reweighting the passed frequencies, ii) capture most of the actual turning point and iii) produced stationary cyclical components.

The empirical discussion centres on the cyclical behaviour of house prices in the cities under consideration. The first set of analyses present the characteristics of the cycles based on the frequency-based filter and model-based filter, as mentioned in Sections 3.3.1 and 3.3.2. Next, we distinguish between these filters to evaluate which method is close to the classic cycle properties mentioned in Section 3.4. Finally, we check whether the cycle is produced in a stationary process.

3.5.1 Non-parametric Filters

This section discusses the findings which emerge from the non-parametric filtering method. The sample spectral density function (or periodogram) is plotted to look for periodic signals and, hence, to distinguish between the mentioned possibilities.[24] Such a periodogram is a frequency domain characterisation of a population of stationary time series. The idea behind using this periodogram is to show the periodic components and contribute evidence about the relative strengths of the various frequencies. In fact, the periodogram estimates the significance of different frequencies in time-series data to identify any intrinsic periodic signs that explain the variation in the time series. In this context, a relatively large value of the periodogram value at an identified frequency indicates more importance in explaining the oscillation in the observed series.

In the filtering context, the filter's capability is measured once the stochastic cycles at the unwanted frequencies are completely removed. Put differently, the dominant peak (trough) area occurs somewhere around a frequency between $\lambda = 0.03$ and $\lambda = 0.17$, corresponding to periods of about 32 and 6 months, respectively.

[24] Since the present study was designed to choose the appropriate filtering method, the results of the periodogram of all the filters are presented in a single graph for the entire sample.

Moreover, the periodogram would be a flat line at the lowest value outside the range recognised in the vertical lines. These results are shown below in Figure 3.2, Figure 3.3 and Figure 3.4. In these figures the x-axis shows the natural frequencies while the cyclical component of the filter is drawn on the y-axis. In addition, vertical lines at the natural frequencies correspond to the classical cycle which is mentioned in the literature.[25]

It is interesting to note that in all cases the periodogram of the H-P filter (see Figure 3.2) shows low periodicity and high periodicity. In more details, the points in the left-hand vertical line are strong evidence that this filter has no capacity to filter high periodicity stochastic cycles. Additionally, the observations in the right-hand vertical line reveal that the low-periodicity stochastic cycles show no tendency to be clustered around zero that is associated with the minimum value in the periodogram which is -6 in our case.[26]

However, the case of Rome (see the second line of Figure 3.2) is somewhat unexpected; the H-P filter shows convergence toward -6 and evidence of smoothing can be found. It may be the case therefore that the variations in Rome should be considered as high frequency.

Similarly, the results from B-K filter are not very encouraging. As shown in Figure 3.3, the removed stochastic cycles are more fixed than in the H-P filter only on the right-hand side and there are cases of some cities that tend to be smoothed toward -6. However, the high periodicity stochastic cycles still have too many points above -6. It is possible to remove more of the unwanted stochastic cycles by changing the filter symmetric moving average. Nevertheless, this process is inappropriate since larger values will increase the missing observations in the filtered series.

Interestingly, there are also differences regarding the C-F filter, as shown in Figure 3.4. This filter filters out the unwanted stochastic cycles among all the cities reasonably well (particularly in the low periodicity). Furthermore, some cities, namely, Amman, Tokyo, Seoul and Singapore, produce an exact smoothing at -6.

[25] As documented in the literature, the business-cycle components of 32 periods and 6 periods. The natural frequencies refer to the standard frequencies divided by 2π (Claessens *et al.,* 2012; Burns and Mitchell, 1946).
[26] More details about the minimum value are presented in the appendix.

However, again it is somewhat surprising that no convergence is noted in the high periodicity.

To assess whether these methods offer measurements close to the classical cycle reported in Table 3.2, the cycle component is plotted against the turning point indices identified by the shaded areas.[27] Following the literature, and as discussed in Section 3.4, this paper applies the BB-algorithm to divide house price series into upturns and downturns (e.g. Harding and Pagan, 2002). Another essential note is that the plotted series present every upturn (downturn) in the cycle. However, we seek only the turning points under the conditions mentioned in Section 3.4.

Generally, the filtered series has a progressive phase drift which affects each frequency component differently. Moreover, the phases between the two components are wavering over time. Therefore, the shape of the original signal is not preserved. Unsurprisingly, the H-P filter, as stressed in Figure 3.5 (conforming to the finding in the previous literature) is a high-pass filter and produces a high volatility cycle while the fluctuations in the cycle exceed the turning point indices agreed by the shaded area. In addition, the H-P filter failed to capture the turning point at the start and end of the period. However, in a few cases, the cycle presents a turning point which resembles the classical one. Therefore, it is not easy to see whether or not the decomposed cycle touched the shaded turning point.

Considering the cycle component in the B-K filter, the results, as shown in Figure 3.6, indicate that the filter captures most of the turning point indices in London, Rome and Amman but produces an undefined turning point in New York and Hong Kong. Moreover, in Seoul, Singapore and Dublin the cycle cannot reach the last turning point indices due to the omitted observation problem discussed in Section 3.5.1.

The experimental evidence for the C-F filter in Figure 3.7 reveals that the turning point in the cycle touched most of the trough indices in the cities. Furthermore, in some situations this filter demonstrates significant agreement between the filtered cycle and the classical one. However, again there is an unwanted turning point in the cases of New York and Hong Kong.

[27] it should be borne in mind that there are no official dates for housing turning points, and researchers need to identify the contractions and expansions for themselves

Together these results provide valuable insights into the capabilities of the non-parametric filter approach. At the outset, not all the recession (detected in produced cycle) coincides with the typical troughs (peaks) in the house price cycle. Likewise, the decomposition methods applied so far reveal that the associated influence of individual components varies over time. Additionally, the C-F filter probably shows a closer association with the classical cycle than other filter-based approaches do. Therefore, it appears to be outperforming other approaches to this point. However, these results are not very encouraging for making any final conclusion. This must wait until the performance of the model-based filter is seen.

Figure 3.2 sample spectral density function (H-P Filter)

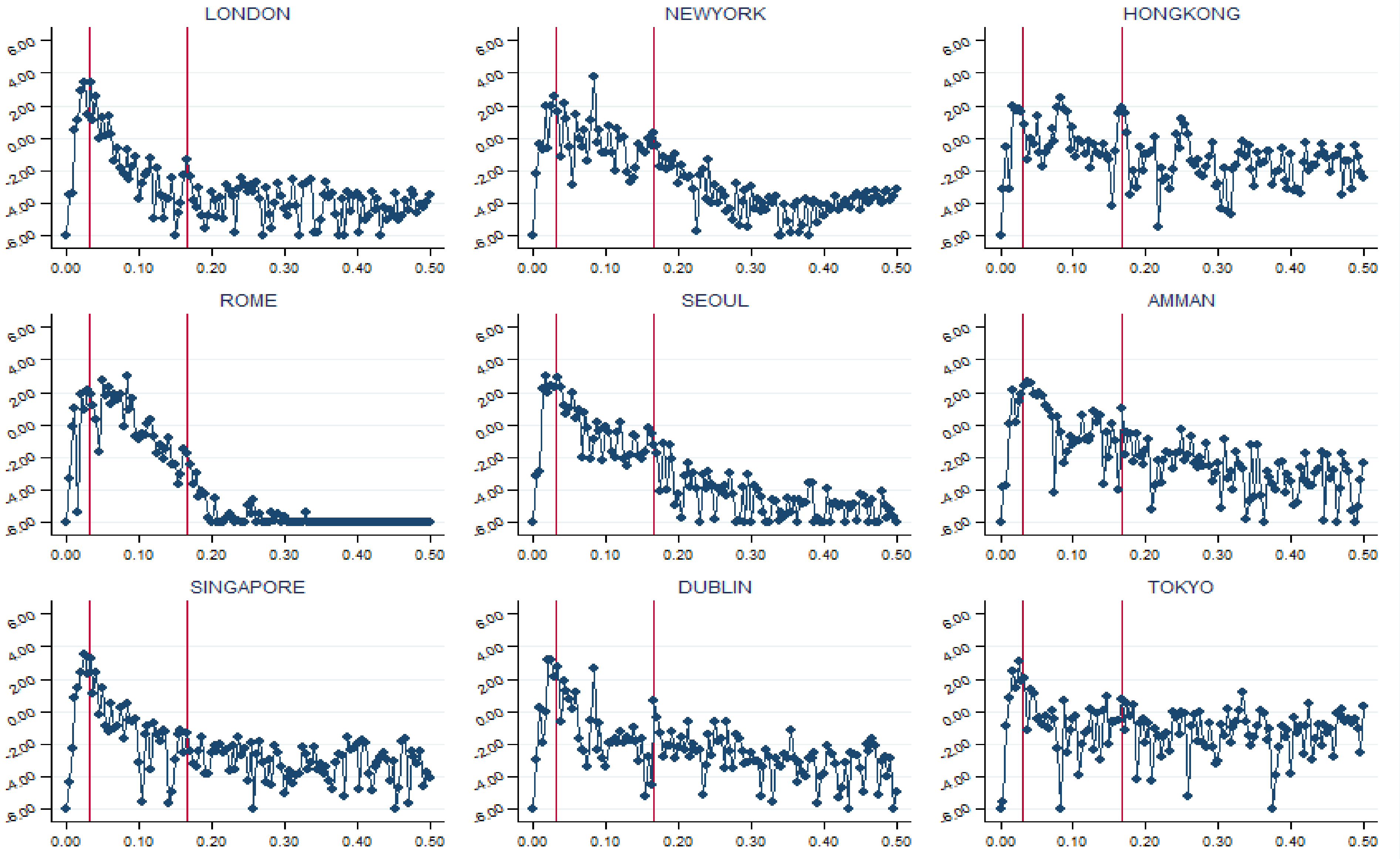


Figure 3.3 sample spectral density function (B-K Filter)

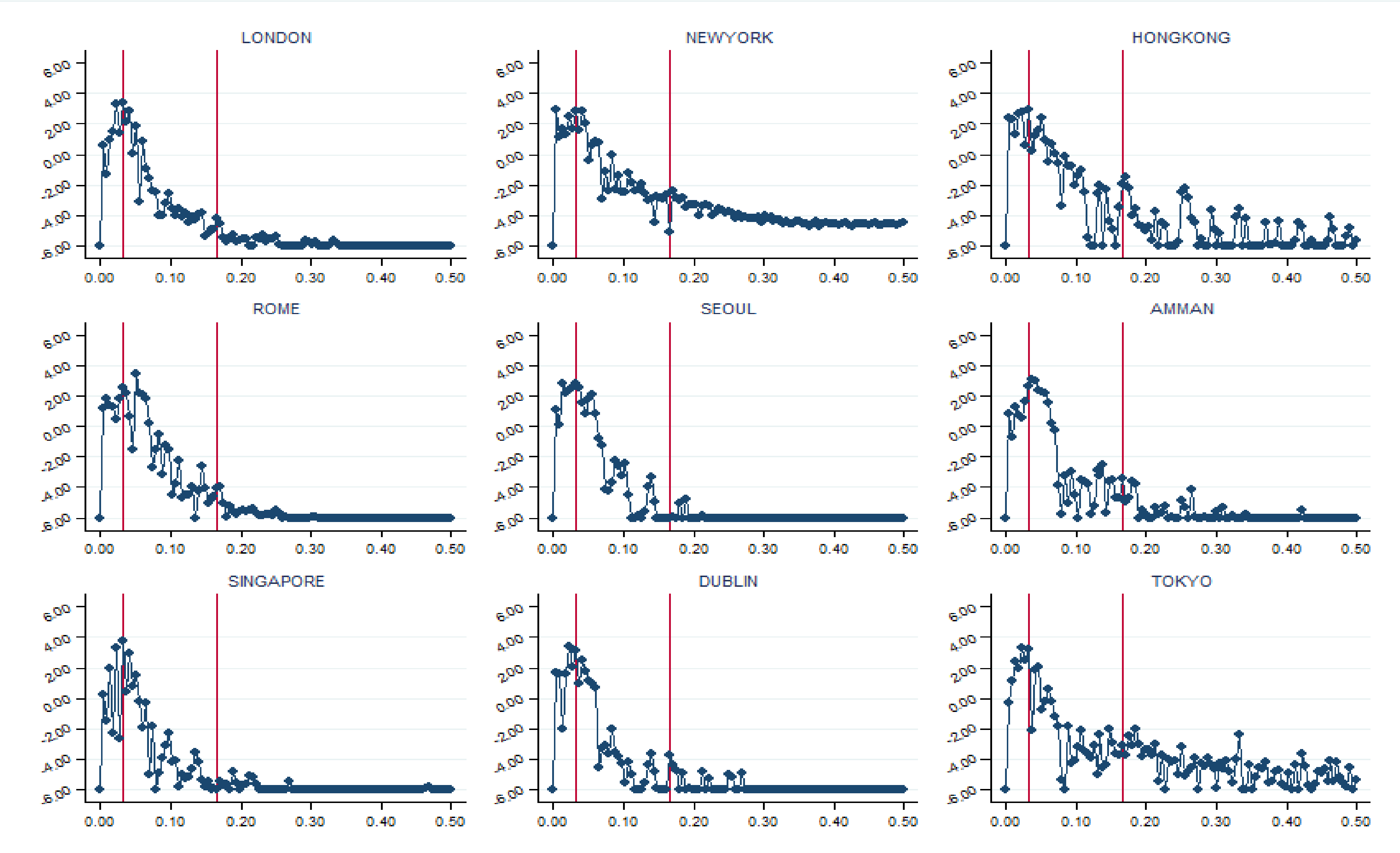


Figure 3.4 sample spectral density function (C-F Filter)

