UNIVERSITY of SOUTHAMPTON

FACULTY OF SOCIAL SCIENCES

SOUTHAMPTON BUSINESS SCHOOL

Essays on Dynamic Interactions between Housing Markets and the Macroeconomy

by

Kun Duan

Thesis for the degree of Doctor of Philosophy

May 2019

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Abstract

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This thesis sheds new light on the complex interaction between housing prices and macroeconomic system by modelling three defining pillars on which the building block of the relationship edifice rest, viz., *space*, *credit disaggregation*, and *memory of shocks*. The thesis contains three main chapters. Apart from Chapter 1 (Introduction), Chapter 2 sets the tone of the first important contribution by introducing the role of *space* in analysing impacts of macroeconomic interventions on cross-country housing price dynamics. This chapter first builds a theoretical framework to model and explain housing market *disequilibrium* by identifying spatial frictions among a panel of spatially-adjacent countries. A spatial-dynamic housing production function is introduced for the purpose. This chapter finds and identifies the presence of a significant overestimation bias of the effects of macroeconomic variables on housing price variations in a traditional non-spatial model. To overcome this problem and to lend consistent and unbiased estimates of effects relevant for policy, a dynamic spatial Durbin model is proposed. Robustness exercise under different scenarios lends credibility to the proposed strategy.

Chapter 3 focuses on solving a mystery surrounding the real effects of *credit* in cross-country housing market. Since 'credit' lies at the core of housing demand and supply and is controlled stringently by macroeconomic policy, to understand its real effects one needs to go beyond convention. This chapter proposes *disaggregation* of credit into *credit to the real economy* and *credit to the asset markets* to exactly identify both housing demand and supply credit-circulation channels where each component of credit exerts distinct impacts on housing price determinations. A conceptual framework is first developed to justify the strategy of *disaggregation*. Moreover, business cycles fluctuations are removed to align individual countries interaction-effects at the same level as other target countries, while economic policy uncertainty is also introduced to control for information asymmetry. An estimation by a panel vector autoregressive (PVAR) methodology shows that the proposed disaggregation strategy serves as a better approach for policy exercise regarding the optimal allocation of credit to the real economy and to the asset

markets. The chapter demonstrates that that (i) there is a mutually positive reinforcing relationship between *credit to the real economy* and housing prices, (ii) the impact of *credit to the asset markets* on housing prices is negative and negligible in the short-run and positive and significant in the long-run. In addition, only *credit to the real economy* is found to stimulate economic growth in contrast to the insignificant impact of *credit to the asset markets*.

Modelling possible slow-convergence of shocks within a complex interactive system is crucial as it provides a robust predictive power by quantifying the extent to which estimated macroeconomic effects are meaningful for a policy design. In this spirit, Chapter 4 introduces a long-memory cointegration approach to unravel distinct effect-transmission channels through which housing market and macroeconomic system co-move. By employing a fractionally cointegrated VAR model, we demonstrate that there is a gradual price adjustment towards the housing market clearing while the effects of shocks on equilibrium adjustments are inherently slow and non-linear. This identification strategy is able to not only gauge impacts of housing demand- or supply-exclusive variables, but also the ones that have dual roles through both demand and supply sides, respectively, in equilibrium housing price determinations and dis-equilibrium error corrections. Eventually, an overall equilibrium housing price determination function is derived by solving simultaneous housing demand and supply functions. Chapter 5 summarises the main results of the thesis, points out limitations of the work and discusses future research directions.

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Declaration of Authorship

I, Kun Duan, declare that this thesis titled, 'Essays on Dynamic Interactions between Housing Markets and the Macroeconomy' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.
- Parts of this work have been published as:
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Signed: ______________________________

Date: ______________________________

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To My Parents and My Wife

Chapter 1

Introduction

1.1 Research Context and Background

Studying the nexus between the housing market and the macroeconomy is of paramount importance for many reasons. There is a clear argument in the literature emphasizing that housing forms a major component of a macroeconomic system (Leung, 2004). When it comes to capital stock, Greenwood and Hercowitz (1991) find the greater value of residential capital stock than that of business non-residential capital stock. Examining the case of USA, Davis and Heathcote (2005) find that the total market value of the home stock roughly equals to the annual Gross Domestic Product (GDP). In the United Kingdom (UK), this figure was even 3.5 times larger than that of the GDP in 2017.[1] Moreover, it is now well-established that an irrational bubble and then a collapse of housing prices can give rise to a chain reaction of chaos diffusing through every layer of an economy - both micro and macro. Ultimately, for managing such a chaos, the intervention of macroeconomic policy is solicited as it is strongly believed that macroeconomic fundamentals are directly and tightly interlinked to asset market fluctuations. Yet, despite developed theories and numerous empirical attempts, a slow and long road to recovery of an economic system implies that there are indeed many unanswered questions - which have thus far been overlooked.

Despite the establishment of a large literature on the distinction of rational and irrational bubbles, consumers sentiments do not seem to follow a set recommended pattern, thanks to the ever changing psychological boundaries in interaction with the socio-economic system. When consumers are subject to persistent uncertainty, irrational bubbles become an almost rule of law, triggering continuous mis-pricing. Muellbauer and Murphy (2008) point out that both mis-pricing housing prices, which deviates from the rational level determined by macroeconomic fundamentals, and the mis-specification of macroeconomic fundamentals are the two significant reasons that lead to the burst of 'real estate bubble' and the breakdown of the housing market as well as the overall economy.

Moreover, housing also constitutes a dominant share of the households' expenditure and their total wealth. According to the Consumer Expenditure Survey, housing accounts for about 22.2% of total households' expenditure in the United States (US), which is ranked the first against other consumption categories (Chetty and Szeidl, 2007). Significant housing price fluctuations would direct the consumption expenditure level of households by affecting their perceived wealth (Bernanke and Gertler, 1989; Bernanke et al., 1999; Campbell and Cocco, 2007; Case et al., 2005; Kiyotaki and Moore, 1997) or altering their borrowing constraints (Campello and Giambona, 2013; Chaney et al., 2012; Cooper, 2013; Goodhart and Hofmann, 2008; Ling et al., 2016). Meanwhile, it has been widely embraced in existing literature that macroeconomic fundamentals

[1] Author's calculation. Data are from the Office for National Statistics (https://www.ons.gov.uk/economy/grossdomesticproductgdp) and the Financial Times (https://www.ft.com/content/c253d6c2-fc51-11e7-a492-2c9be7f3120a).

directly exert marked and unavoidable impacts on determining housing prices and individuals' consumption expenditure, as well as the relationship between them (Attanasio and Weber, 1994; Campbell and Cocco, 2007; King, 1990; Muellbauer and Murphy, 1997).

Modelling an imperfect economic system, which itself is an amalgamation of multitudinous forces of nature, is a herculean task, especially when incomplete and asymmetric information pervades the core interaction mechanism of a complex system. A natural integration of - 'what is observed in natural circumstances' and 'the tools available to understand their dynamics' - is limited by our knowledge. The 'gap' that remains due to the imperfect integration becomes greater day by day and leaves an undesirable impact on the net predictive power of the model that is adopted. Thanks to the development of independent fields of various disciplines in sync with fast computing techniques, it has now become possible to integrate high-dimensional interactions within a single empirical setting. Challenges remain, yet the continuous development provides hopes for a better understanding of the very complex interaction between the housing market and the macroeconomy (Arestis and Gonzalez-Martinez, 2016; Cesa-Bianchi, 2013; Duan et al., 2018a,b).

Despite the proven significant linkage between housing prices and the macroeconomy, there is an obvious disconnect between the housing and macroeconomics research. Indeed, far little literature focuses on studying the relationship between them through theoretical and empirical perspectives. Moreover, conventional macroeconomic studies and textbooks either simply consider housing as one of the consumption goods or totally ignore its role (Leung, 2004), while the mainstream macroeconomics also ignores the role of the housing market in the overall economy (Dimand, 2002; Klein, 2001; Solow, 2001; Tobin, 2002). Although existing relevant research has started to realise the importance of this interaction, it nevertheless exhibits flaws involving the adoption and application of appropriate research methods and strategies, as well as the accurate identification of macroeconomic fundamentals. To fill in this gap and grapple with a rational interpretation of this dynamic nexus, three effective instruments have emerged, viz. *'space'*, *'credit disaggregation'*, and *'long-memory shocks'*.

In the context of spatial science, as an important determinant of housing price diffusion, 'space' has been emphasised as a central medium through which macroeconomic shocks move across spatially interdependent housing markets. Expanding on the idea of Rosen (1974), earlier researchers point out the importance of a clear identification of spatial dependence and spatial heterogeneity in studying the impact of hedonic factors on the housing price determination across regions within a single-country setting (Basu and Thibodeau, 1998; Can, 1992). From a macroeconomic viewpoint, housing prices are also found to be empirically correlated either across regions within the same country or across spatially-adjacent countries, indicating the significant cross-border synchronisations of housing price. Meanwhile, such phenomena are attributed to the comovement in macroeconomic fundamentals of both housing demand and supply functions as well as the implementation of macroeconomic policy in the context of spatially-interdependent housing markets (Arestis and Gonzalez-Martinez, 2016; Bagliano and Morana, 2012; Beltratti and Morana, 2010; Cesa-Bianchi, 2013; Fereidouni et al., 2016; Terrones and Otrok, 2004; Vansteenkiste and Hiebert, 2011). In spite of the highly-recognized importance of macroeconomic adjustments in interpreting cross-country housing price movements, a failure to account for the medium role of space in the dissemination of macroeconomic shocks could bias the measurement of their real effects. However, far little literature contributes to this strand of discussion.

In addition to 'space', 'bank credit' plays another instrumental role in the price determination of the asset market, particularly when asymmetric information driven by the existence of economic policy uncertainty characterises the broad economic environment (Bernanke, 2007; Kindleberger, 1978; Minsky, 2015). In terms of the effect of credit on housing prices, existing empirical literature reports inconclusive results regarding signs of the impact and the causal relationships (See Tables B.10 and B.11 in Appendix B for a summary of the literature). It is argued that such conflicting results are due to the assumption of credit in the aggregate form (Werner, 1997, 2012), which could disregard the micro-level information regarding the different components of credit that flow into distinct money-circulation channels through housing demand and supply perspectives, respectively. Thus, conclusions drawn from the aggregated credit would offset and confuse the real interactive nexus between credit and housing prices in the context of macroeconomy. Instead, the thought of credit disaggregation originally proposed by Keynes (1930), who suggests segregating credit aggregates as the one *to the real economy* and the one *to the asset markets*, can furnish a rational approach to disentangle such complex dynamics. Indeed, the strategy of 'disaggregation' has helped reconcile conflicting empirical evidence regarding the role of credit in economic activities (See, Jordà et al., 2016; Unger, 2017; Werner, 1997, 2012, for instance). However, its relevant studies and applications in the housing market are surprisingly sparse so far.

In the context of 'long memory' time-series modelling, macroeconomic shocks in the system could be persistent and slowly converged towards a long-run constant mean (Jones et al., 2014). A failure to account for this feature in conventional empirical methodologies, in which a unit root assumption is simply assumed instead, would give rise to unrealistic and questionable conclusions. Moreover, in the housing market, it is well known that its price naturally behaves a gradual adjustment process towards the market equilibrium rather than an instant market clearing as conventionally assumed (DiPasquale and Wheaton, 1994). Overall, how to model the long-memory shocks while considering the gradual price adjustment process in the macroeconomy-housing market interaction system can be a challenge that calls for a correct application of a long-memory cointegration framework in the system through both theoretical and empirical perspectives.

Indeed, the strategy of disaggregation is not only applicable to bank credit variable as earlier discussed, but also to other macroeconomic fundamentals that determine housing price dynamics. There is an compelling evidence that specific macroeconomic variables can play dual roles in determining housing prices through both housing demand and supply functions, respectively (See, Arestis and Gonzalez-Martinez, 2016, for instance). Thus, an omission of the micro-level information of these determinants and a mere measurement of their aggregated effects instead would result in the elusive 'housing price puzzles' (McCarthy and Peach, 2002). Indeed, separately studying how these macroeconomic variables contribute to the housing price determination through both functions is of great importance and necessity. Their real impacts can be accordingly disentangled through a clear identification of distinct effect-transmission channels in the macroeconomy-housing market interaction on both demand and supply sides. Surprisingly, existing relevant studies merely focus on the housing price determination using housing demand function (Cesa-Bianchi, 2013; DiPasquale and Wheaton, 1994; Muellbauer and Murphy, 1997), housing supply function (DiPasquale, 1999; Glaeser et al., 2008; Green et al., 2005; Quigley, 1979; Saiz, 2010), or both of them in a combined function (Arestis and Gonzalez-Martinez, 2016; Duan et al., 2018a,b). However, rather few of them gauge the interaction separately through both functions in a long-memory cointegration framework.

1.2 General Research Contributions

The general research contributions of this Ph.D. thesis are threefold:

- To gauge the contributions of macroeconomic policy interventions on housing price dynamics by identifying spatial spillover effects among cross-country spatially-interdependent housing markets.
- To disentangle the interactive relationship between different disaggregated credit and housing prices through housing demand and supply credit-circulation channels in a macroeconomic context.
- To interpret the equilibrium housing price determination by identifying distinct effect-transmission channels in the macroeconomy-housing market interaction through both housing demand and supply sides, respectively, in a long-memory cointegration framework.

1.3 Research Aims

The research aim of this Ph.D. thesis is to disentangle the complex dynamic relationship between housing prices and macroeconomic fundamentals by employing three significant instruments, including *'space'*, *'credit disaggregation'* and *'long-memory shocks'*, through both theoretical and empirical perspectives. This Ph.D. thesis sheds new light on issues that are jointly consequential to academics and practitioners in fields of real estate and macroeconomics. This work also contributes to applicable suggestions regarding the implementation of macroeconomic interventions to regulate the housing market and the overall economy.

Moreover, it is noteworthy that the research focus of this thesis is residential real estate markets rather than commercial real estate markets. Overall, the thesis is dedicated to the housing market analysis to investigate how fluctuations in macroeconomic fundamentals contribute to housing price movements by directing levels of the housing demand and supply, and in turn, how housing price dynamics separately influence the investment intentions/behaviours of both housing buyers and suppliers for house purchase and construction, and by extension, the broader economy. Thus, to avoid any confusion, it is necessary to clarify that the terms real estate market and housing market are used synonymously, and the term housing price refers to the price of homes throughout the thesis.

Specific research aims of each core chapter are presented as follows.

The research aim of Chapter 2 is to develop a spatio-temporal research framework to identify spatial spillover effects in a cross-country context, to distinguish between intra- and inter-border macroeconomic effects, and to gauge the real impacts of macroeconomic policy interventions on housing price dynamics using a dynamic spatial panel estimation instead of conventional non-spatial methodologies.

The research aim of Chapter 3 is to discuss the complex and interactive relationship between credit and housing prices in a macroeconomic context by segregating credit aggregates into *credit to the real economy* and *credit to the asset markets*, and to test the theoretical explanations using a panel vector autoregressive (PVAR) model by controlling for the existence of business cycles and persistent economic policy uncertainty.

The research aim of Chapter 4 is to identify distinct effect-transmission channels in the macroeconomy-housing market dynamics on both housing demand and supply sides in a long-memory cointegration framework, to separately interpret the equilibrium housing price determinations on both sides using a fractionally cointegrated VAR model, and to eventually derive the overall housing price determination by solving simultaneous demand and supply functions.

1.4 Research Objectives

The research aims of this Ph.D. thesis can be expressed as specific research objectives in each main chapter, followed by conclusions.

The research objectives of **Chapter 2**:

- To identify a medium role of spatial spillovers in modelling the macroeconomy-housing market relationship among spatially-interdependent countries through a theoretically elaborated spatial housing production function.
- To empirically quantify the impacts of macroeconomic policy inventions on cross-country housing price dynamics by using a dynamic spatial Durbin model.
- To demonstrate the superiority of a spatially-embedded model in solving the overestimation bias suffered in conventional non-spatial methodologies.
- To afford insightful policy implications for the exact role of macroeconomic interventions in determining the cross-country housing price movements.