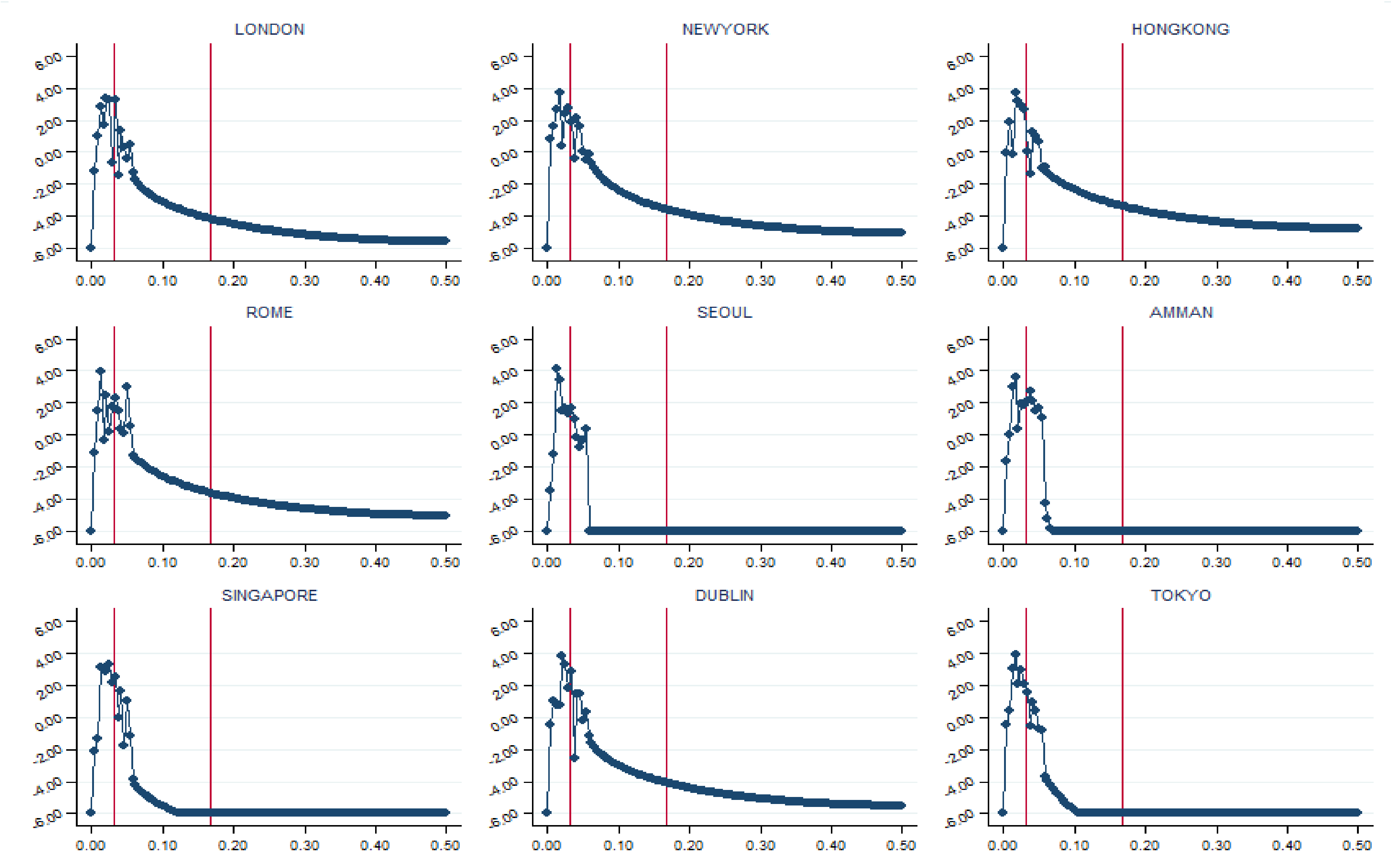
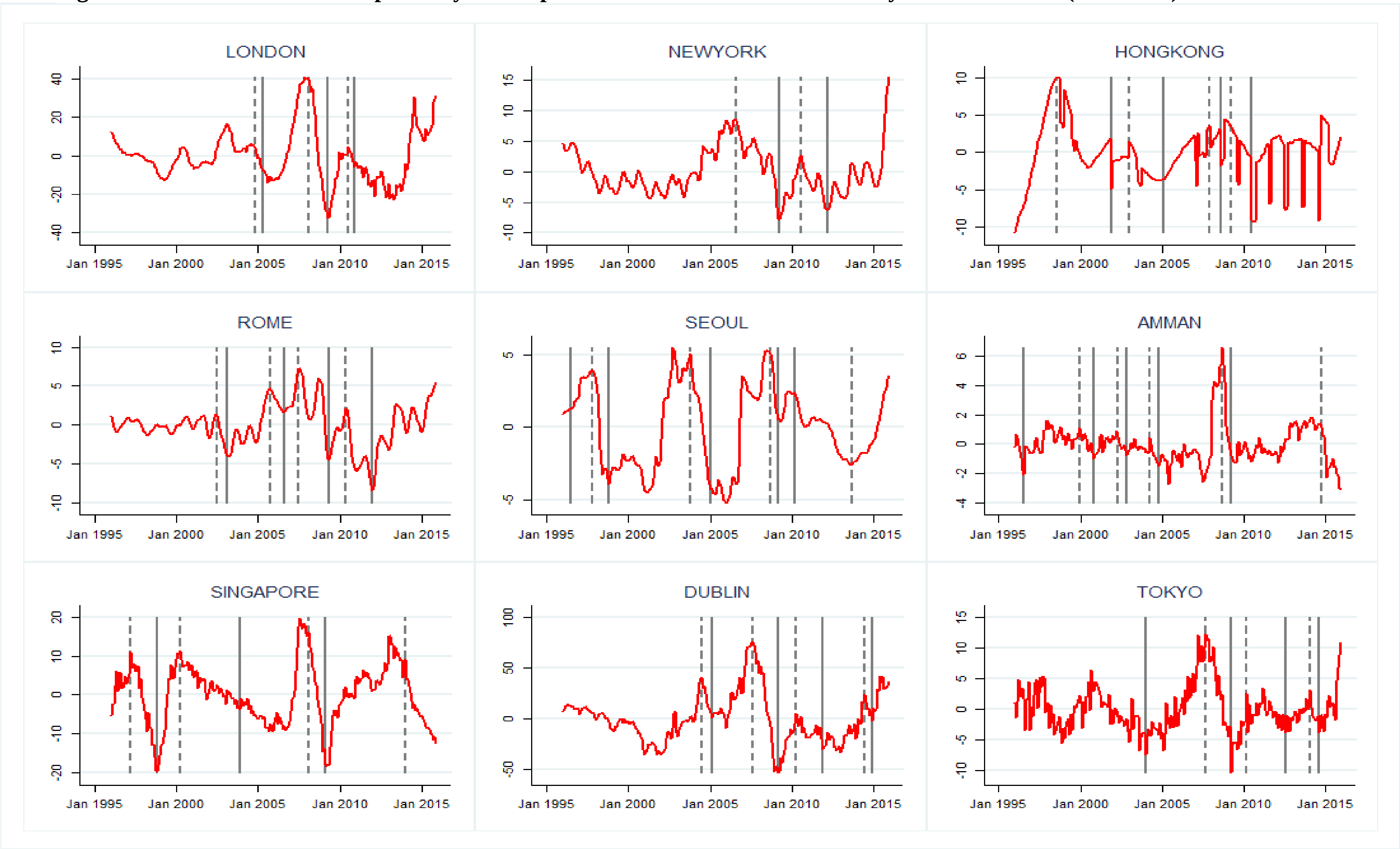
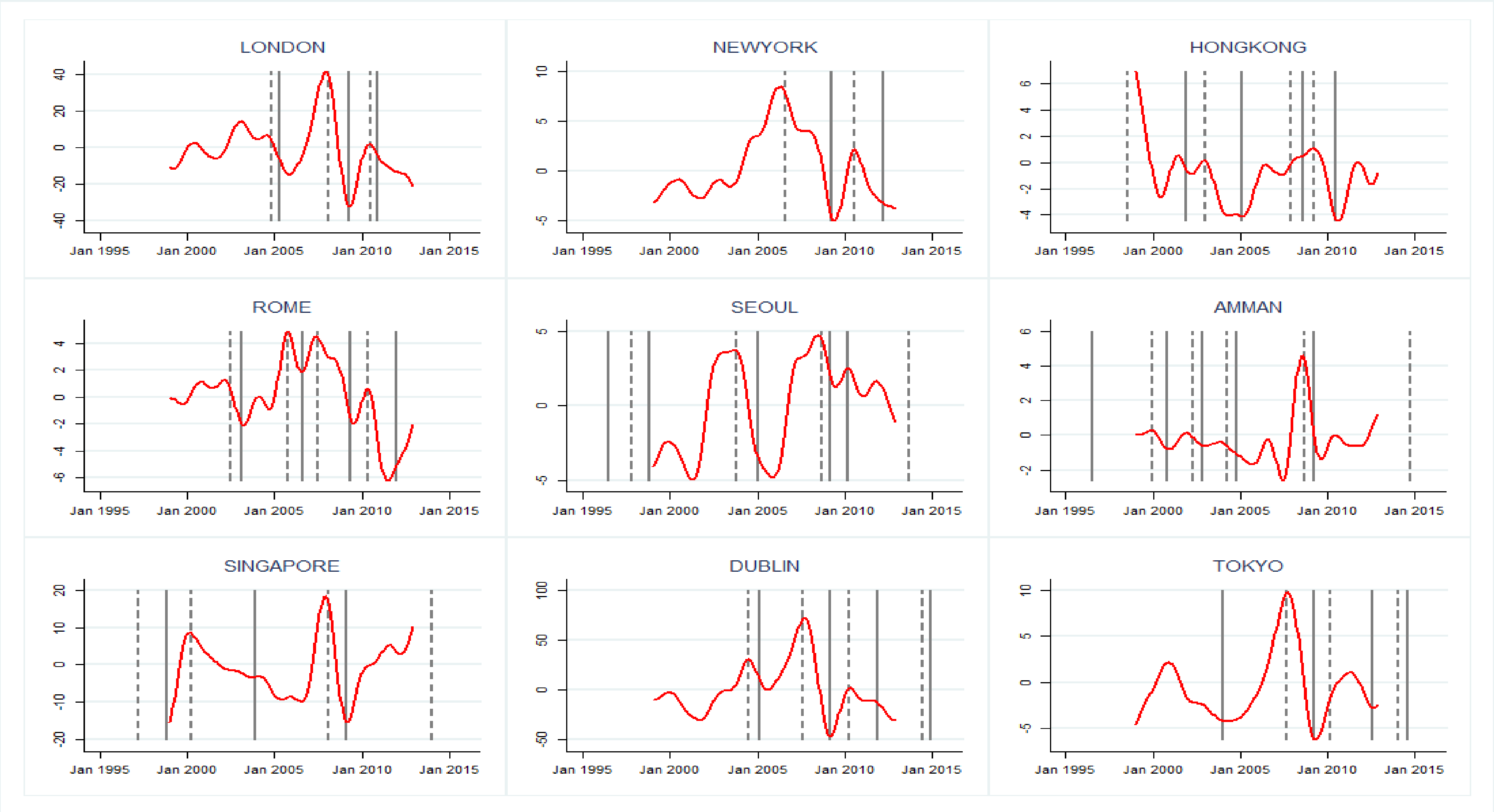


Figure 3.5 the estimated house prices-cycle component with recessions identified by the shade areas (H-P filter)