The research objectives of **Chapter 3**:

- To theoretically explain the importance and necessity of credit disaggregation through housing demand and supply credit-circulation channels in interpreting the credit-housing price dynamics in a macroeconomic context.
- To empirically formulate and gauge the interactive relationship among different disaggregate credit, housing prices, and other macroeconomic variables including nominal GDP by using a PVAR model.
- To recognize the existence of business cycles and persistent uncertainty in determining dynamics of the relationship.
- To contribute to policy insights regarding the optimal credit allocation to the real economy and to the asset markets.

The research objectives of **Chapter 4**:

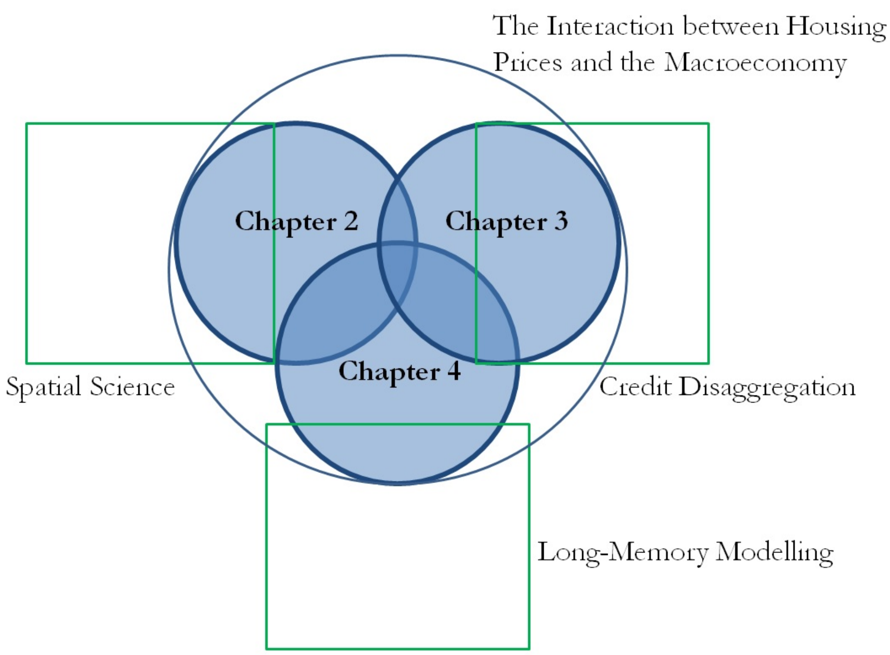
- To both theoretically and empirically formulate the determinations of equilibrium housing prices through both housing demand and supply perspectives, respectively, in a long-memory cointegration framework.
- To remove the periodic cycles from the raw series and to identify the long-memory shocks in the macroeconomy-housing market interaction and the slow price adjustment towards the market clearing by using a FCVAR model.

- To conduct the model forecasting exercises to examine the model performance.
- To derive the overall equilibrium housing price determination function by solving simultaneous housing demand and supply functions.
- To offer policy suggestions in interpreting the role of distinct effect-transmission channels of macroeconomic fundamentals in housing price determinations.

1.5 Structure of the Thesis

This Ph.D. thesis is structured grounded on both theoretical and empirical investigations of the macroeconomy-housing market interaction through three significant instruments, viz. the role of 'space', the thought of 'credit disaggregation', and the persistence of 'long-memory shocks'. It develops ways to conceptualise, model and test with empirical rigour the intricate relationship by adopting an interdisciplinary framework that integrates spatial science, credit theory and fractional time series modelling. The thesis makes an effort to embed such an integrated framework within a market equilibrium theory to investigate the relationship. As a consequence, three main chapters of the thesis are devoted to different directions and emphases by employing different instruments, while addressing the common research question. The logical relationships among these three main chapters are illustrated in Figure 1.1.

Figure 1.1: **The Overview of Thesis Structure**



Specifically, in Chapter 2, rather than using conventional non-spatial methodologies, we identify 'spatial spillover effects' in a cross-country context as a medium in quantifying the impacts of macroeconomic policy interventions on housing prices movements in a dynamic spatio-temporal research framework. As a continuation, in Chapter 3, we release the strict limitation of single causal direction of variable relationships and disentangle the complex and bi-directional interaction between housing prices and credit through the thought of 'credit disaggregation' in a macroeconomic context. As an extension of Chapter 3 by considering the importance of disaggregation, Chapter 4 further identifies distinct effect-transmission channels in the macroeconomy-housing market interaction, and explores the equilibrium housing price determinations through both demand and supply channels, respectively, in a long-memory cointegration framework. Brief introductions of each main chapter and the concluding chapter are presented as follows.

1.5.1 Chapter 2: *How Effective are Policy Interventions in a Spatially-embedded International Real Estate Market?*

Chapter 2 introduces the role of 'space' in analysing the effect of macroeconomic policy interventions on cross-country housing price movements. We build an empirically testable analytical model and test our theoretical predictions for a panel of European countries over the period 1985-2015. Our aim is to demonstrate that while macroeconomic policy exerts a significant impact on international housing markets, the magnitude of such impacts may be overestimated in the absence of spatial frictions. To test our hypotheses, we employ a spatial dynamic panel method and quantify *intra-* and *inter*-country differences of the effects of macroeconomic policy interventions on spatially interdependent housing markets. Endogeneity issues arise in our estimation, which we ameliorate by employing the spatial Durbin model for panel data. Following this approach, we include spatial, temporal and spatio-temporal lags for identification purposes. We show that a spatially-embedded model produces relatively smaller and correct signs for macroeconomic variables in contrast to the traditional non-spatial model. It is concluded that empirical estimates from the traditional model are consistently over-estimated. These have significant policy implications for the exact role of macroeconomic interventions in housing price movements. A battery of robustness tests and evaluations of predictive performance confirm our results.

1.5.2 Chapter 3: *To Segregate or to Aggregate? Uncovering the Real Effects of Credit on Housing Price Dynamics*

The centrality of bank credit in asset price determination is well known, yet confusion persists in extant literature about its magnitude and directions of the impact. To uncover the dynamic interaction between credit and housing prices, Chapter 3 proposes a theoretical framework in line with a housing market disequilibrium and argues that, it is the *disaggregate* rather than the *aggregate* credit, which holds quantitatively important information in characterising the interaction through housing demand and supply credit-circulation channels, respectively. The strategy of disaggregation is even more meaningful when the economies face persistent policy uncertainty leading to asymmetric information. To examine our theoretical explanations, a panel VAR model is developed using a quarterly panel dataset covering nine industrialised countries. By employing suitable identification strategies and treating business cycle fluctuations, we find theoretically expected results that, *credit to the real economy* and housing prices engage in a mutually positive reinforcing relationship. *Credit to the asset markets* exerts a negligible negative effect on housing prices in the short-run, while its effect turns significant and positive in the long-run. Moreover, only *credit to the real economy* exerts a significant effect on boosting economic growth in contrast to an insignificant effect of *credit to the asset markets*. Robustness exercises provide strong supports for our main findings. In particular, controlling for persistent economic policy uncertainty strengthens the interaction between different disaggregated credit and housing prices. Adverse information such as persistent uncertainty and the global financial crisis exerts negative impacts on the key macroeconomic variables including housing prices and nominal GDP. These results contribute to valuable policy insights regarding the optimal credit allocation to the real economy and to the asset markets.

1.5.3 Chapter 4: *Memory and Dynamic Co-movements in Housing Prices and Macroeconomic Fundamentals: A Fractional Cointegrated VAR Approach*

Chapter 4 identifies distinct effect-transmission channels in the macroeconomy-housing market interaction through housing demand and supply functions, respectively, in a long-memory cointegration framework. Through this strategy, we can not only gauge the effects of housing demand- or supply-exclusive factors, but also the ones that have dual roles in determining housing prices through both the functions. Moreover, both the slowly-converged shocks with a long-memory decay in the interaction and the gradual price adjustments towards the market clearing are explicitly identified. To model our theoretical underpinning, we employ a fractionally cointegrated vector autoregressive (FCVAR) model using a quarterly dataset for the US from 1975Q1 to 2016Q1 to separately formulate and estimate equilibrium housing price determinations through both the functions, respectively. Consistent with our theoretical expectations, both the short-run corrections towards equilibrium and the long-run cointegrating relationships between housing prices and macroeconomic fundamentals are gauged through both the functions. Eventually, an overall equilibrium housing price determination function is derived by solving the simultaneous housing demand and supply functions. In addition, robustness checks that apply rational restrictions to unrestricted FCVAR estimations further confirm our results.

1.5.4 Chapter 5: *Conclusions*

Overall concluding remarks and policy implications of the thesis are presented in Chapter 5. Research contributions of the thesis have also been summarised in this chapter. In addition, this chapter also acknowledges the potential limitations of current work and outlines future research directions.

Chapter 2

How Effective are Policy Interventions in a Spatially-Embedded International Real Estate Market?

2.1 Introduction

2.1.1 Context and contribution

A growing body of empirical evidence supports the hypothesis that macroeconomic policy interventions, at both national and international levels, significantly determine house price movements both within and across a country's geographic boundary.[1] For instance, a rise in interest rates can dampen housing demand in a country as house purchases become costlier. In fact, such policy strategies are often employed in an economy to control inflationary impacts of excess demand. Similarly, the government may wish to boost housing demand by announcing tax reductions and interest rate cuts. On the other hand, housing supply can be enhanced by increasing credit flow to real-estate developers so that they are motivated to invest in new housing construction projects. To summarize, macroeconomic instruments[2] can be considered as credible tools for controlling housing demand and supply. These results are interesting as the determination of housing prices can move beyond hedonic variables and can find a natural control mechanism in macroeconomic adjustments. Undoubtedly, while these observed findings have opened up a new direction of research in the real estate market context, consideration of spillover effects in an empirical model can lend better predictive power to the effects of macroeconomic variables. A failure to account for such effects may result in over-reaction of the macroeconomic system and policy-ineffectiveness in the housing market.[3] The current chapter contributes to this sparse literature and aims to fill a gap by introducing the role of 'space' in modeling real estate prices and the macroeconomic relationship.

Indeed, no economic actions are free from the dynamic effects of 'space'. The vast literature of economic geography shows that 'space' can act as a medium through which agents can learn and adapt. Therefore, the real effects of a shock in one location is felt in 'moderation' in an adjacent location. Such an observation means that the model under consideration is stationary in the spatio-temporal domain; that is, the spatial effects decline over time and 'distance'.[4] Under the assumption of a 'spatial attribute', then any

[1]Notable work in this regard include Hilbers et al. (2008), Beltratti and Morana (2010),Vansteenkiste and Hiebert (2011), Bagliano and Morana (2012), Cesa-Bianchi (2013) and Arestis and Gonzalez-Martinez (2016), among others.

[2]We use macroeconomic policy intervention, policy adjustments and instruments interchangeably throughout the chapter. Two distinct sets of macroeconomic policy variables are used. First, variables such as interest rate and taxation on property are under direct control of monetary and fiscal authorities. Second, there are general macroeconomic variables, such as current account balance and unemployment rate, which are indirectly determined by policy interventions.

[3]If policy makers do not have adequate knowledge of the extent of the spillover effects, they may unknowingly overemphasize the role of macroeconomic interventions for disequilibrium corrections in the housing market and ultimately lead to the 'overheating of the economy'.

[4]If frictions in one location completely transfer to another location, they give rise to spatial non-stationarity. A non-stationary spatial model, similar to a non-stationary time series model, possesses undesirable properties of the estimators, and thus gives rise to very large standard errors.

policy adjustment in a specific location, should have a large impact on the local economy, but a smaller impact in adjacent economies. In sum, given our current context of a housing price-macroeconomy interaction setting, any inference without spatial dynamics may lead to biased inferences about the true effect of the macroeconomic adjustment process in housing price movements. Interestingly, 'space' as a determinant seems to be missing from the existing theoretical construct for country-specific empirical studies of housing price dynamics.

Accordingly, we argue in this chapter – using both analytical results and empirical insights – that although macroeconomic policy adjustment is important in controlling housing price fluctuations, its interactions with the spatial attribute are also equally important.[5] We show empirically that disregarding 'space' from an estimation produces over-estimated effects of macroeconomic variables on housing prices. This estimation bias can lead to over-emphasis of the role of the macroeconomic adjustment process in dealing with housing price fluctuations and under-reaction of the housing market over time. We contribute to the literature in the following ways.

First, we consider an interdependent international house price model. The interdependence in our work is modelled by spatio-temporal spillover effects. We define 'space' by geographical locations, where it is supposed that within a common-market economic boundary (viz.,the European market), the locational effects can play an important role towards realizing the true effects of macroeconomic variables in housing price movements. Our approach is also different from common practice where regional-level hedonic pricing behavior is studied within a single country setting. Wherever a multi-country context has been employed, there is little we know of the explicit treatment of 'space' within the existing theoretical framework. In this sense, ours is among the very few studies which examine the moderating role of space in macroeconomy-housing market studies from an international perspective.

Second, we develop an empirically testable analytical framework that models spatial-spillover effects in the cross-country macroeconomy-housing market relationship. We study the properties of this model and empirically determine the extent of bias in the estimates of macroeconomic policy variations in the housing market. This bias is then quantified by estimating a dynamic spatial panel model for European countries over the last three decades. We estimate our model, where we clearly distinguish between direct and indirect effects of these variables, and then go on to test the predictive power of the model with a series of robustness checks. To the best of our knowledge, ours is the first such study to develop a spatial framework for modeling the cross-country macroeconomy-housing market relationship.

[5] Within a single-country cross-region context, some research demonstrates that interstate migration and spatial attributes may control to a large part the extent of government intervention in house price fluctuations. See, for instance, Hendershott (1995) and Wozniak and Murray (2012) among others.

2.1.2 Why Europe?

We choose a panel of European economies for our empirical investigation. The choice is motivated by a number of factors. First, European economies share a 'common market' and follow similar macroeconomic governance structures (see Campos et al. (2014)). From this perspective, all economies within Europe can be regarded as belonging to a common economic region. Moreover, these economies share geographic borders. On the whole, both economic and geographic proximities make Europe a unique case to study interdependent housing market dynamics. Second, studies indicate that real estate in Europe – in all its forms – accounts for nearly 20% of economic activity. The commercial property sector alone directly contributed EUR 285 billion to the European economy in 2011, about 2.5% of the total economy and more than both the European automotive industry and telecommunications sectors combined. It directly employs over four million people, which is not only more than the car industry and the telecommunications sector, but also greater than the banking sector.[6]

Our study produces a number of important results. We find that the positive contribution of 'space' is consistent across model specifications. Our robustness checks, such as estimation by considering the effect of a global financial crisis and introduction of total factor productivity in the construction sector, confirm our theoretical predictions. Two broad results emerge from our exercise: first, in the absence of 'space', there is a significant over-estimation bias regarding the true impact of macroeconomic variables in housing prices. Second, there appears to be a spatial herding behavior among countries because countries, in general, share a positive and significant spatial dynamic behavior over time.

The rest of the chapter is structured as follows. Section 2.2 presents an overview of the literature. Section 2.3 presents our theoretical framework and derives the empirical estimation equation. Section 2.4 discusses data and preliminary results leading to the analyses of the main results and sensitivity checks in Section 2.5. Finally, Section 2.6 concludes with the main findings of the chapter.

2.2 Literature

The housing market is essentially spatial in nature. However, the extant research is divided with regard to their treatment of 'space' while studying the factors that govern housing prices in both intra- and inter-region contexts. Because, in our research we emphasize the instrumentality of 'space' in international housing price movements, it is important to shed light on the way 'space' has been introduced in various empirical

[6]See European Public Real Estate Association Report: www.epra.com/.../Real_estate_in_the_real_economy_-_EPRA_INREV_r.

models. Moreover, as we also underline the importance of the role of macroeconomic policy intervention in housing price fluctuations, a thorough knowledge of the existing research in this regard is also important. Keeping these contexts in mind, we briefly present an overview of the existing research from two perspectives: (i) spatial/non-spatial standpoints and (ii) international dimension of the determinants of housing prices.