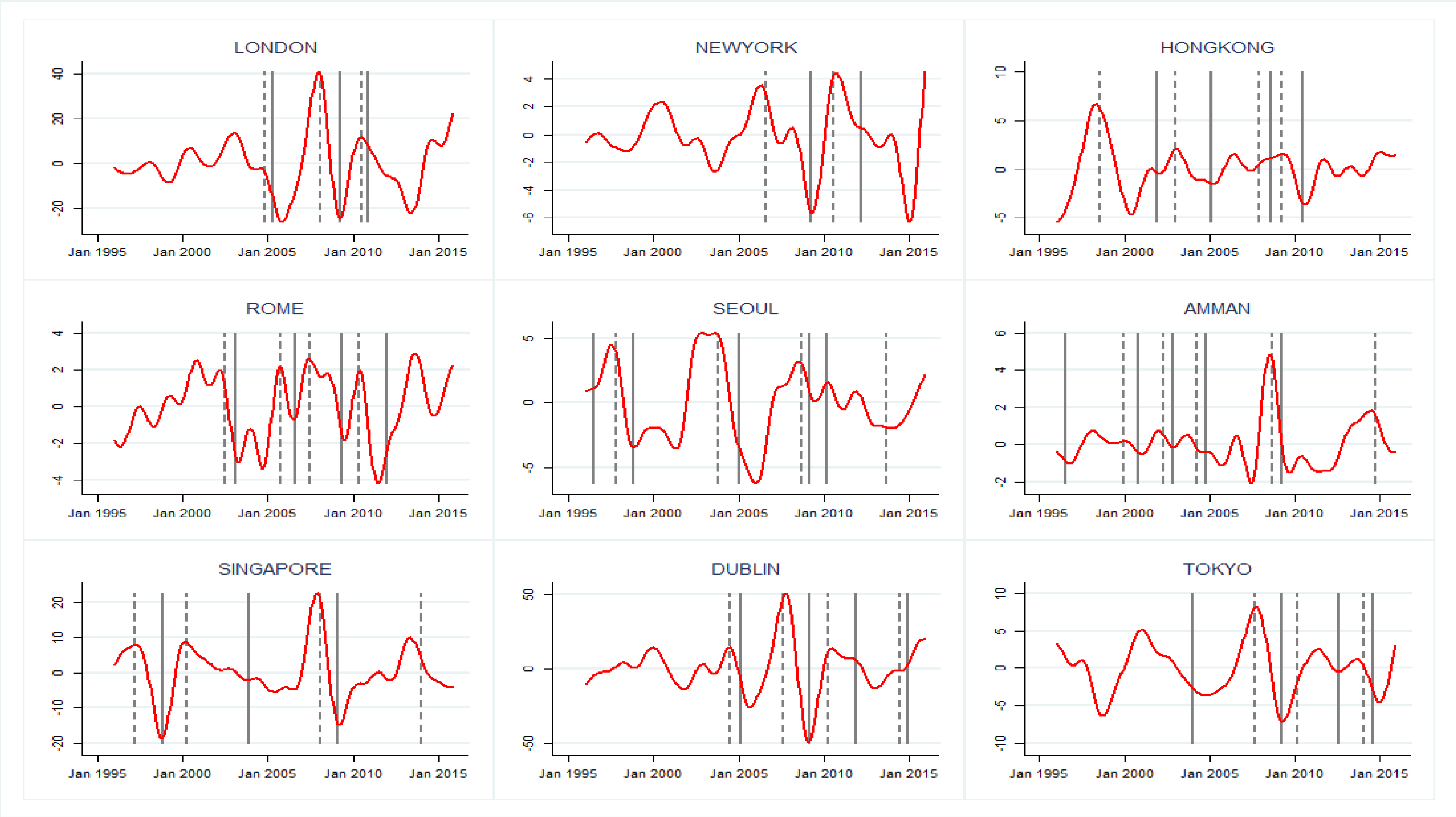
Dashed line stated the peak date while the solid line stated the trough date.

Figure 3.6 the estimated house prices-cycle component with recessions identified by the shade areas (B-K filter)



Dashed line stated the peak date while the solid line stated the trough date.

Figure 3.7 the estimated house prices-cycle component with recessions identified by the shade areas (C-F filter)



Dashed line stated the peak date while the solid line stated the trough date.

3.5.2 Model-Based Filter

To measure the cycle through the Unobserved Component Model (UCM), researchers identify three parameters, namely, the frequency with which the random components are centred; a damping factor, referring to the distribution of the random components around the central frequency; and the variance of the stochastic-cycle process that acts as a scale factor. The results in Table 3.3 provide the largest set of significant clusters of the UCM. One interesting finding is that the frequency among the whole sample is very small, which indicate that the cycle is centred on low-frequency components. In addition, the high damping factor shows that the cyclical components are close to the estimated central frequency.

The most significant finding to emerge from the results is that first, the frequency centres around 10% or 20%. Therefore, most of the estimated house prices cycles have lengths between two and five years.[28] These results are consistent with the findings of previous research in this field (e.g. Galati *et al.*, 2016; Borio, 2014). More specifically, and consistent with the findings as regards the classical cycle presented in Section 3.4, we note that the cycle in Tokyo lasts longer than any other in the sample. Furthermore, it is interesting to find evidence of significant heterogeneity between metropolitan areas not only in comparison with Asia's metropolitan areas but also among the EU cities. Specifically, in the EU metropolitan areas we observe clear differences between house price cycles of Rome and Dublin on the one hand and London on the other.[29] In addition, in the Asian metropolitan areas, the house price cycles in Hong Kong and Tokyo appear to take longer than in Amman, Singapore and Seoul. This result may be explained by the fact that the housing sectors operated in different ways in different countries.

Second, the significant variance (scale factor) of the stochastic cycle process is strong evidence of a cyclical pattern. These findings are supported through the spectral density of the cyclical component which shows the variance of the process associated with each frequency. Put differently, the area underneath the curve bounded by the necessary characteristics of two frequencies denotes the variance in

28 The values in the table presented in a monthly period.
29 A similar division is revealed in Schüler *et al.* (2015).

this frequency range. Moreover, the area underneath the curve shows the variance of the series.

An implication of plotting this spectral density is that it shows how tightly the important components can be scattered around the estimated central frequency. As shown in Figure 3.8, the cyclical component is tightly clustered at the low-frequency peak. It can thus be suggested that the cycle phases exhibit long term duration. Moreover, in all cases the cut-off at the low frequencies as well as high frequencies is sharp. The latter is partly due to the high estimated damping factor since it implies a somewhat high persistent cycle component.

Third, the cycles are determined through a damping factor between 85% in Singapore and about 99% in the rest of the sample. This result reveals that the cycle component of a series is first order. In other words, the sample cities under consideration conform in only one cycle.[30]

In addition, a peak in the spectral density graph becomes sharper as the damping factor tends towards unity. This peak represents high variance in a frequency band centred on the peak. As shown in Figure 3.8, most of the cities have a sharper peak. These results probably indicate that the sharper peak simply means small steps. In addition, the peak intensity (peak area) in this figure represents the sum of all the spread of the expansion duration, regardless of peak shape. The indications from these results are that the duration of expansions in these cities seems to be longer than that of the contractions.

The analysis of the spectral density function in Figure 3.9 reveals encouraging significances. In all cases of this study, the undesirable stochastic cycles are mostly filtered. In detail, Hong Kong, Tokyo, London and Seoul converge and are smoothed together towards -6. However, it is somewhat unexpected to find that New York, Amman and Rome take a longer time to fully smooth out and some of the high periodicity is slightly unsmoothed.

To develop a full picture of the capability of UCM, the cyclical components are plotted against the turning point indices in Figure 3.10. Again we keep in mind that not this entire upturn (downturn) represents peak (trough) in house prices.

[30] According to Durbin and Koopman (2012), the cycle component of a series is first order if the damping factor is closed to unity. Otherwise, we should test for a second order cycle.

Interestingly, the downturns in the simulated cycle substantially agree with the classical trough indices in the shaded area, with the exception Rome and New York, in which unwanted downturns are produced. Another important finding is that heterogeneity is observed not only across cities but also over time. In the case of Rome, Amman, Dublin and Tokyo, the house price cycles have larger amplitude in the after-2005 period while the opposite is found in Seoul.

Table 3.3 Main estimates of house prices cycle

	frequency	damping	period	Variance (level)	Variance (cycle)	Likelihood	AIC	BIC
London	0.207***	0.997***	30.354	[0.000]	[0.065]	716.68	-1425.36	-1411.44
	(-0.006)	(-0.006)						
New-York	0.511***	0.990***	12.296	[0.000]	[0.050]	848.9	-1691.79	-1681.35
	(-0.005)	(-0.007)						
Hong-Kong	0.122***	0.999***	51.502	[0.000]	[0.034]	808.96	-1607.91	-1590.51
	(-0.004)	(-0.002)						
Rome	0.384***	0.853***	16.362	[0.000]	[0.011]	914.19	-1820.39	-1806.47
	(-0.033)	(-0.023)						
Seoul	0.209***	0.995***	30.063	[0.000]	[0.044]	775.31	-1542.46	-1528.54
	(-0.015)	(-0.006)						
Amman	0.252***	0.976***	24.933	[0.000]	[0.074]	1000.03	-1989.72	-1972.32
	(-0.043)	(-0.058)						
Singapore	0.158***	0.985***	39.767	[0.000]	[0.011]	539.52	-1069.05	-1051.65
	(-0.017)	(-0.012)						
Dublin	0.173***	0.979***	36.319	[0.000]	[0.045]	657.57	-1306.01	-1295.57
	(-0.012)	(-0.023)						
Tokyo	0.101***	1.000***	62.21	[0.000]	[0.049]	584.76	-1159.52	-1142.12
	(-0.005)	(-0.021)						

Significant codes: ***: 1%, **:5%. *: 10%. Standard errors are in round brackets, while probabilities are shown between square brackets.

Figure 3.8 the spectral density of the cyclical component

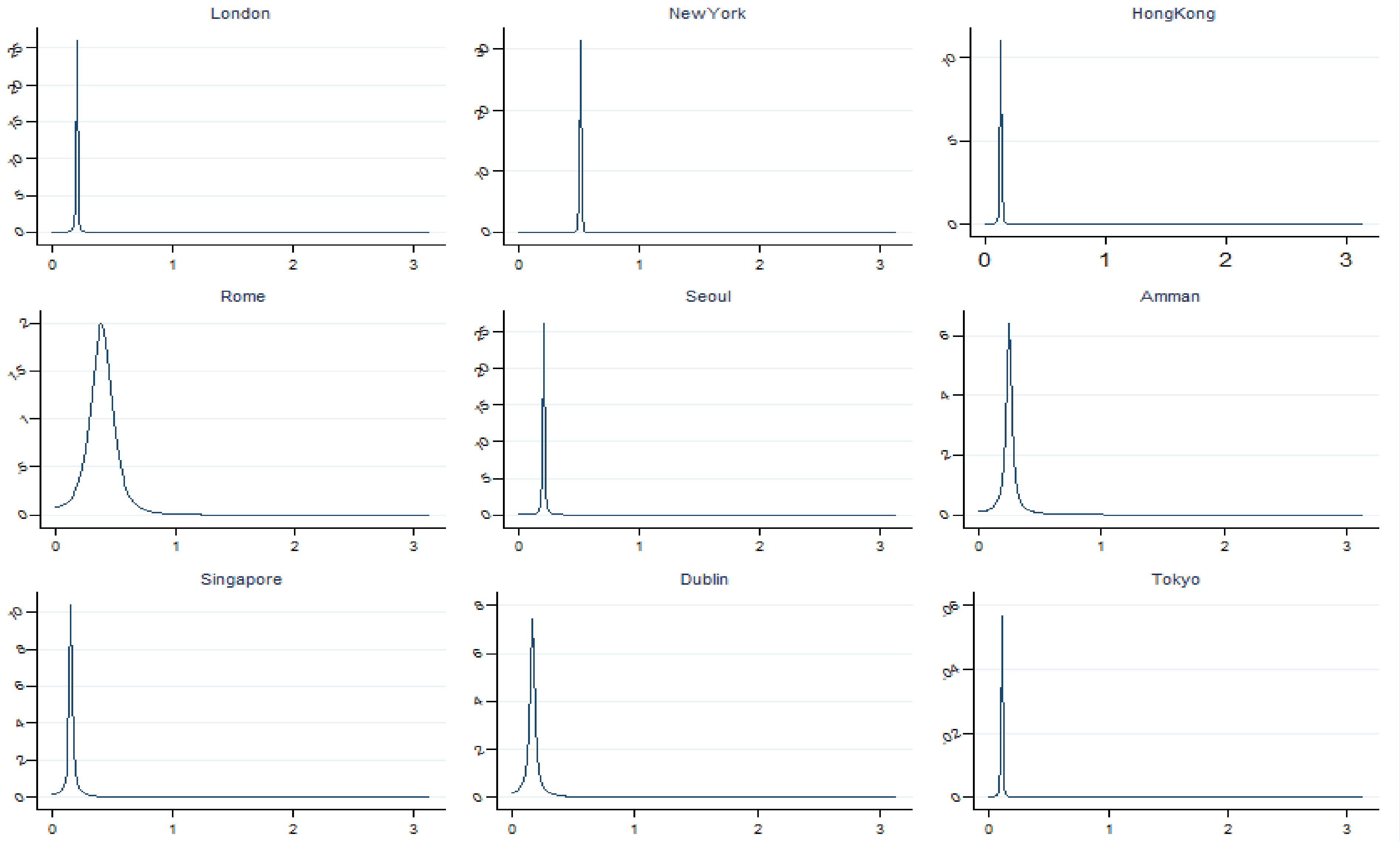


Figure 3.9 sample spectral density function (UCM-Filter)