2.2.1 Spatial and non-spatial standpoints

To the best of our knowledge, there is insufficient evidence on the tripartite relationship among housing prices, macroeconomic interventions and spatial dynamics. In Table 2.1 we present a summary of the effects of macroeconomic and other variables on housing prices with/without consideration of space.

Table 2.1: **Overview of Effects of Macroeconomic and Other Variables on Housing Prices**

Variables	Effect on housing prices	Evidence from literature
Current account balance	Negative	Arestis and Gonzalez-Martinez (2016)
Personal disposable income	Positive	Égert and Mihaljek (2007) Posedel and Vizek (2009) Kuethe and Pede (2011) Arestis and Gonzalez-Martinez (2016)
Unemployment rate	Negative	Égert and Mihaljek (2007) Kuethe and Pede (2011)
Interest rate	Negative	Lizieri and Satchell (1997) Posedel and Vizek (2009) Fereidouni et al. (2016) Arestis and Gonzalez-Martinez (2016)
Mortgage loan volumes	Positive	Mian and Sufi (2009) Favara and Imbs (2015) Arestis and Gonzalez-Martinez (2016)
Taxation on dwellings over house price	Positive	Poterba (1992) Hilbers et al. (2008) Arestis and Gonzalez-Martinez (2016)
Residential investment	Positive	Arestis and Gonzalez-Martinez (2016)
Total factor productivity	Positive	Moro and Nuño (2012)

Although the spatial approach can be considered as a more informative approach for modeling housing prices-macroeconomy interactions, non-spatial approaches have been widely applied to date. Within the latter approach, researchers have frequently employed vector autoregression (VAR) models, threshold autoregressive (TAR) models, and non-spatial panel or time-series methods to study the determinants of housing prices. Using a VAR method in an international context, Stevenson (2004) investigates whether house prices experience a ‘ripple effect’ among countries (viz., Ireland and Northern Ireland in their investigation).[7] In the case of Central and Eastern European (CEE) countries, Égert and Mihaljek (2007) demonstrate that housing prices are determined by conventional macroeconomic fundamentals. Focusing on the role of the productivity gap, Moro and Nuño (2012) argue that total factor productivity (TFP) gaps between the aggregate economy and construction sector can significantly explain the dynamics of housing prices particularly in the US and Germany.

‘Space’ as a determinant of housing price diffusion has been emphasized by researchers who argue that it is the central medium through which shocks move across housing markets. Indeed, expanding on the original idea of Rosen (1974), earlier research has already argued that observed housing prices can be regarded as the implicit price of tied attributes of corresponding property in a well-defined spatial location (Basu and Thibodeau, 1998; Can, 1992). Can (1992) recognizes the importance of spatial effects in inter-regional housing markets and provides specifications and procedures to estimate such a model using characteristics of spatial dependence and spatial heterogeneity. She concludes that an estimation environment which considers both neighborhood and spatial spillover effects is superior to the one that does not allow for the role of space.

Following the outbreak of the global financial crisis (GFC) in 2008, recent works have begun to emphasize the explicit role of macroeconomic policy on housing price behaviour. Beenstock and Felsenstein (2007), for instance, examine the linkage between property transaction prices and macroeconomic policy variables by using the spatial vector autoregressive (SpVAR) model. The authors are able to detect significant interactions among four macroeconomic variables (viz., income, population, housing prices and housing stock) in nine sub-regions in Israel between 1987 and 2004. More recently, Holly et al. (2011) employ a price diffusion model to study the diffusion patterns of house price shocks in both spatial and temporal dimensions and test the validity of a ‘ripple effect’ in this context. They find that the adjustment to shocks of real house price changes comes from spatially adjacent regions. The authors also demonstrate that changes in real house prices in London are directly affected by those in New York due to the close linkage these cities share with regard to the financial market characteristics. This is among many studies which demonstrate that an international transmission of a housing price shock is both a theoretical and an empirical possibility. Arestis and Gonzalez-Martinez (2016) is among the very few studies which considers international co-movements of housing prices. A study of synchronization of housing price cycles

[7] See, for instance, Posedel and Vizek (2009) for an investigation in the context of transition and EU-15 countries.

across countries can thus offer a statistical evidence of the cross-country correlation of housing prices over time.

2.2.2 The international dimension: Synchronization of housing price cycles

Indeed, while the majority of studies have focused on inter- and intra-regional dimensions of housing prices within the geographic boundary of a country, some researchers have used international context recently to show, for instance, that cross-country housing cycles are largely synchronized (particularly in the aftermath of the 2007 housing bubble in the USA). Among others, Beltratti and Morana (2010) build a factor vector autoregressive model in the case of G-7 countries, and demonstrate that there is a strong evidence of global synchronization of real house prices. This can be regarded as an indication of the linkage between international housing markets and macroeconomic conditions (Terrones and Otrok, 2004). On a similar note, Vansteenkiste and Hiebert (2011) find evidence of spillover effects of house prices among seven countries from the Euro Zone. They also find a significant long-run permanent effect of real interest rates on real house prices. In a related study, Bagliano and Morana (2012) apply a factor VAR framework incorporating 50 countries to study both within-US and international transmission mechanisms of financial and macroeconomic shocks, and examine the effect of US house prices on both advanced and emerging economies. More recently, Cesa-Bianchi (2013) provide evidence that real house price returns are strongly correlated across both advanced and emerging economies.

Very recently, Fereidouni et al. (2016) examine the dynamic interactions of housing price among major economic regions in Malaysia and Singapore. The authors find that shocks to housing prices not only move within a single country but also move across borders. The results are consistent with the theory of 'ripple effect'. Arestis and Gonzalez-Martinez (2016) are among the first to spell out a clear linkage between macroeconomic fundamentals and housing price dynamics. Based on the dataset of 17 OECD countries spanning the period 1970-2013, the authors find evidence of correlation among countries' house prices, which they attribute to the co-movement in the fundamental factor of supply and demand functions of housing markets as well as the state of macroeconomic policy in a country. They find that house prices and current account imbalances are positively correlated as these two variables are driven by common macroeconomic fundamentals. While the critical interplay of macroeconomic adjustments is important in understanding international housing price movements, the omission of 'space' as a medium of diffusion of policy shocks can lead to an over-(under-)emphasis of the role of macroeconomic policy in housing price determination. In light of this argument, an empirically testable theoretical construct can help us intertwine 'space' in the macroeconomy-housing price relationship. We present this as an analytical model below.

2.3 Theoretical Construct and Estimation

2.3.1 Theoretical construct

To guide our empirical construct (to be presented in the next section), we need to build a testable theoretical model that embeds spatial spillover effects within a housing price-macroeconomic interaction setting. We combine the interface literature of macroeconomics and economic geography with real estate theory to build an analytical model. Our strategy is as follows. First, we present briefly the classical housing-market equilibrium model and study its properties leading to the introduction of 'space' in the housing production function. Second, we build our empirical equation following the theoretical construct and discuss various estimation issues.

2.3.1.1 Classical housing-market equilibrium

Concerning the role of macroeconomic (policy) variables in housing market fluctuations, Hilbers et al. (2008) classify policies that may affect house prices in four types: fiscal (for rents and income), monetary (for interest rates), structural (supply and demand for housing) and prudential (for the financing of the housing market). We follow Arestis and Gonzalez-Martinez (2016) and then extend their framework to a spatial setting.

Let us denote the equilibrium housing prices (hpi^*) as a solution to the demand-supply system for housing prices. This equilibrium is an outcome of the forces within a competitive housing market. The demand equation for housing (HP_D) is supposed to be determined by seven factors, viz., house prices (hpi), current account balance (cb), personal disposable income (pdi), unemployment rate (ur), real interest rate of house buyers (rir_d), mortgage loan volumes ($credit$) and taxation on dwellings over house prices (tax).

$$HP_D = f_D(hpi^-, cb^-, pdi^+, ur^-, rir_d{}^-, credit^+, tax^-) \tag{2.1}$$

Following convention, housing demand (HP_D) is negatively related to house prices (hpi), current account balance (cb), unemployment rate (ur), real interest rate of house buyers (rir_d) and taxation on dwellings over house prices (tax). Moreover, HP_D is also assumed to be positively determined by personal disposable income (pdi) and mortgage loan volumes ($credit$).

We select housing demand factors from macroeconomic fundamentals covering the aspects of the linkage with external trade, the affordability level, the whole economic condition, and the direct policy interventions, respectively. First, rather than limiting our analysis in a closed economic system, we include current account balance (cb) to capture how the housing demand can be affected by the interaction between international and domestic economies. It is well known that cb, as a representation of net foreign inflows, reflects the gross level of households' consumption on final and intermediate goods and services, including housing consumption, in a given economy. The increase in the latter is a direct demonstration of heightened housing demand, as well as housing prices. Second, through the perspective of housing affordability, its levels can positively affect the households' intention of house purchase and ultimately the housing demand. Accordingly, both personal disposable income (pdi) and mortgage loan volumes ($credit$) are selected to represent the housing affordability through the aspects of income levels and borrowing cost levels, respectively. Third, as a representation of the economic condition as a whole, unemployment rate (ur) is included, while an increase in its levels can dampen the households' intention of the housing demand. Moreover, to demonstrate the impacts of direct policy interventions from both monetary and fiscal authorities on affecting the housing demand, we consider interest rate for housing buyers (rir_d) and taxation on dwellings over house prices (tax), respectively. An increase in rir_d will increase housing buyers' borrowing costs and then dampen their housing demand; a rise in tax also tends to weaken housing buyers' property purchase intentions. In addition, the change in housing price levels (hpi) can also positively affect the housing demand.

In addition to the channel of the housing demand function, it is well-known that macroeconomic policy interventions can also impact housing price movements through the channel of the housing supply function. However, this is surprisingly under-researched in current housing related literature. Under the housing-market equilibrium framework, the housing supply level in equilibrium could be affected mainly through two channels, viz. price change expectations and investment intentions. Specifically, the supply of housing units can be affected by housing prices, which changes will directly affect the profitability of housing suppliers for housing development and then determine the suppliers' housing construction purposes. Moreover, changes in residential investment can direct the overall level of credit/money provision for the housing supply purpose involving housing construction and refurbishment. As a result, the suppliers' housing investment intentions will be affected due to changes in their available loans for the housing supply, and therefore the level of housing supply will also change accordingly. Hence, the housing supply function in this chapter can be built as the following specification.

As shown in (2.2), the housing supply equation is assumed to be determined by three factors, viz., house prices (hpi), real interest rate for housing development (rir_s) and residential investment (rri). Thus,

$$HP_S = f_S(hpi^+, {rir_s}^-, rri^+) \tag{2.2}$$

Following arguments in the literature, we assume that house prices (hpi) and residential investment (rri) exert positive effects on real estate supply. In contrast, the supply is negatively influenced by real interest rate of house developers (rir_s). Regarding the selection of housing supply factors from macroeconomic fundamentals, as discussed above, the supply factors can affect housing prices mainly through two channels, viz. price change expectations and investment intentions. First, due to the feature of laggard appreciation of current housing prices, an increase of housing prices (hpi) can lead to an optimistic expectation of profitability for housing constructions and therefore the housing developers' investment intentions, i.e. the housing supply, will increase accordingly. Second, through a perspective of investment intentions, given an exogenous shock of housing price increase, current housing stocks will provide potential capital gains to their house owners. Thus, they become more inclined to put their properties for sale in the housing market, i.e. an increase in residential investment (rri), to pursue extra profits. This will correspondingly boost the housing supply. In addition, the housing supply will be negatively affected by an increase in interest rate for housing developers. Indeed, a change in interest rate levels can affect the developers' credit lending abilities, which further influence their investment intentions for housing constructions and then the housing supply.

Hence, under the hypothesis of a fully competitive market equilibrium, the market clearing condition can be obtained by equating both demand function (2.1) and supply function (2.2), which gives rise to the following housing-market equilibrium[8]:

$$hpi^* = f_{hpi}(cb^-, pdi^+, ur^-, rir^-, credit^+, tax^-, rri^-) \tag{2.3}$$

In the equilibrium, personal disposable income (pdi) and mortgage loan volumes ($credit$) are expected to exert a positive effect on housing prices, while current account balance (cb), unemployment rate (ur), real interest rate (rir), taxation on dwellings over house prices (tax) and residential investment (rri) leave a negative impact on housing prices.

2.3.1.2 Spatial spillover model with macroeconomic interaction

From the above it is now clear that – under a competitive market condition – macroeconomic policy adjustment can leave notable effects on housing prices. However, such a market condition does not allow persistence of frictions that may arise in the market

[8] Following Arestis and Gonzalez-Martinez (2016), we use, for the sake of simplicity, only one real interest rate (rir) in the credit market. This is relevant to both house buyers and builders/developers. Detailed descriptions and sources for all variables mentioned above can be seen in Table 2.2. Moreover, the theoretical justifications of signs of all incorporated independent variables have been discussed in details in Arestis and Gonzalez-Martinez (2016).

due to incomplete information, spatial interdependence, stochastic shocks and imperfect market structure. To accommodate these realistic possibilities, the above competitive market equilibrium can be extended. To achieve this, we present the following framework.

Assume that there are N countries, indexed by $i = 1, \ldots, N$. We model each country's housing production with respect to three factors: (i) M (general macroeconomic policy variables, such as current account balance and unemployment rate, etc.) (ii) HD (other policy instruments directly controlled by monetary and fiscal authorities, such as taxation on property over housing prices and real interest rate, etc.). Our third factor (iii) is D_{ij} (spatial attributes), which we introduce in the housing production shortly. Our basic housing production function is presented as follows:

$$hpi_i(t) = A_i(t) \left(M_i(t)^{\alpha} HD_i(t)^{1-\alpha} \right)^{\gamma} \tag{2.4}$$

The function $A_i(t)$ describes the aggregate level of productivity of a country i. γ measures the extent of returns to scale, whereas α delineates the importance of general macroeconomic policy factors in housing prices. We express the function $A_i(t)$ as:

$$A_i(t) = \Gamma(t)(mh_i(t))^{\delta} \prod_{j \neq i}^{N} A_j(t)^{\beta D_{ij}} \tag{2.5}$$

The dynamics of $A_i(t)$ depend on three terms. *First*, we suppose that a part of the productivity growth is exogenous and identical to all countries: $\Gamma(t) = \Gamma(0)e^{\mu t}$ where μ is the constant rate of growth and is independent of the growth of M and HD. *Second*, we assume that each country's $A_i(t)$ increases with the aggregate level of general macroeconomic policy variables (M_i) per other policy instruments (HD_i) available in the country. This gives rise to $mh = M_i/HD_i$ and denotes the proportion of general macroeconomic policy variations with respect to other policy instruments determining housing prices. The parameter δ, with $0 < \delta < 1$, describes the strength of home externalities generated by the macroeconomic policy adjustments. Moreover, we introduce knowledge spillover from macroeconomic policy adjustment and assume that such a strategy not only improves sound macroeconomic conditions but also increases the level of knowledge for all investors in the economy through knowledge spillover. However, there is no reason to constrain these externalities within the barriers of a country. In fact, we can suppose that the external effect of knowledge embodied in macroeconomic adjustment in one country extends beyond its border but does so with diminished intensity because of spatial friction generated by distance or border effect for instance. Indeed, in a highly interdependent world, any policy adjustment followed in one country becomes a common knowledge in other countries. Depending on the extent of geographic and relational (i.e., economic) proximities among countries, then this knowledge transmission can give rise to a hyperbolic effect of policy intervention over time.