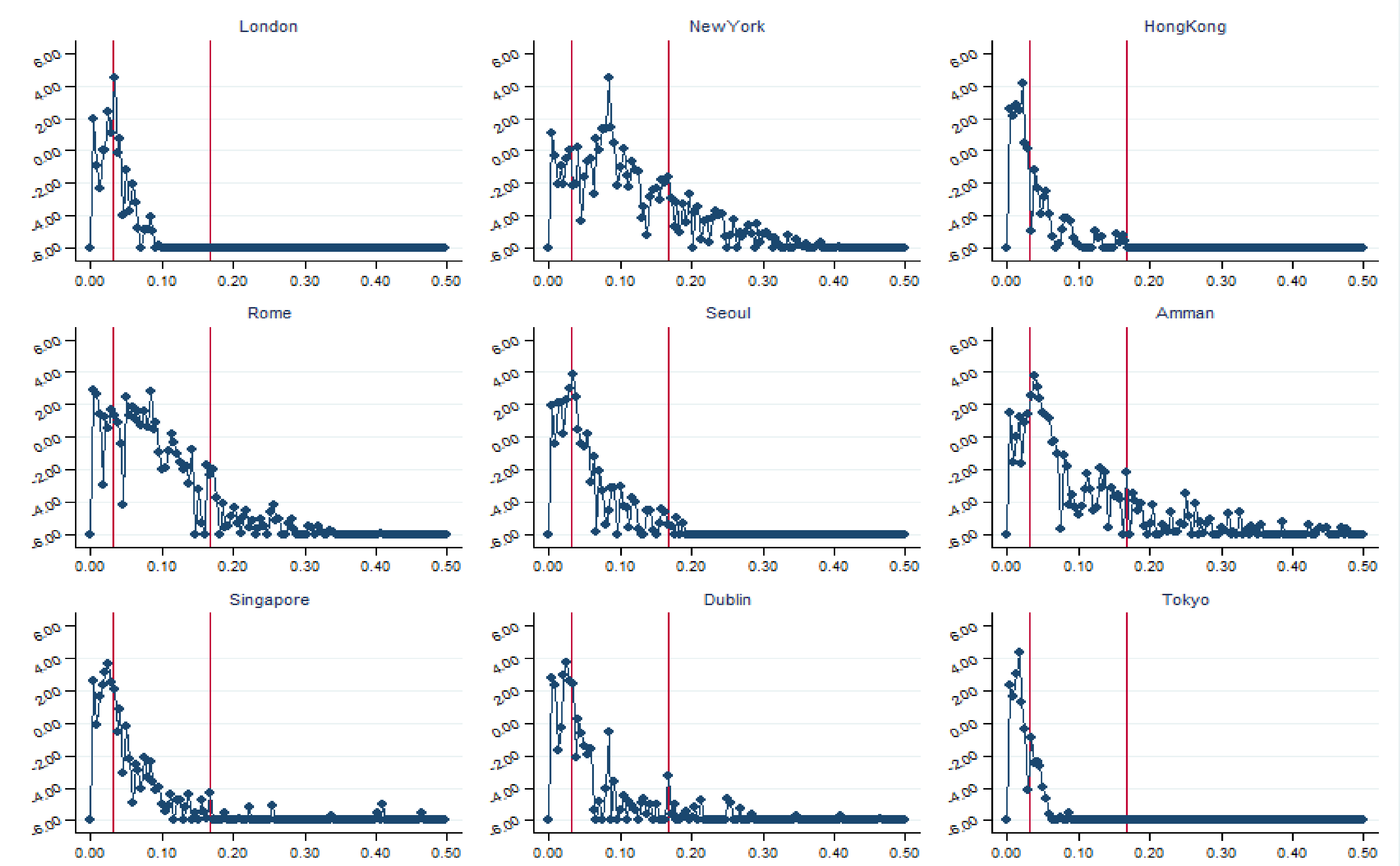
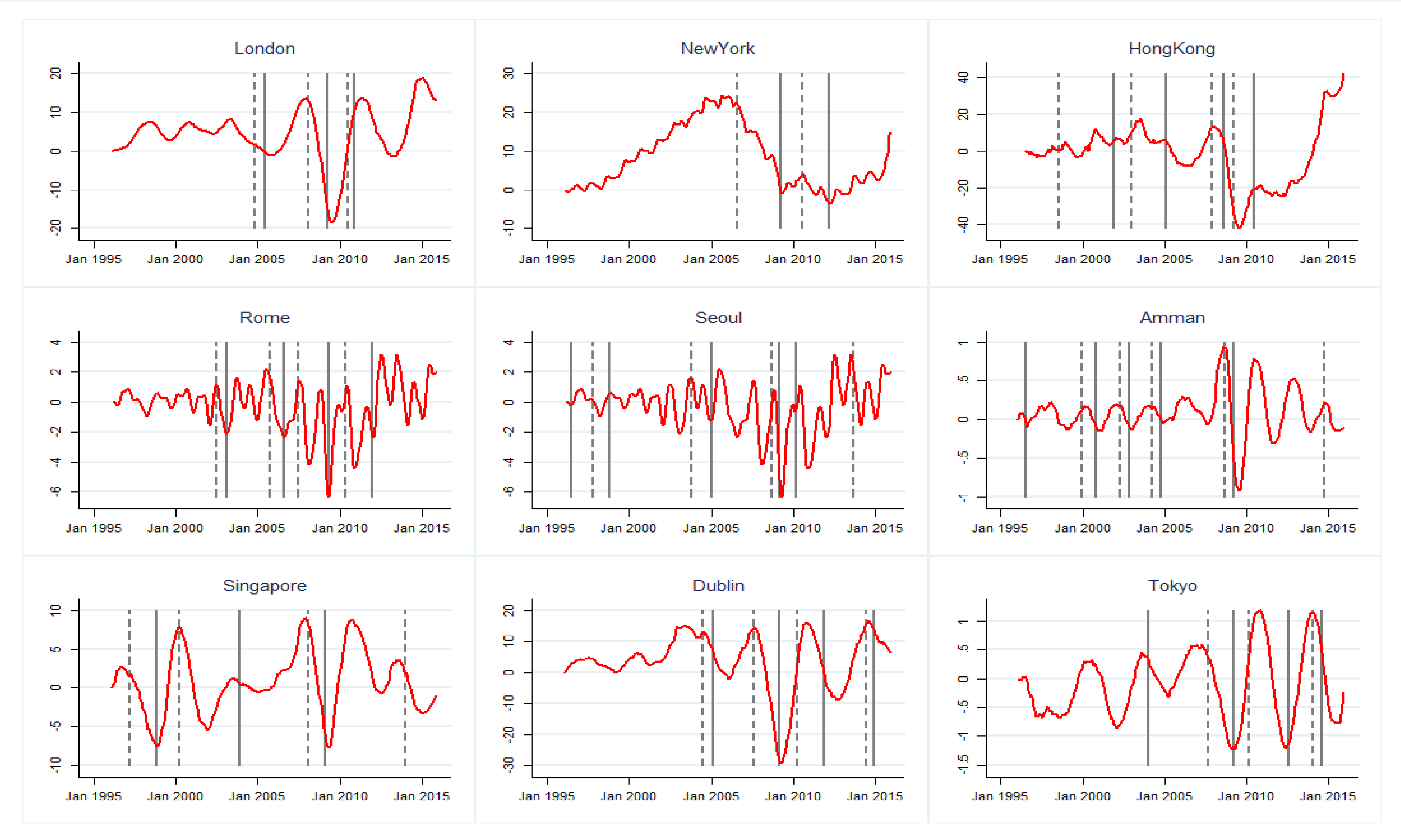


Figure 3.10 the estimated house prices-cycle component with recessions identified by the shade areas (UCM)



Dashed line stated the peak date while the solid line stated the trough date.

3.5.3 The Viability of the C-F Filter and the UCM

As discussed in Sections 3.5.1 and 3.5.2, neither the H-P Filter nor the B-K Filter can be used to isolate the frequency of the cycle component.[31] At the same time, it seems that both the C-F filter and UCM did a reasonable job concerning the cyclical behaviour of the house prices. However, further work has to be done to evaluate the capability of these two approaches. Following the discussion in Section 3.3, this part investigates how the characteristics of the cycle component are closed to the classical filter as well as the stationarity of these cycles. It is important to bear in mind that a filtered cycle will not present the exact characteristics of the classical one presented in Section 3.4. Indeed and in the light of a finite-length sample, it is impossible to propose a filter that will preserve all frequencies without reweighting the passed frequencies (i.e. one that completely removes those outside it in a given range). For this reason, the ideal filters refer to such filters as present a stationary cycle as close as possible to the actual one.

Comparing the results, it is interesting to note that the features of the two cycles presented (i.e. a cycle through the C-F filter and another through UCM) are significantly close to the actual one in terms of defining the turning points. However, in terms of the amplitude of the cycle as presented in Figure 3.7 and Figure 3.10, we note that the UCM-filtered series suffers less from compression than the others, while the C-F filtered series loses approximatively 50% of its original amplitude. In this case, the UCM filters preserve phase, and induce neither frequency nor time shift in the filtered data. However, the C-F filtered series has a progressive phase drift which affects each frequency component differently; this in turn, leads to the shape of the original signal to be distorted.

If the debate is moved toward the econometrical properties of the cycle, a better filter should produce a stationary cycle. The C-F filter has two serious shortcomings: it is time-varying and asymmetric. The latter indicates that, on the one hand, nothing can be said about the stationarity of the cycle, even if the original series is itself stationary. The signals here are that the non-stationary filters do not preserve purely harmonic evidence (Iacobucci and Noullez, 2005). In the case of the model-based filter, the cycle is modelled as a stationary stochastic process, the

[31] Both filters fail in the periodogram test, as previously verified.

damping factor restricted between 0 and 1. Considering all the above evidence, therefore, it seems that the UCM is more appropriate for measuring the cycle in house prices.

3.6 CONCLUSION

In this investigation, the aim was to measure the statistical properties of the house prices cycle in large metropolitan areas. This work contributes to the existing knowledge of cyclical activity analysis by providing a longitudinal analysis which captures the statistical properties for a house price cycle. Additionally, it provides a reasonable level of discrimination between the cyclical decomposition techniques for capturing suitable measurement for house price cycles.

The results of this study were gained by testing several techniques for analysing the cyclical behaviour of individual house price variables. In addition, the structural change was explored through the time variation in the characteristics of the house price cycle. The main results are, first, that the NBER method shows that, on the one hand, the average upswing and downturn phases of the cycle seem to be evenly unbalanced in length across cities and over time. On the other hand, there are notable differences in the characteristics of the cycle across cities, especially in term of fluctuation and excess area. These finding are consistent with Schüler *et al.* (2015) and Claessens *et al.* (2012). Second, comparing the results of some nonparametric filters, it seems that the C-F filters outperform other types of filter since the properties of this one are associated with those of the classical cycle. Third, the model based filters show evidence of substantial variation in the period and amplitude of these cycles, both across cities and over time, consistent with the findings of Stremmel (2015) and Borio (2014). The capability of the mentioned technique was tested against properties of the classical cycle as well as the stationarity of a simulated cycle. In this case we found that the UCM was more appropriate for measuring the cycle in house prices.

The results of this chapter emphasise the degree of asymmetric in the house price cycle. These results matter not only for modelling house price cycles for developing a good policy, but, importantly, for policy coordination discussions since they may reflect the important role of the metropolitan area in the financial system.

3.7 Appendices

Appendix 1

The Periodogram is used to examine the cyclical behaviour in a time series by identifying the dominant frequencies of the series. In the filtering approach, no cyclical behaviour should be realised outside the cycle length under consideration. Put differently, a spectral density around zero is preferred.

Suppose we express the house prices series as a single cosine (sine) wave time series (Robinson, 1995)

$$Y_t = A\cos(2\pi\omega t + \varphi), \tag{3.21}$$

where the variable A determines the maximum absolute height of the curve (amplitude of the cycle). φ defines the starting point for the cosine wave measured in angle degrees. $\omega = \frac{1}{T}$ stands for the frequency of interest during the period T that is required to complete a single cycle of the cosine function.

The maximum and minimum value associated with zero frequency can thus be calculated using the average amplitude and duration, as shown in Table 3.3 in section 3.4. Before calculating these boundaries, it is necessary to mention that the value of $2\pi\omega t$ ranges from 0 at t = 0 to 2π at t=240.

Consider the full cycle period of T = 15 and t = 1, 240; the frequency is ω = 1/15. Thus it takes 15 time periods to cycle through the cosine function. From Table 3.3, it can be seen that the average of contraction phase in all cases is about -5.82. Using Equation 3.21 with these values, we find that the minimum border associated with zero frequency is about -5.72.

4 CHAPTER FOUR

Financial Stability Policies Rules in the House Prices Cycle: Evidence from the Hong-Kong Sar

4.1 INTRODUCTION

The uncertainty generated by house price swings is a source of macroeconomic fluctuations, which affect the economic growth due to the interaction between housing markets and the economic cycle. Such uncertainty increases the hazards of economic recession (Detken and Smets, 2004; Epstein and Zin, 1989). If the volatility is excessive, the supply side will be unable to tackle both volatility and affordability.[32] As a result, demand side and credit controls (e.g. maximum loan-to-value ratios) may prevent credit from fuelling unsustainable house price booms (Park et *al.*, 2010; Andrews, 2010; Bernanke *al.*, 1999).

The theoretical impact of changing price and financial stability policies on house prices cycle movement has been closely investigated in both developed and developing countries. On the one hand, house prices influence the availability of bank credit through the wealth effect, the financial accelerator effect and the Tobin's Q effect (Bodman, 1998; Sichel, 1991).[33] On the other hand, credit conditions influence the demand for houses, which in turn, change the prices (Crowe *et al.*, 2013; Posedel and Vizek, 2009; Goodhart and Hofmann, 2008; Iacoviello, 2005). Such relationships have also been strongly emphasised in the aftermath of the financial crisis, and the literature reveals an increased attention to asset price developments, especially among central banks.[34] In the policy-oriented literature, a considerable number of empirical studies have documented a directional causality running from property prices to bank lending or in the opposite direction (Borgy *al.*, 2009; Gerlach and Peng, 2005; Hofmann, 2004).

A much-debated question is how price and financial stability policies are effective in reducing the systemic risk generated by house price cycles. Indeed, very

[32] The supply side is considered a long-term solution for failures in the efficiency of the financial market, which it does not affect in the short term.
[33] This effect is mainly related to the role of asymmetric information in credit markets which gives rise to moral hazard or adverse selection problems.
[34] This is due to the central collateral role of asset prices such as the prices for dwellings.

few scholars have examined the ability of macro-prudential, bank lending and monetary policy to control the duration and the amplitude of a cycle in certain states by influencing the probability of changing those states. The purpose of the present paper is to explore the impact of considered price and financial stability policies on house price cycles. [35]

This chapter sets out to answer the following questions: first, how do different policies affect the duration of the house price cycle? Second, what is the direction of causality (if any) between the volatility of house prices and such policies? Also, to what extent do these policies affect the volatility oh house prices? And finally, does this effect vary from one phase to the next?

From the policymaker's perspective, answering these questions helps to operate and optimise policy intended to reduce the consequences of the recession phase. It also enhances our understanding of the relationship between the house price cycle and price and financial stability policies in several ways. First, to the best of the author's knowledge, this is the first study to examine the durational dependences in the house price cycle in relation to macro-prudential policy, bank lending and monetary policy. It is also the first to investigate the duration of dependence using a proportional survival model with covariates. A key insight from this type of analysis is that the probability of an event at any point in time can be inferred from the distribution of the actual series. The latter has advantages of investigating the length of a current phase of the cycle. Moreover, the findings provide a useful guidance for policy makers interested in finding the most appropriate policy for affecting this duration.

Second, although many applied studies have tested the causality between house prices and demand-supply factors, the literature is notably silent when it comes to clarifying the issue of causality between price and financial stability policies and the conditional volatility associated with returns in the house price cycle. In fact, the theoretical causality relationship indicates that a shock from a policy has a far-reaching impact on the volatility of the house price cycle. Therefore, the study of such causality provides risk managers and policy makers with valuable insights of

[35] The term "price and financial stability policies" refers to the policies that adopted to change the housing market.

this relation that enable them to continuously adjust their policy to accommodate changes in cycle patterns.

Finally, this chapter addresses the impact of considered policies on the volatility in the house price cycle by combining the $ARIMA(p, d, q)$ model with the $EGARCH(m, n)$ model to form a nonlinear time series model. Adopting the $EGARCH(m, n)$ model helps to establish whether the responses of volatility in the house price cycle differ from one phase to another. Put differently, exploring the asymmetry helps to judge how the policy tools, especially borrowing constraints such as the loan-to-value (LTV) ratio, affect the volatility of house prices in different phases.

The Hong Kong house price cycle merits special attention for several reasons. First, according to the Demographia International Housing Affordability Survey,[36] house prices contributed to Hong Kong counting as the world's most unaffordable city; the increase in property prices has exceeded 10% annually in all the last few decades. The increase in house prices reveals that the housing market is dangerously overvalued and house price levels are "fundamentally unjustified". Moreover, the housing market in Hong Kong experienced a significant swing after the Asian financial crisis, with at least four episodes of increases at about 20% and three episodes of sharp declines by 50%. Meanwhile, a single episode of a sharp price increase followed by a downfall of prices was witnessed in other economies (Gerlach and Peng, 2005).

This fluctuation was associated with the high unstable growth of bank lending that has always been one of the largest areas of risk exposure for Hong Kong banks. Since 1991, bank lending has accounted for at least 20% of the banking sector's lending to local borrowers, reaching a peak of 37% in 2002. Moreover, the increase in the demand for housing in the last two decades has been pushed by a combination of stringent regulations on development, low interest rates, and currency stability. Further, the interest rate in Hong Kong is determined by US monetary policy, since the Hong Kong dollar is pegged to the US dollar. As a result, monetary policy may not have any significant impact on the swings in house prices (Gerlach and Peng, 2005; Semlali and Collyns, 2002).

[36] For details http://www.demographia.com/dhi12-media.pdf

Because of these large swings and the limited impact of monetary policy, regulatory policy is used more extensively to limit the impact of property price declines on the economy. For this purpose, Hong Kong has been using macro-prudential policies with the aim not only of targeting house prices but also of helping to limit the amplitude of house price cycles and preventing the collateral damage that other blunter policies cause. The Hong Kong Monetary Authority (HKMA) was founded to protect financial stability, especially from dangerous moves in the housing market (He, 2014). This policy has imposed limits on the LTV ratio to lessen the amplitude of house price cycles.

The results of this chapter reveal several insights on the relationship between house price cycles and considered housing policies. In particular, first, both upswing and downswing phases have been found to be affected by the indicator in question since we find a dramatic increase in the probability of reaching the turning point with time. Second, the causality test reveals a one-way movement running from the loan to value and loan made to the volatility of house prices. Accordingly, house prices respond with more volatility to any change in the loan to value and lending policy indicators (neglecting the sign of this shock). Finally, the evidence of asymmetry suggests that unanticipated house prices increases are more destabilising than unanticipated falls in house prices.

The structure of this chapter is as follows. Section 4.2 provides an overview of the previous literature on the relationship between bank lending and house prices. Section 4.3 deliver the economic model and data issues. Section 4.4 is concerned with the economic model and empirical findings of the impact of lending policy on the duration and volatility of house price cycles. The last section draws the conclusions of our study.

4.2 A BRIEF OVERVIEW OF THE PREVIOUS LITERATURE

The coincidences of the cyclical relationship between policy making and house prices have been widely documented in the literature and several studies have discussed possible theoretical links. In his influential paper, Hott (2011) explains how swings in property prices can be set in motion by irrational participant expectations and play a crucial role in the formation of boom and bust in the house price cycle. Hott also suggests positive feedback between property prices and bank lending and discusses how credit availability[37] affects the housing demand. Niinimäki (2009) discusses the feedback between house price fluctuations and bank lending behaviour when banks finance risky projects against collaterals and overestimate their future appreciation. Barrell *et al.* (2010), focus on the effectiveness of real property prices as an early warning indicator of a banking crisis.

The direction of causality between house prices and lending has also been subject to attention in the literature. Only a few studies consider a unidirectional causality running from house prices to bank lending. On the one hand, an increase in housing prices has a collateral impact on the credit supply and credit demand that leads to an increase in borrowing capacity. On the other, a decline in property prices increases borrowers' mortgage burden. Gerlach and Peng (2005) suggest that the close correlation between property prices and bank lending are caused by bank loans adjusting to property prices, rather than the reverse. Therefore, excessive bank lending is not the source of the boom and bust in the housing market cycles in Hong Kong. Hofmann (2004), however, suggests that the short-run causality in both directions is due to changing beliefs about future economic prospects. Abel and Deitz (2010) find bidirectional causality between housing prices and nonprime lending activities. The authors suggest that the development of nonprime loans stimulates housing demand and hence permits an increase in housing prices. At the same time, a rapid increase in housing prices favours risky loans.

In contrast, a few studies have been attracted to the potential unidirectional causality running from bank lending to property prices. In the theoretical discussion about the Swedish banking crisis in the early 1990s, Englund (1999) highlights the subsequent crisis resulting from a contracting monetary policy at the time of a highly leveraged private sector. Moreover, high real interest rates contribute to break the boom in real estate prices. Similarly, Liang and Cao (2007) show that bank lending and interest rates causes instability in property prices. The study conducted by Koh *et al.* (2005) identifies under-pricing on the part of financial intermediaries on the put option embedded in non-recourse mortgage loans as a potential cause for the observed price behaviour. Mora (2008), however, finds in his research that the

[37] This availability is subject to banks' willingness to supply mortgages.

supply of credit had considerable impact on asset prices. Moreover, the banks increased their property lending when they lost corporate borrowers.

The complexity of this kind of relationship is again emphasised in the study by Goodhart and Hofmann (2008), where the authors show a statistically significant bidirectional link between house prices and bank lending. They also indicate that shocks to money and credit during the expansion period are found to be stronger than at other times. Similarly, Oikarinen (2009) finds a strong two-way interaction between housing loan stock and housing prices, on the one hand and between house prices and consumption loans, on the other. This causality is likely to increase boom–bust cycles in the economy and increase the fragility of the financial sector.

An expansionary fiscal policy may also contribute to the influence of bank lending on house prices where the enhanced present value of future income flows and subsequent expected higher house prices is likely to influence bank lending (Brissimis and Vlassopoulos, 2009). The study conducted by Gimeno and Martinez-Carrascal (2010) offers insight into the way in which overvaluation in house prices can lead to an incorrect sense of not being over-indebted. It also shows that the two variables are in the long run interdependent.

Yet the formidable costs of the last financial crisis led many to agree that monetary policy is not too blunt a tool to be the best response for dealing with real property price booms and busts (Alpanda and Zubairy, 2017; Lee *et al.*, 2016; Posen, 2009). Therefore, the quest to design better policy has shifted the balance to the pre-emptive policy actions that could stop or at least contain the damage to the financial sector and the broader economy when the bust comes. Such macro-prudential tools as loan-to-value ratios (LTV) are strongly advocated. On the theoretical front, various studies incorporating LTV policy in their models have found that the macro-prudential instrument is effective in preventing excessive credit growth.

A seminal work by Park *et al.* (2010) uses loan-to-value ratio and debt-to-income ratio as part of the mortgage loan qualification process to restrict the availability of bank lending for the housing market. They suggest that adjusting bank lending plays a crucial role in responding to changing house prices. Crowe *et al.* (2013) find evidence of a significant effect of LTV policy on the property market, while Lambertini *et al.* (2013) show that the countercyclical LTV rules responding to property prices can reduce the volatility of loans and the ratio loans to GDP. Wong *et al.* (2011) present some international evidence that low LTVs can reduce delinquencies in response to property price busts. In a study investigating Hong Kong's LTV policy, Funke and Paetz (2012) report that a nonlinear LTV policy rule reacts when property price growth exceeds a certain threshold and this policy can reduce the level of household debt.

Collectively, the above studies outline a critical role for the relationship between house prices and policy. Difficulties arise, however, when an attempt is made to choose the most effective policy during boom (bust) periods in the house price cycle. In this context, one question that needs asking is whether such policy affects the duration of the boom (bust) in the house price cycle. Another significant question is whether there any feedback between the housing policies and the level of house prices. As far as the author is aware, no previous study of these questions has been conducted in the context of the house price cycle.

Considering this gap, this study therefore sets out to address these questions. Accordingly, the next section of this study has been divided into two parts: the first part introduces the variables under consideration and the second part deals with the descriptive data.

4.3 VARIABLES AND DATA DESCRIPTION

To evaluate how changes in the macro-prudential, bank lending, and monetary policy influence the duration and the amplitude of the house price cycle in Hong Kong's housing market, three explanatory variables are considered over the period Jun. 1998 - Dec. 2015. In specific, the Current Loan to Value ratio (CLTV) is used as an indicator of macro-prudential policy. Gross Bank Lending (BL) is a proxy with which to examine the role of lending in house prices and to control for the overall amount of lending and mortgage lending practices. Finally, the interest rate (IR) is used to address the impact of monetary policy on the cycle.

Loan to Value

The loan-to-value ratio plays a crucial role in determining the ability of banks to lend against real estate collateral, and the methods of evaluating property used in conjunction with the prudential ceilings. Moreover, relaxed mortgage insurance to obtain a loan favours upward movement in the housing demand (Mian and Sufi, 2011; Adelino *et al.,* 2012). Benetrix *et al.* (2013) state that the impact of the LTV cannot be restricted only to the expansion phase; the presence of liquidity constraints during the bust could accelerate the fall of housing prices. For instance, falls in the housing market reduce the value of the collateral, and consequently borrowers face rising external finance costs and lower equity withdrawal, which curbs the demand for housing. Conversely, increasing housing prices induces expectations about future house price appreciation and increases the 'collateral' value, which in turn weakens the current criteria for obtaining a mortgage. The latter contribute to fuelling the increase in house prices thus boosting the cycle once more (Assenmacher-Wesche and Gerlach, 2008; Gerlach and Peng, 2005).

LTV policy also has an impact on the supply side, given the presence of small constructors who require external financing to start their activities. In specific, any relaxation of the LTV reduces the production cost of housing and in this way housing becomes more affordable. This implies that a more elastic supply and increase in demand have less of an impact on prices. This phenomenon in the short run induces a decline in the cost of housing. However, in the long run dropping prices increase the housing demand. As a result, the expected overall impact is the one that arises from the demand side.

Bank Lending

Mortgage lending is related to house prices since a house considered as collateral in loan operations. Hence, changes in the lending attitudes of the banking sector influence housing demand and prices (e.g. Zhu, 2003; Pain and Westaway, 1996). In this context, evidence suggests that increasing the availability of credit will cause an increase in housing demand, which in turn is reflected in higher housing prices. By contrast, any decline in lending lowers the level of house price, and confines the investments in the housing market (Adams and Füss, 2010; Barakova *et al.,* 2003).

However, it can be harder to affect the demand for housing by increasing bank lending, since doing so may increase the amount paid of repayments, which leads to an increased the risk of defaulting on the loan. More details can be found, for example, in Iacoviello and Pavan, (2013); Goodhart and Hofmann, (2008); Leung, (2004).