This idea is modeled by the third term in equation (2.5). The particular functional form we assume for this term in a country, i, is a geometrically weighted average of the stock of knowledge of its neighbors denoted by j. Housing price interdependence (across economies) is represented by the parameter $0 < \beta < 1$, where it is assumed that the interdependence is *not* perfect because of the presence of possible frictions between the home country i and foreign countries $j \neq i, j = 1, \ldots, N$. The relationship between i and j can be represented by D_{ij}; the higher is the distance between i and j, the smaller is the value of D_{ij} and vice versa. Elements of D_{ij} are assumed to be positive and $D_{ij} = 0$ if $i = j$. Moreover, D_{ij} is non-stochastic and finite so that $0 \leq D_{ij} \leq 1$ and $\sum_{j \neq i}^{N} D_{ij} = 1$. This hypothesis allows us to form relative spatial connectivity among all countries. Moreover, it avoids spatial scale effects and explosive growth of housing prices. The more a given country i is connected to its neighbors, the higher D_{ij} is and the more country i benefits from spatial externalities or spillovers.

Moreover, an appealing strength of the spatial housing production function (2.4) is that it is able to account for the existence of locational heterogeneity among cross-country housing markets through the setting of the total productivity factor, $A_i(t)$, in the function. Based on (2.4), housing price levels in a given country i is not only determined by macroeconomic fluctuations in the same country, but also affected by driving forces from its spatially-adjacent countries j. $i \neq j$. Such external forces can be defined as spatial spillover effects by $A_i(t)$, which are composed by macroeconomic externalities $((mh_i(t))^{\delta})$ and knowledge transmissions ($\prod_{j \neq i}^{N} A_j(t)^{\beta D_{ij}}$) among cross-country housing markets. Indeed, both $(mh_i(t))^{\delta}$ and $\prod_{j \neq i}^{N} A_j(t)^{\beta D_{ij}}$ form the spillover effects to account for the locational variation among target countries, while also providing the theoretical underpinning on explaining the cross-country co-movement between housing prices and macroeconomic fundamentals. In addition, it is noteworthy that this chapter later empirically measure averaged spatial spillover effects among target countries by using a dynamic spatial panel estimation, while explicitly considering spatial fixed effects to control for the adverse impacts of cross-country heterogeneity on the accuracy of empirical estimation results.

Thus, international macroeconomic and housing market interdependence implies that countries cannot be analyzed in separation but must be analyzed as an interdependent system. Therefore, we can rewrite function (2.5) in matrix form (see Appendix A for detailed derivation):

$$A = \Gamma + \delta mh + \beta DA \tag{2.6}$$

with A the $(N \times 1)$ vector of the logarithms of the level of productivity (A_i), where $i = 1, \ldots, N$. mh is the $(N \times 1)$ vector of the logarithms of the aggregate level of macroeconomic variables (M_i) per other common attributes (HD_i). D is the $(N \times N)$ Markov-matrix with spatial friction parameters D_{ij}. We can resolve equation (2.6) for A, if $\beta \neq 0$ and if $1/\beta$ is not an eigenvalue of D:

$$A = (I - \beta D)^{-1}\Gamma + \delta(I - \beta D)^{-1}mh \tag{2.7}$$

We can develop equation (2.7). Assuming $|\delta| < 1$, we can regroup terms to obtain:

$$A = \frac{1}{(1-\beta)}\Gamma + \delta mh + \delta \sum_{r=1}^{\infty} \beta D^{(r)} mh \tag{2.8}$$

where $D^{(r)}$ is the matrix D to the power, r. For country i, then we have

$$A_i(t) = \Gamma^{\frac{1}{(1-\beta)}}(t) mh_i^{\delta}(t) \prod_{j=1}^{N} mh_j^{\delta} \sum_{r=1}^{\infty} D_{ij}^{(r)}(t) \tag{2.9}$$

The level of productivity in a country i now depends on its own level of mh and on the level of mh in its neighborhood. Replacing equation (2.9) in the housing market production function (2.4) and assuming $\gamma = 1$, we can write the spatial housing production function as

$$hpi_i(t) = \Gamma^{\frac{1}{(1-\beta)}}(t) mh_i^{u_{ii}}(t) + \prod_{j \neq i}^{N} mh_j^{u_{ij}}(t) \tag{2.10}$$

where $u_{ii} = \alpha + \delta(1 + \sum_{r=1}^{\infty} \beta^r D_{ij}^{(r)})$ and $u_{ij} = (\delta \sum_{r=1}^{\infty} \beta^r D_{ij}^{(r)})$.

The terms $D_{ij}^{(r)}$ are the elements of row i and the column j of the matrix D to the power of r. This model implies spatial heterogeneity in the parameters of the housing production function. In the absence of externalities, i.e. when $\delta = 0$, we have $u_{ii} = \alpha$ and $u_{ij} = 0$, so that the housing production function takes the conventional form as in (2.4).

Based on the properties described above, we state the following proposition.

Proposition 2.1. *If equilibrium housing production is given by $hpi^*_{i,t} = G(M_{i,t}; HD_{i,t}; f_i(D_t(i,j))$, then spatial frictions (i.e. the function $f_i(D_t(i,j))$ determine the extent to which macroeconomic policy variables affect housing price variations across countries under the hypothesis of fully competitive market equilibrium.*

The proof is straightforward and follows from the analytical equations above. In particular, based on the assumption that spatial frictions affect housing price behavior in countries (i, j), the effect of macroeconomic variations will depend upon the strength of β. This is simply because a higher β represents greater interdependence, and this would ensure faster movements of macroeconomic shocks across borders. Hence, interdependent economies will experience greater and more similar effects of shocks than would have been the case under an atomistic environment. The analytical model presented above needs to be estimated. Recalling that ours is a spatio-temporal case, we discuss relevant empirical methods in the dynamic spatial panel framework in the next section.

2.3.2 Estimation

2.3.2.1 Model selection

We can now use equation (2.10) in an extended form to present our empirical model. The expansion of equation (2.10) in our context is motivated by the presence of bounded rationality in house buyers and suppliers, external uncertainty, incomplete information and imperfect market structure. These together can create excess demand or laggard supply in the real estate market. Therefore, the classical assumption of a fully competitive equilibrium market (that is, housing demand equals corresponding supply in equation (2.3)) is no longer valid. To set our empirical construct free from the strict limitations of a fully competitive equilibrium, we introduce a spatio-temporal partial adjustment model.[9] Indeed, the dynamic spatial panel model provides a mechanism that admits the existence of disequilibrium variations, i.e. it enables us to recognize and interpret the disequilibrium shocks for the dependent variable via its dynamic components, i.e. temporal and spatio-temporal lags. We incorporate these features in equation (2.10) for an empirical specification of the model in the form of dynamic spatial panel regression:

$$hpi_{it} = \alpha + \beta hpi_{i\,t-1} + \gamma \sum_{j=1}^{N} W_{ij} hpi_{it} + \rho \sum_{j=1}^{N} W_{ij} hpi_{it-1} + \sum_{k=1}^{K} X_{it}\zeta_k + \sum_{k=1}^{K}\sum_{j=1}^{N} W_{ij} X_{jkt}\eta_k + \theta_i + \nu_t + \pi_{it} \tag{2.11}$$

$$\pi_{it} = \psi \sum_{j=1}^{N} W_{ij}\pi_{it} + \varepsilon_{it} \tag{2.12}$$

$i = 1, \ldots, N; t = 1, \ldots, T; k = 1, \ldots, K; i \neq j.$

Three spatial interaction features are present in equations (2.11) and (2.12): (i) *endogenous interactions* ($\sum_{j=1}^{N} W_{ij} hpi_{it}$), (ii) *exogenous interactions* ($\sum_{k=1}^{K}\sum_{j=1}^{N} W_{ij} X_{jkt}$) and (iii) *residual interactions* ($\sum_{j=1}^{N} W_{ij}\pi_{it}$). α is the constant parameter vector; γ, η and ψ are coefficients for these spatial dependencies, respectively. Also, hpi_{it} denotes house

[9] See LeSage and Pace (2009) for discussion on the properties of the spatio-temporal spatial adjustment model.

prices (our dependent variable) and X_{it} denotes the vector of independent variables. θ_i and ν_t refer to space-specific and time-period-specific effects.[10] Error terms (ε_t) are identically and independently distributed ($\varepsilon_t \sim N(0, \sigma^2 I_N)$). Besides, due to the requirements of parameter identification (Manski, 1993), the spatial interactions (i.e. exogenous, endogenous and residual interactions) cannot be presented simultaneously (at least one interaction needs to be removed from the specification). Hence, distinct specifications of the spatial panel model can be derived by considering different spatial dependencies (Elhorst, 2010); (i) spatial autoregressive model (SAR) by considering spatial endogenous dependencies (η=ψ=0), (ii) the spatial Durbin model (SDM) by considering both spatial endogenous dependencies and spatial exogenous dependencies (ψ=0), and (iii) the spatial error model (SEM) by merely considering spatial residual dependencies (γ=η=0), respectively. In addition, the static spatial panel model can be extended to include dynamic component by introducing both a temporal lag ($Y_{i\ t-1}$) and temporally spatial lag ($W_{ij} hpi_{it-1}$) of the dependent variable (Debarsy et al., 2012).[11]

In view of the properties of various spatial panel models described above, our preferable specification is the dynamic spatial Durbin model (SDM). The dynamic SDM with fixed effects can be derived by controlling the coefficient ψ in (2.12) to be zero:

$$hpi_{it} = \alpha + \beta hpi_{i\ t-1} + \gamma \sum_{j=1}^{N} W_{ij} hpi_{it-1} + \rho \sum_{j=1}^{N} W_{ij} hpi_{it} + \sum_{k=1}^{K} X_{it}\zeta_k + \sum_{k=1}^{K}\sum_{j=1}^{N} W_{ij} X_{jkt}\eta_k + \theta_i + \nu_t + \varepsilon_{it} \tag{2.13}$$

$i = 1, \ldots, N; t = 1, \ldots, T; k = 1, \ldots, K; i \neq j.$

Although the spatial autoregressive model (SAR) is the most widely used spatial panel specification, it is useful to add elements of spatial exogenous interactions – in addition to spatial endogenous interactions – in the spatial Durbin model (SDM) setting (Lee and Yu, 2016). We note below its key advantages in relation to our empirical analyses.[12]

First, it complies with the identification requirements as noted in Manski (1993) and only suffers the minimum cost of exclusion of spatial residual interactions compared

[10] Both the effects can be regarded as either fixed effects or random effects. However, whether a random effects model is an appropriate specification remains controversial in spatio-temporal estimation (Elhorst, 2012). In principle, a random effects model will only be preferable if data are drawn randomly from the population and the number of the spatial units (N) is large. Moreover, the strict restriction that random variables and error terms are independent is hard to comply with in reality. Elhorst (2012) particularly demonstrates that the fixed effects model is superior to the random effects model in the case of the spatial panel model, given that two prerequisites are satisfied, viz., large time period (T) and no bias of variable omissions. We will demonstrate later that the spatial panel model with fixed effects is a better fit for our data.

[11] We provide a further check on whether both $Y_{i\ t-1}$ and $W_{ij} Y_{it-1}$ are jointly equal to zero. The likelihood ratio (LR) test is used for the purpose to investigate whether the dynamic spatial panel model is preferable in our empirical investigation.

[12] Other notable advantages of SDM in comparison to other spatial panel specifications (viz., SAR and SEM) have been well documented (LeSage and Pace, 2009).

with other spatial models. Second, SDM offers unbiased and consistent estimation irrespective of the real data-generating process (either SAR or SEM) (Elhorst, 2010). Third, it distinguishes the explanatory power of the exogenous variables not only *within* spatial boundaries (*direct effect*), but also *across* spatial contiguous locations (*indirect effect*). Elhorst (2010) demonstrates that the non-spatial model seriously biases the coefficient estimations, and is unable to shed light on the indirect effects (spatial spillover effects) from spatially neighboring units. Fourth, SDM enables us to account for not only spatial dependencies but also spatial heterogeneity across spatial locations by incorporating spatially lagged dependent variable and spatially lagged independent variables, respectively. Fifth, in terms of the *endogeneity* problem (which is typical in an empirical context such as ours), the SDM helps ameliorate endogeneity issues and omitted variable bias.[13]

In addition, in terms of the comparison of spatial model specifications, Lee and Yu (2016) show that disregarding Durbin terms (spatial exogenous interactions) leads to serious estimation biases, while adding irrelevant Durbin terms only leads to indistinct efficiency loss. This is consistent with the theoretical viewpoint discussed above in that SDM is superior to other spatial models. In our estimation, we employ a series of likelihood ratio (LR) tests as in Elhorst (2010) to examine if the SDM is our preferable specification among a set of competitive spatial panel models.

2.3.2.2 Endogeneity concerns and estimation strategy

The accuracy of our estimation results could be biased by potentially-existing endogeneity issues, such as omissions of unobserved independent variables with the spatial autoregressive property, due to the correlation between observed independent variables and model residuals. It has been investigated that considering both contemporaneous spatial endogenous and exogenous interactions in the spatial panel model could provide a sensible way to resolve such issues (Fingleton and Le Gallo, 2010). Regarding the parameter identification, Lee and Yu (2016) document that model parameters in the dynamic SDM, such as contemporaneous spatial dependent lag (WY_t), contemporaneous spatial independent lag (WX_t), and temporally spatial dependent lag (WY_{t-1}) are identifiable regardless of the employed estimation technique by either the generalized method of moments (GMM) or the maximum likelihood (ML).

In terms of the selection of sensible estimation technique for the dynamic SDM as specified in equation (2.13), the choice can be made among the techniques of ordinary least squares (OLS), maximum likelihood (ML), the instrumental variables/2-step least squares (IV/2SLS), and partial derivative (PD). Specifically, as documented

[13]Fingleton and Le Gallo (2010) point out that the particular endogeneity problem due to omitted variables can be accounted for by the SDM specification due to the inclusion of both spatial lagged dependent and independent variables.

by Anselin (1988), the OLS method would induce biased and inconsistent coefficient estimates due to inclusions of lags of the dependent variable (regardless of temporal lag, spatial lag, and temporally spatial lag) in the dynamic SDM. However, we decide to use OLS as the benchmark of the dynamic SDM estimations so as to examine the accuracy of the estimate results from more robust techniques. This chapter prefers the ML method as it is a well-embraced method and has been widely-used in the extant spatial-related literature (See, for example Bao and Ullah, 2007; Elhorst and Fréret, 2009; Koroglu and Sun, 2016; Lee, 2004; Lee and Yu, 2016; Ord, 1975). Moreover, compelling evidence shows that the ML method can resolve the biased and inconsistent estimates suffered by the OLS method due to the existence of endogeneity issues when estimating the dynamic SDM (see, for example Anselin, 1988; Anselin and Hudak, 1992; Elhorst, 2003; Lee, 2004; Yu et al., 2008, among others). Indeed, given that both numbers of time periods (T) and cross sections (N) are large, the ML method can ensure the consistency in dynamic SDM estimations, while potential biases in initial ML estimators can be accordingly identified and well-adjusted to contribute to unbiased estimations (Yu et al., 2008).[14] In addition, estimating the dynamic SDM by using the ML method can also provide a convenient way to check the joint significance of a specific group of target variables through the likelihood ratio (LR) test. This property of the ML method is appealing, which enables us to determine if the preferred spatial model specification is (i) static or dynamic and (ii) SAR, SDM, or SEM, respectively.

The $IV/2SLS$ regression is another widely-applied approach for the spatial panel estimations. Theoretically, the accuracy of estimations can be ensured by using either the ML or $IV/2SLS$ methods as long as their corresponding assumptions, viz. the consistent and asymptotic distribution for the ML estimators (Kelejian and Prucha, 1998), and the correlation between independent variables and model residuals for the $IV/2SLS$ method (Lee, 2004) are respectively hold. This chapter does not use the $IV/2SLS$ method due to the following reasons. Despite its strengths in solving endogeneity issues, it still cannot fully eliminate such issues, for example the adverse impacts of additional endogeneous variables in the regression (Fingleton and Le Gallo, 2010). Moreover, the spatial model specification estimated by $IV/2SLS$ from Fingleton and Le Gallo (2010) includes all three different spatial interactions, viz. $W_{ij}Y_{it}$, $W_{ij}X_{it}$, and $W_{ij}\varepsilon_{it}$. This model setting might give rise to the parameter identification problem pointed out by Manski (1993). In addition, the use of $IV/2SLS$ method could not conduct the parameter joint significance test for a specific group of target variables, in contrast to the ML method. Hence, this chapter eventually prefers the ML method rather than the $IV/2SLS$ method.

[14] Yu et al. (2008) propose a bias-corrected quasi maximum-likelihood (QML) method for the dynamic spatial panel estimation with spatial fixed effects. This QML method has been built by Belotti et al. (2017) through the STATA command "$xsmle$" whereby both the terms $W_{ij}Y_{it-1}$ and Y_{it-1} in the dynamic spatial panel model are set as predetermined variables, i.e. cov($W_{ij}Y_{it-1}$, ε_{it})=cov(Y_{it-1}, ε_{it})=0. Thus, this chapter decides to employ the QML method to ensure the unbiased and consistent estimates for the dynamic SDM. For convenience, the terms ML and QML are used interchangeably throughout the chapter.

The literature also suggests that the partial derivative (PD) estimation of the SDM parameters can shed new light on interpreting different types of parameters (direct/indirect effects of independent variables). Also, it can test the hypothesis of whether spatial spill-over effects exist in the tested empirical specification. Distinct from the classical point estimates, the PD method overcomes the typical problem of invalid comparisons of point estimates from various spatial regression, implying that changing model specifications might lead to heterogeneous inferences (see, LeSage and Pace (2009), for exhaustive discussions of the properties of this method). In addition, the PD method provides us with both long-term and short-term direct/indirect effects of independent variables.

In terms of a location, the *direct effect* refers to the averaged (own-partial) derivative of Y with respect to explanatory variables, X, from the same location. The *indirect effect*, also termed the spatial spillover effect, refers to the averaged (cross-partial) derivative of Y with respect to explanatory variables, X, from the neighboring locations. According to Blanchard et al. (1992) and De Groot and Elhorst (2010), by using the PD method, it is possible to characterize the error correction process so that one can envisage how an economy adjusts back to its long-term equilibrium over time. To summarize, with respect to the estimation method of the dynamic SDM, we employ the ML method to estimate our main model. It will also help us compare our work with the existing literature which invariably applies the ML method for estimation. In addition, the PD can be regarded as an alternative method to check whether direct/indirect effects of the independent variables obtained from the ML estimation are robust or not.

A challenge concerning SDM is the interpretation of the dynamic terms in the model. Tao and Yu (2012) stress the necessity to add a spatially-weighted temporal lag of the dependent variable (WY_{t-1}) in the SDM model because this term can account for 'either policy adjustments or inter-temporal budget constraints'. Its omission may result in serious bias in estimations. The general empirical finding is that this WY_{t-1} can give rise to an estimated negative coefficient, which is sometimes hard to lend a sensible empirical interpretation to. Following Tao and Yu (2012), the negative coefficient may arise when the coefficients of both contemporaneous spatial (WY_t) and temporal (Y_{t-1}) lags of the dependent variable are jointly positive. In our empirical investigation, such a situation may arise. We provide both statistical and empirical interpretations of this result.

2.4 Data Characteristics and Preliminary Observations

2.4.1 Data characteristics

Our empirical investigation uses annual time-series data for 16 European countries and covers a period of three decades (1985-2015).[15] The dependent variable is house prices (hpi), while the independent variables include two types of macroeconomic factors. The first one is the general macroeconomic policy factors, which summarize macroeconomic conditions, such as the current account balance (cb), personal disposable income (pdi), unemployment rate (ur), mortgage loan volumes ($credit$) and residential investment (rri). The second one concerns other policy variables, which represent macroeconomic interventions directly enforced by regulated bodies in respective countries, viz., real interest rate (rir) and taxation on dwellings over house prices (tax). In Table 2.2, we provide the descriptions of the variables and their sources. In addition, this chapter has checked the correlation matrix of independent variables, while no multicollinearity can be detected.

Table 2.2: **Data Description**

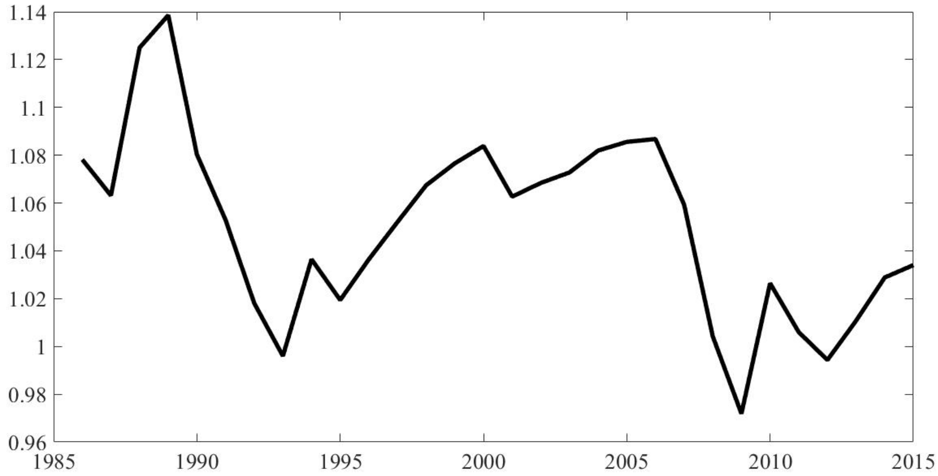
Variables	Descriptions	Data Sources
House prices (hpi)	Nominal price index of different types of dwellings (2005=100)	Federal Reserve Bank of Dallas
Current account balance (cb)	Balance on current transactions with the rest of the world (% of GDP)	AMECO Databank
Personal disposable income (pdi)	Disposable income per capita of working-age population (2005=100)	Federal Reserve Bank of Dallas & AMECO Databank
Unemployment rate (ur)	The number of unemployed persons divided by the labour force	AMECO Databank
Real interest rate (rir)	Real long-run interest rate, deflator GDP	AMECO Databank & International Financial Statistics of IMF
Mortgage loan volumes ($credit$)	Domestic credit to private sector (% of GDP)	Word Development Indicators of the World Bank
Taxation on dwellings over house prices (tax)	The ratios of taxation incomes on dwellings to house prices	OECD Data
Residential investment (rri)	Gross fixed capital formation at current prices: Dwellings	AMECO Databank

Regarding the measurement of housing price index in this chapter, we use a commonly cited method, i.e. repeat sales index, which is initially proposed by Bailey et al. (1963) and later modified by Case and Shiller (1989).[16] It measures price changes while holding constant housing hedonic characteristics by comparing price levels of the same

[15] The 16 European countries include Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK. Our choice of countries is governed by the identification of common geographic and economic borders and availability of continuous data.

[16] Detailed discussions of alternative methods of measuring housing price index and comparisons among all methods can be seen in Chapter 4.

Figure 2.1: **The Cross-country Averaged Growth of House Prices (hpi) (2005=100)**



Note: (i) averaged growth ($growth$) is calculated as $growth = \left(\sum_{i=1}^{N} hpi_{it}/hpi_{it-1}\right)/N$. (ii) the data time period is from 1986 to 2015.

home over two or more sales. Two different indexes constructed by using the same repeat sales measure are available, i.e. SP/Case-Shiller and Federal Housing Financial Agency (FHFA) housing price indexes, respectively, while they track housing price movements distinctly due to their differences in data coverage, inclusion of refinance appraisal values, use of geographical weights, etc (Noeth et al., 2011).

Following Mack et al. (2011), this chapter measures the national level of price changes of existing single-family houses for each target country by using the FHFA HPI rather than the SP/Case-Shiller HPI due to following reasons. First, the FHFA HPI incorporate appraisal values of refinance transactions, whereas the SP/Case-Shiller HPI only include the real housing transactions. Thus, the former can benefit from getting a much richer data sample of observed housing valuations than the latter, and consequently results in an improvement of estimation accuracy of the housing price index. Second, the data coverage of the FHFA HPI is only conforming mortgages (financed by Fannie Mae or Freddie Mac), while that of the SP/Case-Shiller HPI includes both conforming and non-conforming mortgages. However, the data regarding non-conforming loans tend to be available for only limited numbers of countries. Overall, to make the series of housing price index closely and appropriately comparable among target countries in an international context across target period of time, we eventually choose the FHFA HPI as our benchmark method when measuring the housing price index of our target countries.

In Figure 2.1, we present an average trend of house price movements across the 16 European countries. The value in each time period is calculated as the averaged growth of house price indices across economies. There is evidence of a cyclical pattern of house prices in the last three decades; the housing prices experienced a peak in 1989, a marked drop in 1993, and a recovery that continued until 2000. The boom and bust of cyclical behaviors of house prices can also be observed in the following decade (2001-2009). These facts lead us to conclude that housing cycles in our data lasts for about 10-years. In addition, the lowest visible prices in 2009 capture the negative impact of the global financial crisis.

Table 2.3: **Descriptive Statistics: Mean and Dispersion of Housing Prices and its Determinants**

Variables	Austria	Belgium	Denmark	Finland	France	Germany	Ireland	Italy	Luxembourg
hpi	105.507	81.159	73.711	78.615	74.395	99.257	54.992	73.027	72.389
	(41.622)	(40.488)	(31.711)	(32.990)	(34.146)	(11.040)	(35.594)	(27.848)	(38.137)
cb	−1.589	2.979	2.638	1.364	−0.372	−0.628	−0.268	−0.316	10.731
	(1.732)	(1.688)	(2.810)	(4.028)	(1.629)	(7.704)	(2.871)	(1.689)	(3.864)
pdi	86.607	88.117	86.364	87.055	86.674	88.948	71.555	81.119	86.636
	(26.246)	(23.044)	(25.512)	(30.133)	(22.190)	(21.622)	(31.517)	(23.045)	(28.847)
ur	4.413	8.261	6.035	8.855	9.145	7.887	10.726	9.403	3.494
	(0.800)	(1.076)	(1.500)	(3.540)	(0.962)	(1.685)	(4.701)	(1.669)	(1.425)
rir	3.153	3.538	3.514	3.816	3.663	2.608	3.914	3.669	2.602
	(1.753)	(2.001)	(2.711)	(3.001)	(2.037)	(1.734)	(3.646)	(1.921)	(3.216)
credit	92.544	57.498	106.596	72.535	85.490	94.643	83.172	66.660	88.965
	(8.700)	(15.904)	(67.452)	(15.391)	(7.849)	(12.384)	(40.287)	(16.294)	(13.641)
tax	20.924	82.246	77.958	39.014	114.274	26.002	103.385	68.473	239.378
	(7.203)	(13.360)	(12.717)	(4.531)	(15.529)	(5.142)	(26.969)	(20.962)	(41.528)
rri	10.418	14.697	7.978	8.076	87.818	122.545	7.141	64.141	0.803
	(2.832)	(6.125)	(3.429)	(2.973)	(30.816)	(34.271)	(6.936)	(18.099)	(0.402)

Variables	Netherlands	Norway	Portugal	Spain	Sweden	Switzerland	UK	Total
hpi	67.617	87.730	75.464	62.313	83.161	103.314	70.751	78.963
	(32.751)	(45.622)	(23.623)	(32.595)	(42.718)	(15.959)	(39.066)	(36.287)
cb	5.948	7.485	−6.595	−2.851	3.964	8.091	−2.185	1.775
	(2.592)	(6.419)	(3.509)	(3.084)	(3.116)	(3.898)	(1.413)	(5.720)
pdi	84.896	80.186	76.062	78.114	88.749	92.479	84.511	84.255
	(23.228)	(31.813)	(32.015)	(28.672)	(32.388)	(18.971)	(29.934)	(27.259)
ur	5.877	3.832	8.587	16.784	6.381	2.931	7.258	7.492
	(1.484)	(1.087)	(3.153)	(5.002)	(2.533)	(1.297)	(1.968)	(4.090)
rir	3.291	2.721	3.116	3.332	3.375	1.730	2.907	3.184
	(2.166)	(5.264)	(2.788)	(2.296)	(2.351)	(1.334)	(1.853)	(2.686)
credit	98.534	79.186	99.445	106.719	75.604	150.586	128.077	92.891
	(20.356)	(28.696)	(40.707)	(38.531)	(39.079)	(11.009)	(37.467)	(37.444)
tax	79.626	47.766	23.082	77.500	58.272	74.065	168.759	81.295
	(14.641)	(7.328)	(9.798)	(11.175)	(24.070)	(16.019)	(46.575)	(58.600)
rri	22.465	8.211	6.921	53.545	10.097	14.312	52.220	30.712
	(8.557)	(5.409)	(2.224)	(33.299)	(4.498)	(5.047)	(21.393)	(37.891)

Note: standard deviation for each variable is presented in parentheses.

In Table 2.3 we present descriptive statistics. The mean hpi for the 16 European countries is 78.963 with a standard deviation of 36.287. Austria presents the largest mean value of hpi (105.507) as well as a relatively high standard deviation (41.622). Germany exhibits the third largest hpi and smallest standard deviation (11.040), which is nearly four times smaller than Austria. The most volatile hpi among all countries is Norway as it reports the highest standard deviation (45.622). Current account balance seems to be flat as the overall mean value is only 1.775 with relatively low standard deviation (5.720). Luxembourg is the only country with the highest average value of current account balance (10.731), while for Portugal we find the lowest value, which is -6.595. The independent variables, such as pdi, $credit$, and tax, present similar distributional characteristics with respect to mean; the values are 84.255, 92.891, and 81.295, respectively. Notably, tax rate exhibits dramatic fluctuations compared with pdi and $credit$. Besides, on average, ur is 7.492. The country with the highest mean value of ur is Spain (16.784), while the same in Switzerland exhibits the smallest magnitude (2.931). Real interest rate (rir) across countries presents a uniform pattern; the average across countries is 3.184 and various countries seem to move around the average value with no extreme skewness. The highest mean value of rir is in Ireland, which is only a magnitude of 2.814 greater than the lowest counterpart in Switzerland. In contrast, rri varies dramatically across countries. Germany is the country which has the highest average rri (122.545), while the smallest mean value of rri is for Luxembourg (a value of only 0.803).

2.4.2 Preliminary observations

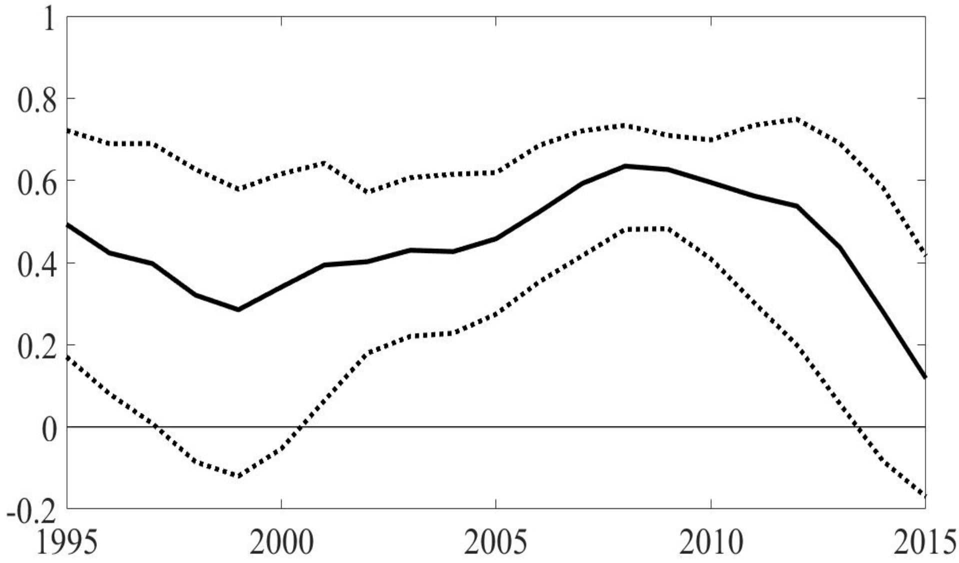
To motivate our main empirical analyses, we first discuss important preliminary empirical facts concerning our data. We focus on three aspects, viz., (i) evidence of correlation of house prices at an international level, (ii) an exploration of the spatial distributions of house prices and (iii) a possible non-stationary nature of the data. Each aspect is presented in the form of a stylized observation.