Real Interest Rate

An expansionary monetary policy and the associated lower interest rates can, for instance, lower the cost of housing, which results in a rising demand. At the same time, however, a reverse movement is that increasing interest rates raise the opportunity cost associated with housing investment. In consequence, both trends work to reduce real house prices (Iacoviello and Pavan, 2013; Igan *et al.*, 2011; Iacoviello, 2005). Detailed examination of such relationships has been conducted by Mishkin (2007), who suggests six direct and indirect ways in which the interest rate affects the housing market: a) directly affecting the user cost of capital, the housing supply, and the expectations for the future movement of prices; and b) indirectly affecting housing wealth changes and the influence of the credit channel on consumption. Moreover, Andrews (2010) argues that between house prices and the interest rate there is a negative correlation, which depends on the degree of competition in the banking sector.

A summary of the explanatory variables under consideration and data sources is presented in Table 4.1.

Table 4.1 Variables and the data sources' description

Variable	Explanation	Description in Data Source
BL	Bank Lending	Gross loans made in Hong Kong obtained from HKMA have been used as a proxy for bank lending.
CLV	Current Loan-To-Value	This variable is derived from the loan-to-value at the source of the mortgage, by dividing the *LTV* value of a particular month by the reported value in the same month of the Hong Kong Midland Property Price 100 Index.
IR	Real Interest Rate	Obtained from HKMA to represent the monetary policy.

HKMA; Hong Kong Monetary Authority.

The dramatic fluctuations in terms of the size and length in the variables of interest produce interesting findings that account more for robustness of the impact of such policy on the duration and size of the house price cycle. Figures 4.1 and 4.2 illustrate the behaviour of house prices and bank lending in Hong Kong during the period under review.

From Figure 4.1 and 4.2 it appears that house prices are closely related to loan to value ratio and gross loan made. In particular, the decline in house prices in 2000 was associated with a notable decrease in the gross loan made. Moreover, after the Asian crisis in 1997, the loan to value ratio increased rapidly until 2005 as a result of the withdrawal of the guidelines issued by the Hong Kong Monetary Authority (HKMA), which limited the ratio of loan to value to no more than 50%. However, house price experienced high volatility at the time. Figures 4.1 and 4.2 also reveal that, after 2004, the change in house prices and other variables moved together during the upturn and downturn periods.

Figure 4.1 Loan to Value Ratio and House Prices in Hong-Kong

Figure 4.2 Gross Loan Made and House Prices in Hong Kong

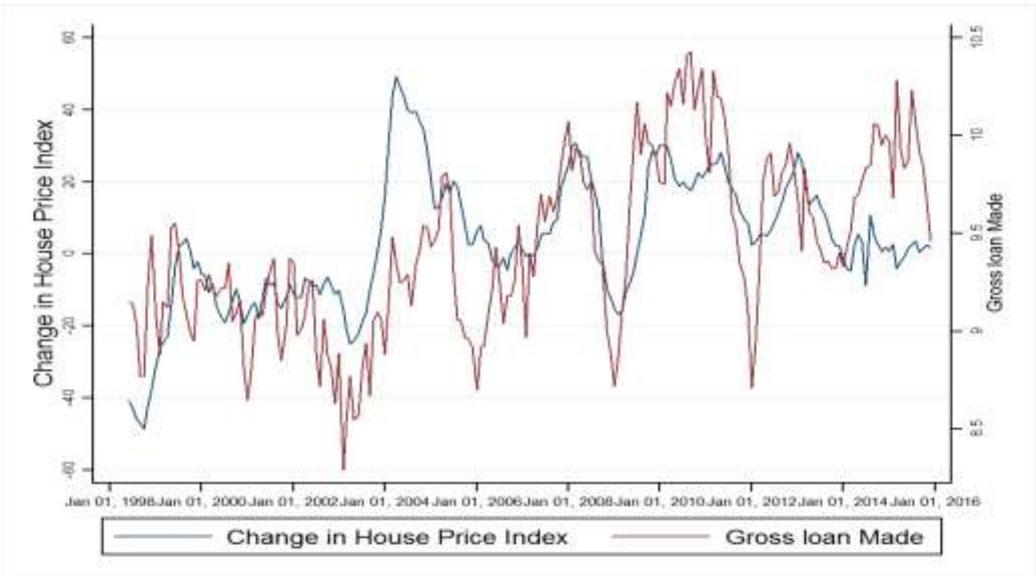


Table 4.2 reports the descriptive statistics for the above mentioned variables over the period Jun. 1998 – Dec. 2015. These statistics indicate that there is a considerable gap between the maximum and minimum observations. The latter are supported by the standard deviation value which strongly endorses the high variability. The Jarque-Bera test for normality reveals that the series are not normally distributed, since this test is significant at the 5% level. This outcome is consistent with the skewness and kurtosis values. Moreover, the skewness statistics show that the distribution has a long right tail and deviation from normality. Accordingly, this analysis gives more support to the suitability of addressing the feedback between the volatility in the house price cycle and the selected policy. Moreover, Volatility clustering is clearly present in all cases gives more insight into applying ARCH/GARCH models for the data under review to address the volatility.

Further analysis shows that the series in first differences are stationary, since the Augmented Dickey Fuller (ADF) rejects the null hypothesis of unit root.

Table 4.2 Descriptive Statistics and unit root test

	House Price	LTV	IR	BL
Mean	4.617	1.782	6.401	9.374
Median	4.620	1.807	5.600	9.325
Maximum	4.816	3.571	9.906	10.432
Minimum	2.452	0.734	4.209	8.286
Std. Dev.	0.505	0.673	1.783	0.439
Skewness	0.277	0.345	0.581	0.335
Kurtosis	1.993	2.687	1.806	2.557
Jarque-Bera	9.017**	4.543**	21.978***	5.106*
ADF	-10.070***	-16.235***	-6.573***	-3.950**

* $p<0.05$, ** $p<0.01$, *** $p<0.001$ Significant value. ADF refer to the Augmented Dickey Fuller test fot the differencing data.

4.4 EMPIRICAL METHODOLOGY AND ESTIMATION RESULTS

The methodology described in this section relates to the econometric models used to investigate the research questions at hand. In Section 4.4.1, duration model is used to evaluate the policies that affect housing market during the contraction and expansion phases in the house price cycle, whereas, in Section 4.4.2 the methodology considered to investigate the relations between housing price volatility and policy measure is briefly described.

4.4.1 Test for Duration Dependences On House Prices Cycle

The properties of the duration analysis is suitable for studying the duration of contractions and expansions since the duration variable is defined as the number of months that a city is in a state of contraction or expansion, depending on which phase is being analysed. To test for the dependence on duration and evaluate the policy during the contraction and expansion phases in the house price cycle, two possible outcomes over any two consecutive periods are considered;[38] first, that the house price cycle experiences a turning point whereby it switches from a period of expansion to a period of contraction and second, that it experiences a turning point when it switches from shrinkage to a period of expansion.

The following sub-section introduces the logical framework for the analysis we undertake in this search for the length of time that each phase (expansion or contraction) lasts.

4.4.1.1 Econometric Methodology

A few techniques have been developed to examine duration dependence in the context of business cycle. One of these techniques is a Markov-switching model (Lam, 2004; Kim and Nelson, 1998), while other studies apply solely nonparametric tests (Diebold and Rudebusch, 1996). Logit models are also of interest for identifying such dependences in cross-sectional data over a specific year (see Kolari *et al.*, 2002; Cole and White, 2012). The key problem with these methods, however, is that they are static models and do not adjust for time, while dependency may change over time, particularly when the sample period is long.

One way to address this concern is to apply survival models. The models with a parametric test have been widely used in econometrics to explain the failure of time regressions in which the effect is observed of the covariates (explanatory variables) on time until the occurrence of some event. Put differently, the survival model reports the odds that no failure event will occur before time (t). Hence, this function is monotone decreasing and equal to unity at $t = 0$. The distribution of such a

[38] These possibilities will be explained in Equations 4.7 and 4.8.

survival function can be defined by the cumulative distribution, survival, or probability density function.

Following the literature of duration dependency, this chapter investigates the existence of duration dependences by using the Proportional Hazard Model (PHM) with time-varying covariates. To this end, the survival function is assessed for both expansion and contraction phases.

Denote by T a non-negative and continuous failure event in the housing market cycle, say the exit to expansion phase given that the current state is contraction, and suppose that this T has the probability density function $f(t)$ and the distribution function $F(t)$. Then the probability of contraction lasting until time t is given by the following survival function (Cleves, 2008)

$$S(t) = 1 - F(t) = P(T > t)\ ; \quad t\epsilon\ [0, \infty). \tag{4.1}$$

We are trying to estimate the direct risk,[39] of reaching the turning point in the house price cycle at time t conditional upon its existence up to time $t-1$. This chapter distinguishes between two different cases: exit to an expansion phase and exit to a contraction phase. Accordingly, the hazard function $h(t)$ for each case can be specified as

$$h(t) = \lim_{\Delta t \to 0} \left(\frac{P(t<T\leq t+\Delta t, T>t)}{\Delta t * P(T>t)}\right) = \frac{f(t)}{S(t)}. \tag{4.2}$$

whereas the density function $f(t)$ can be obtained by deriving the distribution function $F(t)$, that is

$$f(t) = \frac{dF(t)}{dt} = \frac{d(1-S(t))}{dt} = \frac{-d(S(t))}{dt}. \tag{4.3}$$

Equation 4.2 can be re-written as

$$h(t) = \frac{D.S(t)}{S(t)}; where\ D \equiv \frac{dy}{dx}. \tag{4.4}$$

[39] We bear in mind that the word 'risk' refers to the occurrence of such an event. However, this event sometimes leads to good issues, for instance, when the exit is from a contraction phase to an expansion phase.

After integrating both sides on t, the probability density function can be formulated in terms of hazard rate as:

$$f(t) = h(t). exp\left(-\int_0^t h(r)dr\right). \tag{4.5}$$

The proportional hazards model of a type j exit with $K \times 1$ vector of covariate $X_i(t)$ that includes the gross loan made, current loan to value ratio and real interest rate can be written as [40]

$$h(t|X_i) = h_{j,0}(t)\, exp\left(X_i\beta_j\right). \tag{4.6}$$

It is worth noting that the proportional hazards under consideration, $h(t|X_i)$, define the exit indicator as a binary variable. Therefore, the dependent variable in this context is a dummy variable with N observations represent the possible phase changes between any two consecutive periods,[41] namely

$$S^E = \begin{Bmatrix} 1; & S_t = 2\ and\ S_{t-1} = 1 \\ 0; & otherwise \end{Bmatrix}, \tag{4.7}$$

$$S^C = \begin{Bmatrix} 1; & S_t = 1\ and\ S_{t-1} = 2 \\ 0; & otherwise \end{Bmatrix}. \tag{4.8}$$

where S^E and S^C refer to the current state of expansion and contraction, respectively.

The duration (d) of the current phase up to time $t-1$ can also be defined as

$$d = \begin{Bmatrix} d_{t-1} + 1; & S_t = S_{t-1} \\ 1; & S_t \neq S_{t-1} \end{Bmatrix}. \tag{4.9}$$

One issue that arises in the survival model is how to choose the appropriate parametric model among several proposed possibilities. This discrimination cannot be made easily unless the possible shape of the hazard function is unknown.

In such a simple case as that of Cox's model (Cox, 1972), no assumption about the shape of a hazard over time is made and hence the nonparametric part $h_{\mathrm{j},0}(t)$ is undetermined. Therefore, one needs only to estimate a $k \times 1$ vector of

[40] j refers to the type of exit, i.e. either from expansion to contraction or vice versa.

[41] For simplicity, in this chapter we refer to the contraction state by number (1) and the expansion state by number (2).

coefficients (β_j). This semiparametric method proceeds by comparing the subjects at the time when they happen to fail.

A known shape constraint of the hazard model however, is preferred for obtaining the most efficient estimates of β_j possible and hence of obtain an estimate of the baseline of the hazard ratio. These parametric hazard methods use probabilities that illustrate what occurs over the interval $(\mathrm{t}_{0\mathrm{j}}, \mathrm{t}_\mathrm{j}]$ (Balakrishnan and Rao, 2004). In this context, the contribution to the likelihood of a subject being censored at time t_j is given by

$$LH_j = S(t_j | t_{0j}, X_j) = \frac{s(t_j|X_i)}{s(t_{0j}|X_i)}. \qquad (4.10)$$

Different proposed parametric hazard models afford different forms of baseline $h_0(t)$ (e.g. Royston and Lambert, 2011; Cleves, 2008). For instance, the exponential hazard model assumes that $h_0(t) = \exp(\alpha)$, for some α should be estimated. In addition, we have Weibull's model given that $h_0(t) = pt^{p-1}\exp(\alpha)$ and, in this case, we need to estimate α, p, β_j. Another well-known form of hazard baseline is known as the Gompertz model, in which $h_0(t) = \exp(\gamma t)\exp(\alpha)$.

Other possibilities for the baseline can be derived and in these cases the choice of $h_0(t)$ is supposed to parametrise effectively whatever the baseline of hazard is. Certainly, the element of β_j has the standard interpretation. In the case that the hazard function is of unknown shape, however, a purely statistical test should be applied, such as the likelihood ratio test or Wald test, if these parametric models are nested. If they are not nested we can apply such an information criterion as AIC or BIC (Royston and Lambert, 2011; Ibrahim *et al.*, 2005; Petersen, 1986).

The advantage of choosing one of the parametric approaches (not the Cox model) is that these models produce approximations of the ancillary coefficient and therefore they have the ability to predict the actual failure time.