(a) Housing prices at cross-country level depict significant correlation

To demonstrate that cross-country house prices are interdependent by nature, we compute cross-country moving pair-wise correlations over the period 1985-2015. Figure 2.2 presents the trend in these correlations. Likewise, in Figure 2.3, we have presented pair-wise correlations for selected macroeconomic variables.

Interesting patterns of correlation of house prices emerge from Figure 2.2; the correlation varies from 0.3 to 0.6 across countries over most decades, reaching a peak in 2008 possibly due to the subprime crisis, and witnessing a dramatic fall after 2012. Although the correlation tends to have a relatively large error band at the 5% significant level, it remains significant over three decades. This significant correlation provides indirect evidence of house price synchronizations over time. Considering the pattern of correlation for selected macroeconomic variables (in Figure 2.3), we find that the correlation coefficients of real interest rates, mortgage loan volumes, and residential investment among these countries are largely positive and significant. Following our hypothesis of international synchronization of housing prices, we can premise that the correlation of macroeconomic policy variables at international level can determine the cross-country interdependence of housing prices. This premise needs to be tested rigorously, which we undertake in the next section with a dynamic SDM model estimation.

Figure 2.2: **The Cross-country Average of Moving Pair-wise Correlation for House Prices**



Note: the average cross-country pair-wise correlation of x for country i is measured by: $\rho_i = \left(\sum_{j=1}^{N} COR(x_i, x_j) - 1\right)/(N-1)$; $COR(x_i, x_j)$ is the specific pair-wise correlation of variable x between country i and j. N: number of countries; based on the evidence shown in Figure 2.1, we choose 10 years as the rolling window period (for this reason, the X-axis begins with the year 1995).

(b) The distributions of house prices across countries depict significant spatial movements

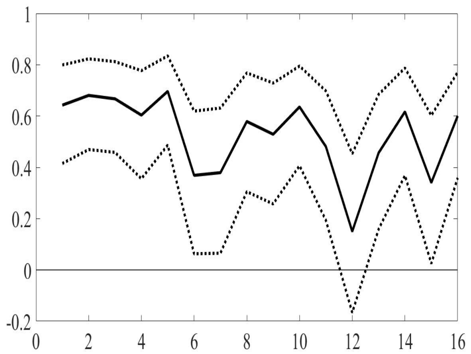
Due to the spatio-temporal nature of our data and the objective of employing a spatio-temporal method to our theoretical construct, it is necessary to provide some evidence of spatial dependence of house prices over time. To do so, we study the distribution[17] of house prices across 16 European countries. For this purpose, we have used geographical coordinates (latitude and longitude) of each country and have identified spatial clusters of low/high housing prices for each year since 1985. The sub-plots in Figure 2.4 present the spatial correlation of house prices for 16 European countries with respect to their mean (left panel) and standard deviation (right panel) of housing prices over the period 1985-2015.

The leading idea in Figure 2.4 is to identify whether the average and dispersion in house prices and corresponding country dispersions share spatial affinities. Indeed, this is the case for our data. If we study the left panel of Figure 2.4, we observe that over the 30-year time periods, countries located in Northern and Central Europe (such as Germany, Norway and Sweden) demonstrate relatively higher house prices than countries in Western and Southern Europe (such as Ireland and Spain) do. We note

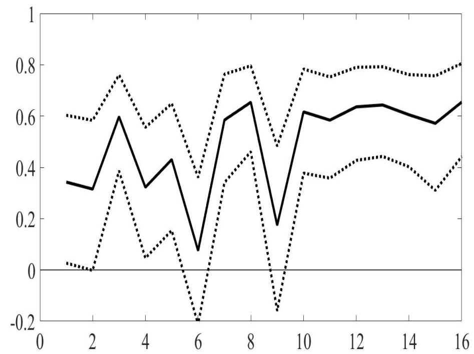
[17] We present here only mean and standard deviation distributions of house prices to save space. Year-to-year-wise distributions are available from the authors upon request.

Figure 2.3: **The Time Average of Cross-country Pairwise Correlation**

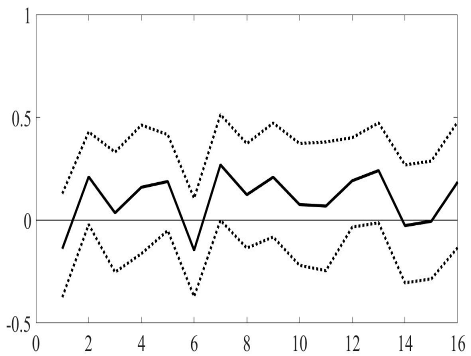
(a) Real Interest Rate



(b) Mortgage loan volumes



(c) Taxation



(d) Residential Investment

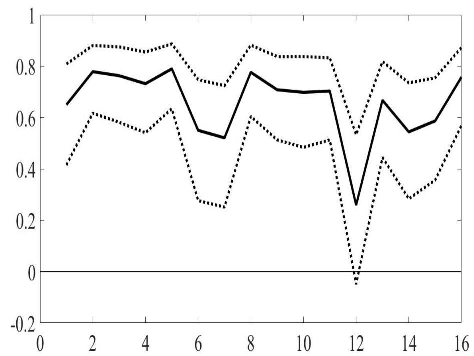
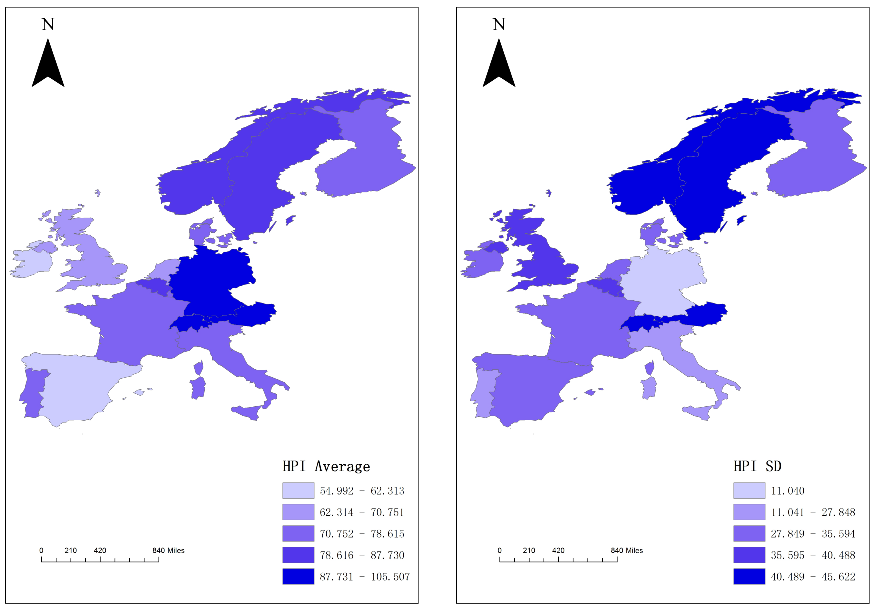


Figure 2.4: **Spatial Distributions of House Prices: Mean and Standard Deviation**



that countries with similar average house prices tend to cluster together indicating that there can be positive spatial autocorrelation of house prices across countries. A similar pattern is observed for the dispersion of house prices (right panel of Figure 2.4); there are similarities in the standard deviation across clusters of countries. For instance, countries in Northern Europe (viz., Norway, Sweden, and Finland, among others) share similar magnitudes of high dispersion, whereas Central European Countries (viz., France, Germany, and Italy, among others) present a cluster of low dispersion of prices. Taking together the results of both panels in Figure 2.4, we observe what we term as 'spatial herding behavior' in the housing market. This graphical evidence of spatial clustering is also supported by Moran's I test.

The results of Moran's I test are presented in Table A.1 in Appendix A. Generally speaking, the majority of Z values are found to be positive indicating the presence of positive spatial autocorrelation of house prices across 16 European countries over the period 1985-2015. This can be taken as evidence of housing price synchronizations across countries. Interestingly, different from the conclusions in existing research in this context, we find that housing prices exhibit negative spatial autocorrelation between 2000 and 2008 (see the negative Z values).[18] This phenomenon can be interpreted as "geographic competition" in contrast to "geographic cooperation" (Griffith, 1987). It implies that the increase in house prices in one region can only occur through the decline of housing prices in the adjacent location under the assumption of finite resource availability in these countries. Most importantly, after the subprime crisis in 2008 we observe a significant positive spatial autocorrelation. Moreover, the strength of the spatial autocorrelation also appears to increase over time (see the Z value). These results motivate us to study international housing prices using a spatio-temporal method. In Section 2.5, we present and analyze results from the estimation of the SDM method in this context.

(c) Cross-country house prices and their determinants possess non-stationary components

Before estimating the dynamic spatial Durbin model (SDM), it is necessary to investigate whether the variables in our study are stationary. This will minimize the risk of running spurious spatial regression in the data (see, for instance, Baltagi et al. (2007); Mur and Trívez (2003)). We perform three types of panel unit root tests, viz., the LLC test (Levin et al., 2002), the IPS test (Im et al., 2003), and the $PESCADF$ test (Pesaran, 2004). The results are summarized in Table A.2 in Appendix A.

We perform an estimation with and without allowing for cross-sectional dependence and the trend term. We find that real interest rate (rir) is stationary – a result which is consistent across majority of test methods. On the other hand, both mortgage loan

[18] A similar phenomenon of negative spatial autocorrelation of house prices has also been reported in the literature, viz., Kuethe and Pede (2011) and Ma and Liu (2015).

volumes ($credit$) and taxation on dwellings over house prices (tax) are found to be non-stationary (using LLC, IPS, and $PESCADF$ tests). The first difference of these variables ($d = 1$) is found to be stationary in each test method. Due to the overlapping results, we prefer to choose the first-difference of the variables in our following empirical estimation.

2.5 Main Empirical Results

We now present the main empirical results and supplement our findings with a series of robustness exercises. Model performance of the SDM specification forms the final empirical exercise of the chapter. To proceed, we first summarize the results of the model selection estimation. This is followed by our analyses of various empirical results related to the SDM estimation.

2.5.1 Model selection

A pre-requisite for selecting the final estimation equation for our SDM model is to decide whether a fixed effects specification[19] is a better model choice than a random effects specification. Following convention, we employ the Hausman specification test. In our case, the estimated Hausman test statistic (following a Chi-square distribution) is 965.20. This is significantly greater than the critical value of 25.00 at the 5% level of significance, implying that SDM with fixed effects is our chosen specification.[20] Although from a theoretical perspective (see Section 2.3 for discussion), SDM is known to perform better than other spatial panel models (such as SAR and SEM), we need to confirm this by using a likelihood ratio (LR) test. Using the LR test we would like to demonstrate that SDM is the most appropriate specification for our data (Elhorst, 2010). On the basis of both equations (2.11) and (2.13),[21] first, we test the null hypothesis $H_0 : \eta = 0$, i.e. whether SDM can be simplified to SAR. The LR statistic is 22.95, which exceeds the critical value of 14.07 at the 5% significance level. The second null hypothesis concerns $H_0 : \eta + \psi\zeta = 0$, i.e. whether SDM can be simplified to SEM. The

[19]We only add spatial fixed effects and remove time fixed effects, otherwise the convergence requirement of ML estimation cannot not be achieved. Furthermore, the role of time fixed effects to account for effects of unobserved spatial autocorrelated variables in the residuals has already been accommodated by the SDM specification via the addition of both spatial endogenous and exogenous dependencies (Fingleton and Le Gallo, 2010).

[20]This result is consistent with the idea of Elhorst (2012) that the fixed effects model is more appropriate than the random effects model in a spatio-temporal setting. Besides, two prerequisites highlighted by Elhorst are applicable in our context. First, we have a sufficiently long time period (T equals to 30). Second, we apply SDM as the spatial panel specification, which is known to treat potential endogeneity problems such as the omission of relevant variables (Fingleton and Le Gallo, 2010).

[21]All parameters mentioned here are the coefficients of different variables on the right hand side of equation (2.13).

estimated LR statistic in this case is 22.43, which is larger than 14.07 at the 5% significance level. Due to the rejections of both null hypotheses, we can now regard SDM as the best model to fit our data. Our final LR test concerns whether a static SDM is preferable to the dynamic one. Accordingly, we test H_0 : β=γ=0 where we obtain the $LR = 2 \times (-1142.2321 + 1284.1955) = 283.9268$. Once again, the LR statistic is greater than the critical value of 5.99 at the 5% significance level, thus strongly rejecting the null hypothesis of a static SDM model in favor of the dynamic SDM model. To summarize the model selection procedure, the various LR tests lead us to select the dynamic spatial Durbin model (SDM) with spatial fixed effects to carry out further estimation.

2.5.2 Discussion of results from SDM estimation

In Tables 2.4 - 2.8, we present the results from OLS and SDM estimation, including the series of robustness exercises. The main estimation results are presented in Table 2.4, whereas results in Tables 2.5 - 2.8 concern robustness exercises. In all tables, variables in 'first differenced' forms begin with a prefix 'd'. In Table 2.4, columns 1 and 3 describe the results estimated by the conventional OLS method without considering spatial spill-over effects, while columns 2 and 4 present results from the dynamic spatial Durbin model (SDM) method. Besides, columns 1 and 2 include all macroeconomic policy factors, while columns 3 and 4 ignore the effect of selected macroeconomic factors on house prices. The "Main" section (upper panel of each table) denotes effects of various independent variables on house prices within a country's geographic boundary, whereas the "Wx" section (lower panel in each table) describes spatial spill-over effects (or across-the-border effects) of independent variables on house prices in the home country.[22]

Several key patterns emerge in the "Main" section of Table 2.4. First, signs of estimated coefficients in all columns are similar and are consistent with the theoretical expectations previously discussed. One exception is that residential investment (rri) is observed to impart a positive impact on house prices. This unexpected effect may be because the sign of rri tends to change over time, implying that it can have a negative impact in the short term and a positive impact in the long term (Arestis and Gonzalez-Martinez, 2016). Another reason concerns the use of gross fixed capital formation at dwellings to represent residential investment. Since this variable includes the construction cost of dwellings, it induces a positive correlation with house prices (Glaeser and Gyourko, 2003).

Second, dynamic parameters in the SDM model impart significant (positive) effects on house prices. For instance, the coefficient of temporal lag of house prices ($L.dhpi$) is

[22]The effect of independent variables in the "Main" and "Wx" sections can be regarded as direct and indirect effects. Note that $L.dhpi$ appears in the 'Main' section, whereas both $Wdhpi$ and $L.Wdhpi$ appear in the "Wx" section.

positive and significant in columns 2 (0.592) and 4 (0.652). Interestingly, in the "Wx" section, the coefficient of the temporally spatial lag of house prices ($L.Wdhpi$) is negative, and it appears to offset the positive effect produced by the contemporaneous spatial lag of house prices ($Wdhpi$).[23] In addition, the summation of effects of temporally spatial lag ($L.Wdhpi$) and contemporaneous spatial lag ($Wdhpi$) of house prices triggers significantly positive effects (0.061 and 0.227 in columns 2 and 4, respectively), which confirm theoretical expectation indicating the presence of positive spatial autocorrelation of house prices. This result can be considered as a transmission mechanism through which house cycles across international borders are synchronized.

Third, in the absence of spatial spillover effects, the impact of macroeconomic variables may be over-estimated (in terms of the absolute values). Specifically, the estimates of taxation on dwellings over house prices (tax) and residential investment (rri) (in column 2) are -0.029 and 0.256, respectively. Considering their absolute values, 0.029 and 0.256, the estimated coefficients appear over-estimated if we omit spatial spill-over effects from estimation (compared with the non-spatial estimation). Moreover, the impact of unemployment rate in column 2 is -0.931, while its corresponding counterparts in column 3 and 4 are -1.698 and -1.317, respectively. In a similar vein, we can conclude again that the estimated coefficients (in absolute terms) are over-estimated.[24] To summarize, we note that the over-estimation bias of the independent variables in the"Main" section can be minimized by including spatial effects in the model specification. In addition, the omission of the macroeconomic instruments can also induce an over-estimation bias in the dynamics of housing prices. It is worth noting that our results (on the significant effect of macroeconomic policy variables, viz., taxation on dwellings over house prices and real interest rates) are also consistent with the existing studies such as Arestis and Gonzalez-Martinez (2016).