The latter prediction can be investigated through Accelerated Failure Time models (AFT), which follow the parameterization

$$Ln(t_j) = X_i\beta_j + \varepsilon_j. \qquad (4.11)$$

The AFT assumes that the failure in house prices time t_j depends on accelerated parameter $X_j\beta_x$ and conforms to the following distribution

$$\tau_j = \exp\left(-X_i\beta_j\right) t_j. \tag{4.12}$$

This model asserts an interest in what happens to $E\{\ln(t_j)|X_i\}$ for different values of the covariates X_i. Equation 4.12 implies that if the accelerated parameter is greater (less) than one i.e. $X_i\beta_j > 1$ (< 1), the time passes more quickly (slowly) for the subject variables and hence failure would be expected to occur sooner (later). Moreover, we should bear in mind that all these parametric models may be fitted by maximising the appropriate partial likelihood function.

In the next section, the principal findings of the current investigation are presented.

4.4.1.2 Duration Dependences Estimation

For the purpose of analysis, this chapter uses the turning point procedure proposed in the literature to date: the peaks and troughs for monthly data over the period Jun. 1998-Dec. 2015. One reason behind limiting the data to this interval is to concentrate on the troubled period in which the Asian financial crisis took place, rather than on stable periods.

We start by describing the classical characteristic investigated through a BB-algorithm mentioned in Section 3.4 of Chapter 33. [42] Table 4.3 split the data into two phases, expansion and contraction. The features of Hong Kong's house price movements include the time that it took them to reach their peak (trough) points measured in months, as well as the amplitude of the phases presented. It is clear from Table 4.3 that there is a notable variation in the pattern of real housing prices between these among two phases. More specifically, the expansion phase is longer than the contraction phase by approximately 8 months, which exposes evidence of asymmetry in the house price cycles in Hong Kong. Unsurprisingly, the average of amplitude is quite different in both phases. Furthermore, the total output of the two phases in the house price cycle increased by 36% during the contraction and 91% in

[42] NB: since we have a different sample sizes for the house prices index in Hong Kong, we reproduce the turning points using the procedure explained in Section 3.4.

the expansion phase. This case may not cause surprise, since the decline associated with this turning point does not qualify as 'major'.[43]

Another significant finding is that the time taken to reach the turning point in the same phase is also quite heterogeneous. For instance, after the Asian crisis (in late 1990) house prices experienced a continued contraction and needed about 43 months to reach the lowest trough point, while only 15 months were required to hit the last financial crisis. Similarly, house prices increased dramatically after 2002 and reached their peak after 34 months, whereas after the last financial crisis the peak point was reached after 44 months.

Table 4.3 Dating of peaks (troughs) in Hong Kong real house prices

Contraction		Expansion	
Trough	Duration to reach lowest trough point	peak	Duration to reach peak point
Dec. 2001	43	Jan. 2003	13
Feb. 2005	25	Dec. 2007	34
Sep. 2008	8	May 2009	8
Aug. 2010	15	Dec. 2015	65
Panel B; Cycle Characteristics.			
Average Duration	22.5	30.00	
Average Amplitude	-0.052	0.068	
Average Cumulative	-0.798	1.95	
Excess area	0.364	0.912	

(1) Duration is expressed in months. (2) Duration and amplitude refer to the average of the duration and amplitude of the cyclical component by the city. (3) Amplitude, cumulative and excess area are expressed in percentages.

To identify duration dependencies between house prices and housing policies, it is necessary to examine separately the impact during expansion and that during contraction. Accordingly, each of the next tables presents the estimated hazard ratio of the parameters of the Weibull model obtained for the house price cycle during contraction (expansion) periods, along with robust standard errors and the p-value of the corresponding z-statistic.[44]

[43] The literature suggests that the major decline (increase) associated with more than a 15% decline (increase) in the cumulative real price (Posedel and Vizek, 2010; Gimeno and Martinez-Carrascal, 2010).

[44] Following the discussion in Section 4.4.1.1 and armed with the information criteria, the Weibull model outperformed the other baseline of hazard models.

The results of the hazard ratio during the contraction period are reported in Table 4.4. Interestingly, as shown in panel C of Table 4.4, the hazard of failure increases with time and, in this case, increases dramatically, since the shape parameter (p) is greater than one. In this case, the existence time in the contraction period increased by a factor of 1.75 compared to expansion period.

It is apparent from Table 4.4, also, that the variables generally have the expected sign. As Table 4.4 shows, a one-unit change in the gross loan made or loan to value approximately increases the hazard of failure to 24% and 16%, respectively, their previous value.

The observed increase in the hazard ratio reveals a decline in the probability that contraction will continue. In other words, the probability of surviving in the contraction phase will increase by 22% in case of loans made and 15% for the current loan to value ratio. However, a change in the real interest rate has a very limited impact on the hazard. One possible explanation is that the interest rate in Hong Kong is determined by US monetary behaviour and thus policy, and any risk premium required by investors to hold Hong Kong dollar assets (Gerlach and Peng, 2005). Another possible interpretation is that the rise in the interest rate will increase the cost of borrowing and the potential buyers will get discouraged. This finding, while preliminary, suggests that the continuation of contraction (and the probability of switching to an expansion phase) will increase only by 8%.

The Weibull model is fitted in the Accelerated Failure Time (AFT) metric to assess the accuracy of the estimated hazard model. Put differently, the AFT give information about how the survival times are differentially accelerated for different levels of a covariate. It is apparent from Panel B of Table 4.4 that the estimated coefficients are negative in the case of a gross loan made and current loan to value.

This coefficient reveals that the time is accelerated by a change in the covariate under review. The most interesting finding is that the gross loan made plays a crucial role in decreeing the duration of contraction. In this context, an increase in gross loan made is estimated to survive the bust phase 8% times longer than other covariates. A rise in a loan to value is also estimated to survive the bust phase 11% times longer than other covariates. Not surprisingly, an increase in the interest rate suggests that the acceleration factor will decrease the downturn period by 5%. This result may be explained by the fact that the interest rate has a negative impact on the demand for housing.

Table 4.4 Weibull regression for a contraction period

	gross loans made	current loan to value	real interest rate
Panel A: Weibull regression – Hazard Ratio			
Haz. Ratio	1.242*	1.158*	0.924**
	(0.036)	(0.02)	(0.031)
Coefficient	0.217	0.147	-0.079
Panel B: Weibull regression -- accelerated failure-time			
Coefficient	-0.11*	-0.084*	0.045**
	(0.042)	(0.009)	(0.021)
Panel C; Goodness of fit			
	Ln(p)	p	1/p
	0.561	1.753	0.571
	(0.097)	(0.17)	(0.055)

The coefficient value = Ln (Haz. Ratio). S.E. in parentheses.
In panel C; the value p and Ln (p) refers to the shape parameter as estimated through Weibull regression, while (1/p) refer to the shape parameter expressed in accelerated failure time.

The experimental evidence during an expansion period, as can be seen from panel C of Table 4.5, indicates that the likelihood of expansion period increased by a factor of 1.56 compared with the risk of exit to contraction period. As expected, growth in the gross bank lending and the loan to value ratio cuts the hazard of failure to 89% and 39%, respectively. What is obvious is that this growth lessens the likelihood of switching the probability of contracting. As a consequence, the probability of continuing to expand increases by 11% in the case of loans made and 61% for the current loan to value.

Be that as it may, monetary policy actions have proved to be relevant to detecting the presence of negative dependence on the duration of the expansion. In this case, a one-unit change increased the hazard to 85% of its previous value. This finding suggests that the probability of continuing in the expansion phase will increase only by 15%.

The results of the Weibull model again are fitted in AFT metric to calculate the actual failure time and prediction of this failure time.[45] The positive sign of the loan

[45] The failure time in this case refers to the switch from boom to bust.

to value ratio and gross loan, as reported in Panel B of Table 4.5, reveals that a one unit rise in a gross loan made is also estimated to survive the contraction phase 7% times longer than other covariates. Interestingly, a change in loan to value will increase the likelihood of expansion by 39% times longer than other covariates. Finally, and in line with expectation, an increase the interest rate will shorten the upturn period by 10% and this suggests that the interest rate has a negative impact on the demand for housing.

Table 4.5 Weibull regression for Expansion period

	gross loans made	current loan to value	real interest rate
Panel A; Weibull regression – Hazard Ratio			
Haz. Ratio	0.893**	0.385*	0.852*
	(0.042)	(0.137)	(0.031)
Coefficient	-0.113	-0.954	-0.160
Panel B; Weibull regression - accelerated failure-time			
Coefficient	0.073**	0.613*	0.103**
	(0.031)	(0.189)	(0.024)
Panel C; Goodness of fit			
	Ln(p)	p	1/p
	0.442**	1.556*	0.643*
	(0.106)	(0.165)	(0.068)

The coefficient value = Ln (Haz. Ratio). S.E. in parentheses.
In panel C; the value p and Ln (p) refers to the shape parameter as estimated through Weibull regression, while (1/p) refer to the shape parameter expressed in accelerated failure time.

The AFT metric gives a greater role to predicting the time before failure with the covariates under consideration. Such predicting assumes that the subject is at risk from time 0 until failure and has a fixed covariate pattern over this period. Table 4.6 illustrates the predicted time to failure obtained through the Weibull model for both the contraction and expansion periods. It is critical to highlight that this table shows the predicted time for the period associated with the turning point presented in Table 4.3. This allows us to compare these predicted values with those of an actual period.

From Table 4.6, it can be seen that the time before a failure associated with a high interest rate and a low loan to value tends to be long, whereas the duration of a contraction phase associated with a high loan to value and a low interest rate appears to be short. These cases clearly show up during the bust period in 1999 compared with 2002. Similarly, a high interest rate declining in the gross loan made, and increasing in the loan to value would be the crucial reason underlying a short expansion, such as took place in the boom of 2000, which lasted for about 25 months.

The most interesting aspect of Table 4.6 is the power of the used survival model to predict duration. This case can be verified through columns 5 and 6 of the table below, in which the predicted times are very close to actual ones. However, the real boom period in 2001 was not as long as predicted, because of the Asian financial crisis which started first in the housing market.

Table 4.6 The prediction of failure time

Turning Point	loans made	LTV	interest rate	predicted duration	Actual duration
Dec. 2001 (T)	8.99	2.52	8.17	27.59	43
Jan. 2003 (P)	8.89	2.99	6.77	12.26	13
Feb. 2005 (T)	9.46	2.17	6.86	26.41	25
Dec. 2007 (P)	9.97	1.62	8.74	33.12	34
Sep. 2008 (T)	9.36	1.66	6.68	9.03	8
May 2009 (P)	9.63	1.69	6.27	7.71	8
Aug. 2010 (T)	10.41	1.24	6.23	13.28	15
Dec. 2015 (P)	9.46	0.62	4.87	66.68	65

T, P refers to trough and peak points respectively.

4.4.2 Housing Price Volatility And Policy

House price volatility is of particular interest because it reflects uncertainty on housing market decisions by affecting the expectations of future prices (Stephens, 2012; Muellbauer and Murphy, 1997). The main cause of this volatility, however, can be differences in supply elasticities. In specific, in conditions of low elasticity for housing supply, the change in housing markets occurs when the markets are affected by shocks (Leung and Teo, 2011).

From a macroeconomic stability viewpoint, what matters may not be this boom (bust) in itself but rather establishing the causes of price volatility. A more proactive policy helps to control the lending either when the market appears to be overheating, or throughout the cycle. Central to the volatility in housing markets, the variations in loan to value ratios, in gross bank lending and in interest rates are likely to have an impact, which is why they can help stabilise housing market outcomes. Therefore, a more proactive policy stance could reduce the risks associated with these shocks.

We sought first to determine the causality relationship between the policies and volatility of the house price cycle in Section 4.4.2.1, and then testing the source of volatility in Section 4.4.2.2.

4.4.2.1 Causality between Policy and House Prices Volatility

The relationships between house prices and their factors are sometime ambiguous and the debate in this area is ongoing. Theoretically, these determinants are expected to cause house price changes and therefore considered to be exogenous. However, in most cases, there may be evidence of two-way relationships. In this investigation, the Granger causality test was applied to examine whether changes in one series caused changes in another (Granger, 1969). The latter methodology is preferred if the series is not cointegrated.

Suppose that the volatility in house price series, say HP, can be predicted using the past values of gross loan made, BL, current loan to value, LTV, or interest rate, IR, and considering other relevant information, including past values of HP, then the Granger causality tests of any two stationary series, say, HP_t and BL_t are used as a first step in estimating the following VAR model:

$$HP_t = \alpha_1 + \sum_{i=1}^{n} \beta_i * BL_{t-i} + \sum_{j=1}^{m} \gamma_j * HP_{t-j} + \varepsilon_{1t}, \tag{4.13}$$

$$BL_t = \alpha_1 + \sum_{i=1}^{n} \theta_i * BL_{t-i} + \sum_{j=1}^{m} \delta_j * HP_{t-j} + \varepsilon_{2t}. \tag{4.14}$$

Examining this causality also requires that the optimal lag length for each series should be specified. The proper lag order in this context, after considering the Schwarz information criteria (SIC), is fixed at 4. The F-statistics in the second column of Table 4.7 reveal statistically significant unidirectional causality from the loan-to-value to the volatility of house prices, on the one hand, and from gross loan made to the change in house prices, on the other. However, the causality between the interest rate and the volatility is significant at 10%.

Under the Linked Exchange Rate System, these relations are somewhat intuitive since Hong Kong is precluded from exercising an independent monetary policy. Moreover, the LTV policy is effective at reducing the systemic risk associated with boom and bust cycles in the housing market. This view is supported by Gerlach and Peng (2005), who find that property price movements in Hong Kong derive largely from bank lending.