We now turn our attention to the "Wx" section. The coefficient estimates presented here correspond to spatial-spillover effects. In other words, the estimates represent the responses in housing prices to the changes in independent variables among spatially contiguous countries. These effects are also sometimes termed 'indirect effects'. We find that some variables, such as taxation on dwellings and residential investment, impart significant negative and positive spatial spill-over effects on house prices, respectively. Both variables present significant direct effects as well (in the same direction as their corresponding indirect effects). Interestingly, the indirect effects of some independent variables show opposite signs with their corresponding direct effects.

[23]Based on the non-linear restriction of the dynamic spatial panel model, Tao and Yu (2012) propose a theoretical framework to justify the way the coefficient of $L.Wdhpi$ can be negative in the case that coefficients of both temporal lag ($L.dhpi$) and contemporaneous spatial lag ($Wdhpi$) of house prices are positive.

[24]We remove macroeconomic variables and 'space' in column 3, whereas we remove macroeconomic variables in column 4.

Table 2.4: **Main Results (Non-spatial Model and Dynamic SDM)**

Variables	col.(1)	col.(2)	col.(3)	col.(4)
Main: Within-country effects				
dcb	−0.117	−0.024	−0.175*	−0.045
	(0.100)	(0.079)	(0.106)	(0.080)
dpdi	0.414***	0.123	0.612***	0.177**
	(0.103)	(0.083)	(0.110)	(0.086)
dur	−0.982***	−0.931***	−1.698***	−1.317***
	(0.204)	(0.183)	(0.203)	(0.175)
drir	−0.075	−0.043		
	(0.083)	(0.066)		
dcredit	0.056***	0.007		
	(0.021)	(0.017)		
dtax	−0.052***	−0.029**		
	(0.016)	(0.012)		
drri	0.456***	0.256***		
	(0.052)	(0.041)		
L.dhpi		0.592***		0.652***
		(0.034)		(0.035)
C	1.451***		1.434***	
	(0.339)		(0.369)	
Wx: Spillover effects				
Wdcb		0.589**		0.641***
		(0.250)		(0.249)
Wdpdi		−0.675***		−0.415**
		(0.218)		(0.210)
Wdur		0.265		0.430
		(0.380)		(0.364)
Wdrir		−0.131		
		(0.157)		
Wdcredit		0.035		
		(0.044)		
Wdtax		−0.064**		
		(0.031)		
Wdrri		0.297***		
		(0.114)		
Wdhpi		0.343***		0.519***
		(0.076)		(0.059)
L.Wdhpi		−0.282***		−0.292***
		(0.085)		(0.083)
Residual variance (σ^2)		8.215***		9.110***
		(0.524)		(0.585)
R^2	0.406	0.656	0.274	0.587
Country Fixed Effects	Included	Included	Included	Included
Observations	480	464	480	464
No. of Countries	16	16	16	16

Note: *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; standard errors are in parentheses.

Consider for example, the case of current account balance (cb). We note that instead of the observed negative direct effect as in the "Main" section, cb now presents strong positive spatial spill-over effects (0.589 and 0.641, respectively in columns 2 & 4). Besides, personal disposable income (pdi) is also observed to exert a positive direct effect on house prices, which is theoretically expected.[25] However, this positive direct effect in the "Main" section can be offset by the large negative indirect effect in the "Wx" section as shown in columns 2 and 4, respectively. The coefficient of the indirect effect of personal disposable income witnessed a 0.26 point increase after omitting macroeconomic interventions (column 4) in comparison with the situation before removing macroeconomic variables from the estimation (column 2). In addition, in terms of model fit, the observed highest R^2 in column 2 also reflects the fact that both spatial spill-over effects and macroeconomic policy interventions are of paramount importance in interpreting house price fluctuations across international real estate markets. Overall, the significant spillover effect of macroeconomic variables help us understand the fundamental reasons behind international house prices synchronization.

The above results have implications for the 'catching up' problem of house prices across countries. Indeed, due to the co-movement of macroeconomic fundamentals and the evidence of synchronized housing price cycles, we can conclude that cross-country house prices depict spatial clustering. This inference is consistent with previous studies such as Cesa-Bianchi (2013) and Arestis and Gonzalez-Martinez (2016).

2.5.3 Robustness

We perform a number of robustness checks to establish the generality of our results. Four directions are considered: alternative estimation method, introduction of new variables in our estimation, structural break, and extension of the sample span. We study the results from each investigation below.

2.5.3.1 Alternative estimation strategy: Estimation by Partial Derivative (PD) method

Following Elhorst (2014) we know that the dynamic SDM can also be estimated by using the partial derivative (PD) method so that both long-run and short-run direct and indirect effects of the independent variables can be discerned. Results obtained by the PD method can be compared directly with the one we already have obtained by the ML method.[26] Table 2.5 presents results from the PD estimation of the SDM model. Columns 5 and 7 are for the dynamic SDM estimations that include different types of macroeconomic factors. Conversely, results in columns 6 and 8 concern dynamic SDM estimations after removing macroeconomic policy factors. Moreover, columns

[25] Örsal (2014) also find a positive effect of real GDP per capita on house price fluctuations.

[26] The analytical derivations concerning direct/indirect effects are available from the authors upon request.

5 and 6 report the short-run direct/indirect effects, and columns 7 and 8 display the corresponding long-run direct/indirect effects. Specifically, both direct effects ("Main" section) and indirect effects ("Wx" section) of independent variables estimated by either PD or ML depict similar patterns in both sign and magnitude. Pronounced in the long-run period, both direct and indirect effects of each independent variable become larger in absolute values compared with that of the short-run period.

2.5.3.2 Replacing residential investment by TFP

As a further sensitivity analysis, we replace residential investment by total factor productivity (TFP).[27] Because TFP is often regarded as a better proxy for construction cost, it depicts strong positive correlation with construction cost and can exert positive impact on house prices (Moro and Nuño, 2012). Besides, as mentioned above, residential investment in our chapter is represented by gross fixed capital formation at dwellings, which includes the construction cost of residential buildings. The results are presented in Table 2.6. In terms of the "Main" section, the results broadly mimic our main estimation (Table 2.4). Our replacement variable for residential investment, the TFP in the first difference, is also found to have a significant and positive impact on house prices. It leaves a similar direct effect in the non-spatial panel model (column 9) and the dynamic SDM model (column 10) (the estimates are 25.680 and 25.150, respectively). The impacts of unemployment rate, real interest rate, and taxation on dwellings over house prices are also consistent with the results from the main regression, depicting a significantly negative effect over the full sample span. In addition, the significant positive autocorrelation of housing prices in both spatial and temporal dimensions also confirms the existence of house price synchronizations. Apart from the positive impact of TFP in the "Main" section, we also find that there is a positive spatial spill-over effect on housing prices (45.970) and this result is consistent with the results in the main estimation (in Table 2.4).

2.5.3.3 Sensitivity to structural break

Are our results sensitive to the structural break in the data? To investigate this, we have performed an estimation for two sub-sample periods, viz., before and after the subprime crisis (we identify this for the year 2008). We perform a Chow test (with known breakpoint) to investigate if the parameters are stable over time. For our sample, the null hypothesis of time stability for a break point in 2008 is rejected, at the 5% level of significance (the Chi-square statistic is 34.72). Indeed, it is well-known that housing prices witnessed a sharp decline during the subprime crisis (Posedel and Vizek, 2009).

[27] Due to data unavailability for TFP, the sample span for this exercise is therefore limited to 10 European countries between 1995 and 2010.

Consequently, the patterns of spatial autocorrelation have also experienced enormous variations before and after 2008. This can be observed from the estimates of Moran's *I* statistics (shown in Table A.1 in Appendix A). Following this test, we estimate and present two separate results with respect to pre- and post-subprime crisis periods. The results are summarized in Table 2.7. Consistent with the results of full sample estimation (Table 2.4), we find similar signs and magnitudes of coefficients for both subperiods (see the effects in the "Main" section). In fact, a study of the variables, viz., unemployment rate and residential investment (in the "Main" section) confirms these inferences. However, we find that the absolute values of the direct effect on changes of house price after the subprime crisis (in column 14) are greater than that of the post crisis period (column 12).

In terms of spatial spill-over (indirect) effects, we find distinct differences in estimated coefficients before/after the subprime crisis. The indirect effects of independent variables before the crisis are similar in magnitudes to the estimates in our main regression (Table 2.4). However, the significance of indirect effects for each independent variable in the aftermath of the crisis period appears to have changed dramatically. For instance, only mortgage loan volumes appears to have a significant indirect effect in the post-crisis period, which is in contrast to the insignificant effects in the pre-crisis period. The implication is that the outbreak of the subprime crisis has significantly affected the direction and magnitude of spatial spill-over effects (probably making them unstable).

2.5.3.4 Broadening the sample coverage

Our final sensitivity analysis concerns sample enlargement, as it is well-known that change in sample size can have a measurable impact on the coefficient estimates. Accordingly, we have expanded our sample by including additional countries (results are presented in Table 2.8). In particular, we have added four more countries[28] to the original sample. The total number of countries now stands at 20.[29] Table 2.8 summarizes the results from this investigation. Results in columns 15 and 16 concern all macroeconomic variables, while the results in columns 17 and 18 refer to selected macroeconomic variables related to house price fluctuations. Results in columns 16 and 18 present estimations where 'spatial attributes' forms a part of the explanatory power of the model. In terms of the "Main" section, the direct effects of all variables are similar to the ones we obtained in our main estimation (Table 2.4). Moreover, the magnitudes of direct effects of all independent variables in absolute terms are greater than their counterparts in the main regression, except for residential investment. This variable depicts a small direct effect than that of the comparable estimates in the main model (0.201 or 0.422 in

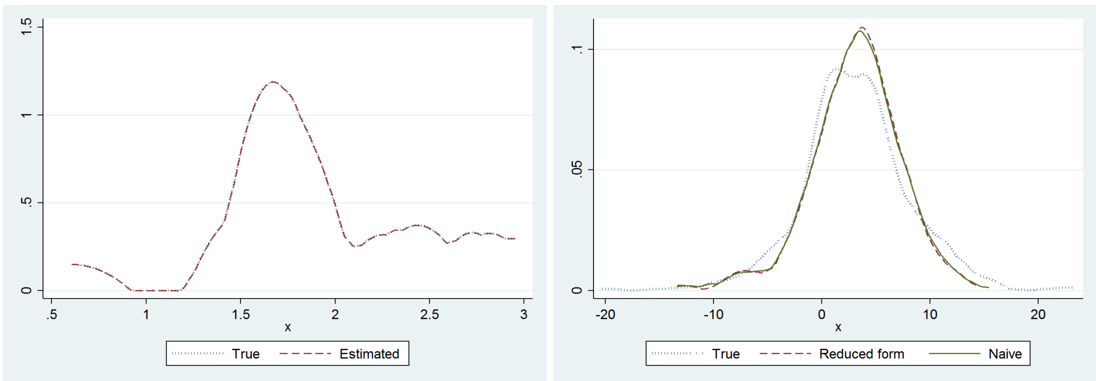
[28] These are the Czech Republic, Greece, Iceland, and Slovakia.
[29] Due to the lack of data, we have limited the period of investigation to 16 years (2000 to 2016).

the model that considers either spatial spill-over effects (see column 16) or a non-spatial model (see column 15)).

Similar to the implications regarding the consideration of space in our main estimation, we also find in Table 2.8 that in the absence of spatial spillover effects, the impacts of macroeconomic policy variables are overestimated. Due to the change of the spatial weight matrix (recalling that we have 20 countries in the new sample) the spatial spillover effects (in the "Wx" section) appear to be slightly different from the main estimations (Table 2.4). However, both signs and magnitudes of the indirect effects in Table 2.8 remain similar to those our main model (Table 2.4). Furthermore, commensurate with the main estimation results, the finding of positive spatial autocorrelation of house prices in Table 2.8 also provides indication of house prices synchronization at the international level.

Figure 2.5: **Dynamic SDM Model Post-estimation**

(a) Predicted Fixed Effects (b) $Reduced$ and $Naive$ Predictors



2.5.4 Model performance

How does our SDM method perform vis-a-vis other model specifications? An answer to this question holds the key to ensuring that the results from the SDM estimations are robust and policy-informative. To examine the predictive performance of our dynamic SDM model, we implement two types of post-estimation routines. The latter is based on the comparison of differences in the estimated density of model specifications (Belotti et al., 2017). First, we study the predictive performance of the spatial fixed effects as a deviation between true value (simulated from our dynamic SDM model) and its estimated value. Second, we calculate predicted values of the dependent variable, housing prices (hpi) by using $reduced$ and $naive$ forms, respectively.[30] The results are presented in Figure 2.5. We note that the distributions of both true and estimated spatial fixed effects are highly overlapping. In addition, we expect that our main model (the dynamic

[30]There are two different statistics to calculate the predicted values based on unique equation forms and information sets. See Belotti et al. (2017) for details.

SDM model) should display better performance in predicting the values of the dependent variable. In Figure 2.5, while there exists slight deviations between true hpi and two different predicted hpi, it might be due to the fact that both predictions are computed without considering the spatial exogenous interactions and the dynamic terms.[31] Overall, the predictive powers of the SDM associated with both the spatial fixed effects and dependent variable indicate better performance of the model of choice.

2.6 Conclusions

Macroeconomic policy interventions significantly affect house price movements over time; however, adjusting for spatial spillover effects in the model can greatly improve the explanatory power of these variables. To test these predictions in a cross-country setting, we introduce a theoretical model to justify the inclusion of 'space' in the house price-macroeconomy interaction environment.

Our analytical model demonstrates that spatial spillover effects can capture knowledge transmission across countries due to variations in macroeconomic policies. Our empirical estimation in a common market setting provides significant evidence of dynamic spatio-temporal interdependence in house prices. Macroeconomic interventions are found to significantly determine house price equilibrium; however, 'space' is found to play a moderating role towards producing the real effects of these variables. Thus, an important result is derived from our investigation: disregarding spatial spillover effects leads to a consistent over-estimation of the real effects of macroeconomic variables. As a result, in the absence of 'space', an over-emphasis of the role of macroeconomic adjustment policy might lead to a counter-cyclical response of the aggregate economy and under-reaction of the housing market over time. In addition, evidence of significant spatial effects in our chapter also speaks in favor of the current findings of international housing-price cycle synchronization.

[31] Due to the current technical limitation of post-estimation for the SDM model estimated by using $xsmle$.

Table 2.5: **Robustness Check 1: Dynamic SDM Estimated by Partial Derivative (PD) Method**

Variables	col.(5)	col.(6)	col.(7)	col.(8)
	Short Run Direct		Long Run Direct	
dcb	0.011	0.017	−0.011	0.274
	(0.076)	(0.082)	(0.186)	(1.007)
dpdi	0.094	0.150*	0.269	0.340
	(0.082)	(0.087)	(0.204)	(0.517)
dur	−0.935***	−1.341***	−2.289***	−4.166***
	(0.172)	(0.163)	(0.429)	(1.383)
drir	−0.043		−0.095	
	(0.064)		(0.158)	
dcredit	0.009		0.021	
	(0.017)		(0.041)	
dtax	−0.032***		−0.075***	
	(0.011)		(0.028)	
drri	0.274***		0.645***	
	(0.043)		(0.104)	
	Short Run Indirect		Long Run Indirect	
dcb	0.877**	1.265***	1.748**	6.856
	(0.370)	(0.483)	(0.789)	(14.550)
dpdi	−0.957***	−0.641	−1.968***	−3.072
	(0.324)	(0.419)	(0.725)	(6.585)
dur	−0.072	−0.546	0.317	−6.547
	(0.540)	(0.666)	(1.156)	(19.920)
drir	−0.213		−0.403	
	(0.238)		(0.495)	
dcredit	0.056		0.111	
	(0.067)		(0.143)	
dtax	−0.114***		−0.213**	
	(0.043)		(0.099)	
drri	0.590***		1.045***	
	(0.158)		(0.392)	

Note: *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; standard errors are in parentheses.