The overall implication of these findings is that the volatility of house prices and policies that affect housing market is well integrated in Hong Kong with the direction of causality running from policy indicators to the volatility of house prices. Moreover, the lack of causal relations between interest rates and house prices suggests that there is no integration between them.

Table 4.7 Granger causality between policy and the volatility of house prices

Null Hypothesis	F-Statistic	Prob.
Loan To Value does not Granger Cause **Volatility Of House Prices**	18.818*	0.000
Volatility Of House Prices does not Granger Cause **Loan To Value**	0.789	0.456
Interest Rate Does not Granger Cause **Volatility Of House Prices**	2.271***	0.086
Volatility Of House PRICES does not Granger Cause **Interest Rate**	0.638	0.529
Gross Loans Made does not Granger Cause **Volatility Of House Price**s	10.674*	0.000
Volatility Of House Prices does not Granger Cause **Gross Loans Made**	0.365	0.694

Significant code.* p<0.01, ** p<0.05, *** p<0.1

4.4.2.2 The Impact Of Policy On The Volatility Of House Price

Having discussed the direction of causality between house prices volatility and the policies adopted, this section seeks further insight into the relationships between house prices and the determinants being considered. It also tests for any evidence of an asymmetry effect on this volatility to gauge the relative importance of the policy during the phases of the cycle.

4.4.2.2.1 Econometric Methodology

A variety of methods have been used to model the volatility. For instance, the Autoregressive Moving Average (ARMA) model is the most widely used kind of model to determine the relationship between the historical and future volatility of a time series, given that the variance assumed to be constant (Kirchgässner *et al.*, 2012; Brockwell and Davis, 2006). However, constant variance is a very rare event and hence an assumption of conditional variance (i.e. non-constant variance) leads to biased results in the ARMA (ARIMA) specification. The Autoregressive Conditional Heteroscedasticity ($ARCH$) model and Generalised $ARCH$ ($GARCH$) are supposed to capture the volatility with which the variance varies over time (Hansen and Lunde, 2005; Baillie and Bollerslev, 1992).

Recently, a hybrid ARIMA − E$GARCH$ model has combined the $ARIMA(p,d,q)$ model with the $GARCH(m,n)$ model to form a nonlinear time series model in order to increase the reliability of volatility measures. This combination allows the conditional variance to be modelled with fewer parameters than a $GARCH$ specification alone would (Liu *et al.*, 2011; Chen *et al.*, 2011). Following the literature (e.g. Bowden and Payne, 2008; Ling, 2007; Tang, Chiu and Xu, 2003; Nelson, 1991), the volatility in this model can be written as

$$y_t = \sum_{j=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t, \tag{4.15}$$

$$\ln(h_t) = \omega + \sum_{j=1}^{n} \left(\alpha_j \left(\frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} - \sqrt{\frac{2}{\pi}} \right) + \gamma \, \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} \right) + \sum_{i=1}^{m} \beta_i \ln(h_{t-i}). \tag{4.16}$$

Equation 4.15 represents the mean equation for monthly houses prices, while Equation 4.16 stands for the conditional variance equation. Moreover, β indicates the degree of volatility persistence and ω is the mean of the volatility equation. The size effect (how much volatility increases) denoted by α, whereas the γ measure the sign effect whereby asymmetric effects are present in response to a shock when $\gamma \neq 0$.

The sufficiency of these models can be evaluated to give critical guidance in choosing the most appropriate models. These methods include the goodness of fit Measurement; R^2, Akaike's Information Criterion (AIC) and Schwartz Information Criterion (BIC) (Schwarz, 1978; Akaike, 1974). Other evaluation methods are the diagnostic checking of the fit of the model for instance with the Q-test and Breusch–Godfrey test for the existence of autocorrelation in residuals (Breusch and Pagan, 1979). The strategy for modelling this volatility is to search over alternative $\mathrm{ARIMA(p,d,q)} - \mathrm{EGARCH(m,n)}$ by varying the order of lags and identifying the optimal model using the Schwartz Information Criterion (BIC).

4.4.2.2.2 House Prices Volatility and Policy Estimation

To address the issue of to what extent the conditional volatilities of house prices are dependent on the shock, we proceed to test whether the asymmetric volatility can be influenced by the housing policy. Therefore, and following the seminal work of Tsai and Chen (2009), the considered variables are put into the variance equation of the adopted model.

The estimated parameters of the conditional mean and variance equations, along with their diagnostic tests, are reported in Table 4.8. These results have been divided into three categories; panel A and Panel B show the parameters of ARIMA-EGARCH equations and the evaluation results of modelling sufficiency are stated in Panel C.

Starting with diagnostic tests, and according to BIC and AIC, $ARIMA(1,1,1) - EGARCH\,(1,1)$ dominate other possibilities and appear to be the best choices. Moreover, the LM-test for the ARCH effect and the Breusch–Godfrey test for autocorrelation reveal no evidence of misspecification in the model.

On examining the table, it is found that the parameters in mean and volatility equations are significantly estimated in all instances. Specifically, the results of $\mathrm{ARIMA}(1,1,1) - \mathrm{EGARCH}(1,1)$ indicate that the volatility is quite persistent, since the sum of the α effect and β effect is close to unity. In terms of the variance equations, It appears from the size effect, α, that a shock to house prices has the greatest impact on volatility (irrespective of the shock direction). In addition, the volatility persistence β is significantly predictive; thus, allowing for asymmetry tends to reduce the persistence in the conditional volatility.

Furthermore, the shocks have a noticeable impact by the indicators in question on the volatility of house prices and, in this case, house prices respond with more volatility, whatever the sign of this shock. However (unsurprisingly), the change in interest rate is found to have no impact on the volatility of house prices. A possible explanation for this may be that the swings in house prices may not be affected by monetary policy, since the Hong Kong dollar is restricted by the monetary policy of the US and therefore in the period of interest regulatory policy was used more extensively to limit the impact of property price booms on the economy (see e.g. Gerlach and Peng, 2005; Semlali and Collyns, 2002).

In addition, the estimation of the sign effect and degree of asymmetry (γ) reveals a strong indication of the presence of the inverse leverage effect, which is in line with the finding of existing literature (e.g. Tsai and Chen, 2009; Miller and Peng, 2006) [46]. Put differently, asymmetric volatility still exists in the market after controlling for the influence from the policy factors. The positive sign implies that there is inverse leverage effect in which a positive shock has a larger impact on volatility than negative shocks of the same magnitude. The latter indicate that the shock will affect volatility for a quite time in the future. In fact, this asymmetric volatility might account for the defensiveness of the housing market.

Table 4.8 ARIMA-EGARCH modelling results

Pane A; Mean equation	
ε_{t-1}	0.953*
	(0.022)
ε_{t-2}	-0.861*
	(0.046)
Panel B; Volatility equation	
Gross loans made	0.244**
	(0.115)
Loan to value	0.423*
	(0.162)
Real interest rate	-0.118
	(0.137)
α	0.233*
	(0.040)
β	0.825*
	(0.060)
γ	0.769**
	(0.041)
Panel C; Model evaluation	
LM test for ARCH(p) effect	0.8052[a]
Breusch–Godfrey Test Chi-square	1.427[b]
Likelihood	-40.782

Notes; S.E. in parentheses. * p<0.01, ** p<0.05, *** p<0.10 Significant value. (a) The probability of LM test is 0.8052. (b) The probability of Chi-square is 0.2322.

[46] The positive or (anti) leverage effect can be justified as the housing supply in the short term is rigid by definition, this result is consistent with the empirical findings (e.g. Cohary and Rad, 1994; Alberg *et al.*, 2008; Caporin, M., and McAleer 2006)

4.5 CONCLUSION

The direction of the causality between house prices and policy is of interest, since governing policy is used extensively to limit the impact of property price booms on the economy. This paper has discussed the evidence of duration dependence in the house price cycle and had as its second aim to investigate the rule of changing policy on the volatility of house prices.

Using monthly data in Hong Kong for macro-prudential, lending and monetary policy and house prices, this chapter, first, defined the house price cycle as a consequence of the periods of expansion and contraction. Then it applied a survival model to consider the duration dependences in the house price cycle. Here, the impact on the amplitude of the cycle was investigated through a combination of the $ARIMA(1, 1, 1)$ and the E$GARCH(1,1)$ models, with a view to modelling the volatility.

While this essay is still preliminary in nature, it throws up several interesting and important econometric results. First and foremost, it shows that evidence of duration dependences can be found in the house price cycle in both the upswing and downswing phases and that the probability of reaching the turning point increases dramatically with time. Furthermore, the Loan to Value ratio appears to be the more valuable regularisation policy, whereas the interest rate has a very limited impact on the duration of the cycle.

Second, there is evidence of feedback between the return volatility in the house price cycle and policies that affect housing market. Moreover, this causality runs from the loan to the value and the loan made to the volatility of house prices Moreover, there is evidence of a anti leverage effect which implies that unanticipated house price increases are more destabilising than unanticipated falls in house prices.

Together, these findings highlight important policy implications for policymakers and financial regulators: instead of lowering the interest rate, they should think of applying the loan to value policy to expand the duration of expansions.

5 CHAPTER FIVE

CONCLUDING REMARKS

Fluctuations in housing prices have revealed striking persistence over short periods and a dramatic mean decline over longer periods. Therefore, the aftermath of the latest world financial crisis has seen a growing trend regarding the risk to house prices from these marked changes in asset prices. This is perhaps unsurprising because of the role of the housing market in the wealth of the private sector and, therefore, its considerable influence on the whole economy (Canepa and Chini, 2016; Vincent and Morley, 2012; Agnello and Schuknecht, 2011; Adams and Füss, 2010). Moreover, interest in the behaviour of house prices has been further heightened by their evident volatility.

With this backdrop, the present study is designed to review house price behaviour in large metropolitan areas and the statistical properties of the house price cycle; and also to investigate whether macro-prudential, lending and monetary policies affect the length as well as the volatility of this cycle, bearing in mind its two phases, namely, of expansion and contraction. This study adopts modern econometric techniques including the Logistic Smooth Transition Autoregressive method, a filtering technique to decompose the time series, volatility models, and survival models. The contributions and key findings of this thesis are summarised below.

The first essay contributes to the literature on investigating house price behaviour by examining the possible nonlinearities and asymmetry in the house prices in nine metropolitan areas. For this purpose, we employ the LSTAR model to allow the dynamic of house price to evolve smoothly between regimes, since it depends on the sign and magnitude of past realisations of house prices. This method lets us assess whether the behaviour of house prices in these metropolitan areas can be described as either symmetric or asymmetric.

The empirical results show that house price exhibit nonlinear properties; hence, we reject the linear hypothesis. The relatively low speed of transition also suggests that STAR-family models have the capacity to capture these properties. In this case, the LSTAR model outdoes the ESTAR model and varying degrees of asymmetry are detected among the cities. For the purpose of fitting the model, these findings were tested to detect any misspecification problems. In this analysis, we also compared the forecast accuracy of the LSTAR model with that of the AR. The results of doing so indicate that the imprecise linear model leads to inaccurate estimates for the economy, since in practice house prices lead economic activity.

The second essay contributes to the growing literature on time series filtering and investigates the statistical properties of cycles. On the one hand, it extends our knowledge of performing decomposition techniques on empirical data by estimating the actual spectra of the cycle. This work, also, offers valuable insights into the features of the house price cycle, as well as the ability of filtering techniques to explain house price dynamics. First and foremost, our results for the house price cycle were found to be consistent with the literature in term of length, fluctuation, and excess area (Galati *et al.*, 2016; Claessens *et al.*, 2012). Second, the results of the nonparametric filters suggest that the C-F filter outperforms both the H-P filter and the B-K filter. However, this filter pegs out in conditions of stationarity. Third, the model-based filters show evidence of substantial variation in the period and amplitude of these cycles, both across cities and over time, which is consistent with the findings of Stremmel *et al.* (2015) and Borio (2014). Finally, we observe that the UCM are more appropriate to measuring the cycle in house prices.

The third essay investigates the nexus between macro-prudential, lending and monetary policies and house price cycles. With this target in mind, a duration model was estimated to investigate how lending policies such as loan-to-value affect the duration of house price cycles. The volatility of the cycle was also investigated by estimating a combination of $ARIMA(1,1,1) - \mathrm{E}GARCH(1,1)$ model.

The main findings of this chapter are threefold. First, a dramatic increase in the probability of reaching the turning point indicated that lending affects the indicators of both the boom and bust periods. Second, the causality test provided strong evidence of long-run causality running from loan to value and loan made to the volatility of house prices. Third, we found that house prices are positively affected by any change in the bank lending indicator. However, the interest rate is the exception in this case. Finally, the positive leverage effect explains why unanticipated house price increases are more destabilising than unanticipated falls in house prices.

Although we believe that this thesis covers several aspects of house price behaviour, macro-prudential, lending and monetary policy, and the causal relationships drawn from time-series, it also has some limitations. For instance, the data on house price fundamentals (e.g. land supply and cost of building) are one of the main reasons for the limitations in this study. In fact, these factors play a critical role in obtaining a complete picture and richer specifications of house price behaviour. Considerably more work will need to be done to determine the degree of asymmetry and impact of other factors (personal income, population growth, and the unemployment rate) on the duration of the house price cycle.

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