Table 2.6: **Robustness Check 2: The Effect of Replacing Residential Investment by TFP**

Variables	col.(9)	col.(10)
Main: Within-country effects		
dcb	−0.329	−0.187
	(0.290)	(0.200)
dpdi	0.405*	0.048
	(0.220)	(0.170)
dur	−1.330***	−0.736***
	(0.350)	(0.280)
drir	−0.044	−0.818***
	(0.310)	(0.270)
dcredit	0.074	−0.026
	(0.051)	(0.036)
dtax	−0.123***	−0.061**
	(0.044)	(0.031)
dtfp	25.680***	25.150***
	(9.670)	(7.270)
L.dhpi		0.702***
		(0.070)
C	2.611***	
	(0.650)	
Wx: Spillover effects		
Wdcb		0.401
		(0.430)
Wdpdi		−0.488
		(0.410)
Wdur		−0.026
		(0.630)
Wdrir		0.679
		(0.470)
Wdcredit		−0.131
		(0.110)
Wdtax		0.086
		(0.091)
Wdtfp		45.970***
		(17.800)
Wdhpi		0.372***
		(0.100)
L.Wdhpi		−0.217
		(0.150)
Residual variance (σ^2)		5.826***
		(0.660)
R^2	0.315	0.699
Country Fixed Effects	Included	Included
Observations	150	140
Number of Countries	10	10

Note: *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; standard errors are in parentheses.

Table 2.7: **Robustness Check 3: The Effect of the Global Financial Crisis**

Variables	col.(11)	col.(12)	col.(13)	col.(14)
Main: Within-country effects				
dcb	−0.188*	0.015	0.045	0.056
	(0.112)	(0.083)	(0.188)	(0.202)
dpdi	0.293**	−0.040	0.487**	0.319*
	(0.125)	(0.095)	(0.201)	(0.186)
dur	−0.862***	−0.770***	−0.853*	−1.408***
	(0.222)	(0.189)	(0.440)	(0.420)
drir	−0.022	−0.013	−0.155	−0.219
	(0.091)	(0.068)	(0.161)	(0.156)
dcredit	0.054**	0.017	−0.084	−0.052
	(0.022)	(0.016)	(0.067)	(0.080)
dtax	−0.053***	−0.025**	−0.030	−0.075
	(0.016)	(0.011)	(0.047)	(0.051)
drri	0.485***	0.175***	0.346***	0.280***
	(0.069)	(0.050)	(0.105)	(0.103)
L.dhpi		0.667***		0.548***
		(0.041)		(0.080)
C	1.896***		0.761	
	(0.424)		(0.632)	
Wx: Spillover effects				
Wdcb		0.476*		0.331
		(0.271)		(1.210)
Wdpdi		−1.057***		−1.325
		(0.241)		(1.002)
Wdur		−0.525		2.528
		(0.375)		(2.102)
Wdrir		−0.267*		−0.330
		(0.160)		(0.868)
Wdcredit		0.055		−0.553*
		(0.048)		(0.332)
Wdtax		−0.085***		0.057
		(0.029)		(0.154)
Wdrri		0.301*		0.103
		(0.163)		(0.460)
Wdhpi		0.021		0.174
		(0.118)		(0.224)
L.Wdhpi		0.178		−0.155
		(0.123)		(0.270)
Residual variance (σ^2)		5.824***		10.770***
		(0.429)		(1.262)
R^2	0.327	0.686	0.411	0.642
Country Fixed Effects	Included	Included	Included	Included
Observations	352	336	128	112
Number of Countries	16	16	16	16

Note: *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; standard errors are in parentheses.

Table 2.8: **Robustness Check 4: The Effect of Extension to 20 OECD Countries**

Variables	col.(15)	col.(16)	col.(17)	col.(18)
Main: Within-country effects				
dcb	$-0.352***$	$-0.346***$	$-0.531***$	$-0.411***$
	(0.130)	(0.114)	(0.132)	(0.113)
dpdi	$0.535***$	$0.255***$	$0.595***$	$0.217**$
	(0.108)	(0.098)	(0.115)	(0.099)
dur	$-1.405***$	$-1.277***$	$-2.014***$	$-1.671***$
	(0.325)	(0.302)	(0.305)	(0.273)
drir	-0.010	-0.071		
	(0.117)	(0.106)		
dcredit	$0.074***$	0.011		
	(0.026)	(0.027)		
dtax	$-0.062**$	$-0.046*$		
	(0.028)	(0.026)		
drri	$0.422***$	$0.201***$		
	(0.073)	(0.066)		
L.dhpi		$0.500***$		$0.563***$
		(0.046)		(0.044)
C	$2.010***$		$2.324***$	
	(0.448)		(0.474)	
Wx: Spillover effects				
Wdcb		$0.663*$		$0.570*$
		(0.339)		(0.331)
Wdpdi		0.327		0.312
		(0.276)		(0.269)
Wdur		0.766		$0.972*$
		(0.662)		(0.519)
Wdrir		0.193		
		(0.314)		
Wdcredit		0.038		
		(0.079)		
Wdtax		-0.030		
		(0.056)		
Wdrri		$0.455***$		
		(0.169)		
Wdhpi		$0.172*$		$0.386***$
		(0.100)		(0.082)
L.Wdhpi		$-0.340***$		$-0.354***$
		(0.095)		(0.082)
Residual variance (σ^2)		$15.080***$		$16.460***$
		(1.191)		(1.306)
R^2	0.496	0.675	0.399	0.622
Country Fixed Effects	Included	Included	Included	Included
Observations	300	280	300	280
Number of Countries	20	20	20	20

Note: *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; standard errors are in parentheses.

Chapter 3

To Segregate or to Aggregate: Uncovering the Real Effects of Credit in Housing Price Dynamics

3.1 Introduction

Economies are typically credit constrained. Research shows that bank credit[1] plays an instrumental role in the asset market price determination, especially when asymmetric information - thanks to persistent economic policy uncertainty - characterizes the broad economic environment (Bernanke, 2007; Kindleberger, 1978; Minsky, 2015). The extant literature provides conflicting evidence regarding the effect of bank credit: it is shown to be positive (See for instance, Gerlach and Peng, 2005; Oikarinen, 2009; Valverde and Fernández, 2010), to be negative and/or insignificant (See for instance, Coleman et al., 2008; Gimeno and Martinez-Carrascal, 2010).

A helicopter tour of the relevant literature reveals that such conflicting conclusions arise mainly due to two reasons.[2] First, majority of research use credit in its *aggregate* form in both theory and empirical constructs, disregarding perhaps the crucial links that run from various components of credit to the asset market. Second, the literature has mostly concentrated on the demand-side story of the credit and asset market relationship, ignoring the supply-side dynamics. Hence, there is an observed over-emphasis of demand side dynamics of credit in asset price movements, under-representing important role of supply side factors in the price determination. This problem can be solved by linking components of credit to the demand and supply side channels of asset price determination. Indeed, credit - conceptualized in *aggregate* form - masks micro dynamic effects of its *components* and is likely to underestimate its real effects on housing prices over time. While *segregating* credit into components appears a natural and logical strategy, efforts to combine a sound theoretical foundation with a robust empirical model are surprisingly few. The current chapter aims to fill this gap in the literature and focuses on the *disaggregate* rather than the *aggregate* form of bank credit.

Our strategy involves a decomposition of bank credit into *credit to the real economy* and *credit to the asset markets*.[3] The conventional practice is to define *credit to the real economy* as credit that is used for GDP transactions and *credit to the asset markets* as credit that is used for non-GDP transactions. However, the scope of these definitions does not adequately identify separate impacts of the credit flow on the demand and supply channels of a housing market.[4] In particular, the *credit to the real economy* - under conventional definition - encompasses too many elements, which are not specific to the demand side dynamics of a housing market. In this chapter, we redefine *credit to the real economy* and demonstrate how this is clearly interlinked to the dynamics of housing

[1]Throughout the chapter, the terms credit and bank credit are used synonymously.

[2]See Tables B.10 and B.11 in Appendix B for a summary of the literature.

[3]The conceptual foundation of our strategy follows Keynes (1930), who first suggests, following the economic prosperity in the 1920s, that the aggregate deposit-money flow should be split into the different circulation channels: the 'industrial' circulation and the 'financial' circulation.

[4]In Section 3.2 we present a theoretical framework to identify the distinct impacts of credit flow.

demand. Similarly, *credit to the asset markets* is also shown to capture the supply side of a housing market.

At the heart of our conceptual framework lies the classical macroeconomic theory. Using this framework in our empirical estimation, we are able to show that the conflicting evidence on the impacts of credit on a housing market can be reconciled by clearly mapping the effects from the two components of credit to the demand and supply dynamics of a housing market. Moreover, its real impacts on economic growth can be also disentangled by a clear identification of credit flowing to the real economy and the asset markets (see recent empirical applications about the credit disaggregation, Jordà et al., 2016; Unger, 2017, among others). Thus, if we disregard the dynamics that are contained in the disaggregated components of credit, important quantitative information on their true impacts may be lost, leading to, perhaps, an under-emphasis of the role of credit over time.

We contribute to the literature of credit-housing market fluctuations on the one hand and credit-economic growth variations on the other, in the following ways. First, this chapter proposes an innovative theoretical framework, which applies credit disaggregation strategy to the housing market and lays a strong conceptual foundation for the heterogeneous and distinct effects of the two credit components in housing price determinations via the housing demand and supply perspectives, respectively. This strategy can also help dissect the separate effects of the components of credit on the real economy and the asset markets. Second, we improve upon the estimation framework generally employed in credit-housing market study by building a cross-country panel vector autoregressive (PVAR) regression. This way, our approach is able to account for possible cross-country dependence and overcome the strict limitation of the use of a single country setting for empirical analyses. As is well-known, such a research setting - due to the limited knowledge it reflects in terms of data architecture and dynamics - neglects the dynamic cross-sectional spillovers among our target countries and fails to truly present the bi-directional interactions between credit and housing prices. Third, to quantify the dynamic effects of credit under noisy signals, we introduce the role of economic policy uncertainty. It is argued that during a period of persistent uncertainty, credit is measurably rationed to the financial markets, which affects the short- and long-run asset price movements (see Baker et al., 2016). By introducing economic policy uncertainty in our empirical setting, we study how uncertainty governs the extent of dynamic interdependence among credit, the real economy and the housing market.

A common but often neglected problem while studying temporal variables, such as housing prices and credit, is the treatment of the dominating effects of short-run periodic disturbances of business cycles. Indeed, the presence of such cycles often governs the length and breadth of credit shocks in both the asset markets and the real economy. A natural strategy in this circumstance is to remove periodic cycles from these data. We employ the recently developed Hamilton's 'de-cycling' method (Hamilton, 2017) and employ panel VAR estimation with generalized method of moments (GMM) for this 'de-cycled' data. The idea to use GMM in a panel VAR estimation is to mitigate potential endogeneity problems in our empirical relationship. Our research is possibly among the first to rigorously investigate the role of *disaggregate* bank credit in the cross-country housing price dynamics, more so by treating the business cycles fluctuations in the data and endogenizing the role of economic policy uncertainty. Our identification strategy is robust to controls and sample stratification and our results provide clear and meaningful impacts of credit on cross-country housing prices.

Speaking in favour of our theoretical expectations, several unique results emerge from our empirical investigation: (i) *Credit to the real economy* and housing prices clearly depict a mutually positive reinforcing relationship. However, the impact of *credit to the asset markets* on housing prices appears complex, i.e., insignificant negative in the short-run but significant positive in the long-run. (ii) *credit to the real economy* significantly and positively affects economic growth (i.e., nominal GDP), in contrast to an insignificant effect from *credit to the asset markets*. (iii) Controlling for the persistent economic policy uncertainty in the economy deepens the interactions between housing prices and both the disaggregated credit. (iv) Finally, we find significant negative effects of uncertainty level and the global financial crisis on our main economic variables, including housing prices and nominal GDP.

The rest of this chapter is structured as follows. Section 3.2 presents a theoretical framework and summarizes the literature on the role of disaggregate credit. Section 3.3 presents methodology and discusses estimation issues, such as endogeneity. Section 3.4 presents data and some preliminary results. Section 3.5 provides detailed analyses of the main empirical results including robustness exercises. Finally, Section 3.6 concludes with a discussion of the policy implications of our main findings.

3.2 A Framework for Credit-housing Price Interaction

What drives the interdependence between credit and the housing market? Existing literature lays excessive emphasis on both credit in aggregate form and on credit to the demand side. As a result, the theoretical and empirical predictions on the true effects of credit are far from conclusive. To disentangle the real interdependence, a clear conceptual framework and empirical approach is required along with the theory-driven strategy for *disaggregation* of credit. Indeed, there is compelling evidence that credit and housing prices can interact via distinct housing demand and supply credit-circulation channels, both of which are formed by macroeconomic fundamentals (See for example, Goodhart and Hofmann, 2008, among others).

From the perspective of housing demand, assuming credit provision to housing suppliers is fixed (and exogenous), a credit expansion to housing buyers can enlarge housing buyers' wealth and then their disposable income, leading to a growth in housing demand and a rise in housing prices. From the standpoint of housing supply, an increase in housing prices results in an optimistic expectation of housing market participants on future market boom and particularly a rising investment intention of housing suppliers in further housing provisions. This can lower the loan rate and then lead to a credit expansion to housing suppliers. Hence, a rise (decrease) in housing prices is an indication of economic prosperity (recession) reflected by strong (poor) macroeconomic fundamentals that in turn further expand (shrink) bank credit. Conversely, a change of bank lending volumes can also impact housing price movements by shifting the housing demand and supply curves through the mediating effects of macroeconomic fundamentals. In addition, it is well established that macroeconomic fundamentals can also directly control the dynamics of housing prices (Arestis and Gonzalez-Martinez, 2016; Duan et al., 2018a,b) and credit (Bernanke, 2007; Goodhart and Hofmann, 2008). For example, a rise in interest rate can control a heightening inflation level and dwindle housing prices by depressing housing demand, while it can also reduce credit lending to the housing market.

The above discussions show that credit can interact with housing prices through the housing demand and supply credit circulations, respectively. To understand this interaction mechanism and quantify the distinct effects of the credit components flowing to the housing demand and supply sides, this chapter requires a strong conceptual foundation constructed with the credit disaggregation strategy. Specifically, in the following sub-sections, this chapter first introduces the conventional interpretations on the credit-housing price interaction in Subsection 3.2.1. This chapter then briefly summarizes insights from the existing literature regarding the importance of credit segregation in Subsection 3.2.2. Finally, this chapter offers a detailed and comprehensive description about the credit disaggregation thought in Subsection 3.2.3.

Specifically, in Subsection 3.2.3, this chapter explains how we segregate credit aggregates, what are the definition of each disaggregated credit, viz. *credit to the real economy* (cr) and *credit to the asset markets* (cf), and corresponding motivations of segregating credit. This chapter then elaborates on how cr and cf represent credit amounts flowing to the housing demand and supply channels, respectively, and how they separately interact with housing prices through these two channels. Their dynamic relationships are illustrated in Figures 3.1 and 3.2. By doing this, this chapter finds that the existing inconclusive effects of credit aggregates can be reconciled by meaningful and theoretically expected signs, when using credit in the disaggregate form. In addition, the supporting arguments in each sub-section are based on a review of the literature presented in Table B.10 and B.11 in Appendix B.

3.2.1 Credit and housing price relationship: Conventional interpretations

The literature shows that houses (or properties) are often regarded as collateral associated with bank lending, while the prices can positively affect both supply and demand of bank credit through the channel of 'wealth effects'. Such a mechanism is determined by either moral hazard or adverse selection owing to asymmetric information in the credit markets (see for example, Bernanke and Gertler, 1989; Bernanke et al., 1999; Kiyotaki and Moore, 1997). Specifically, due to the underlying feature of 'a lagged appreciation of current housing prices' (Abraham and Hendershott, 1996; Muellbauer and Murphy, 2008; Murphy, 2018), the increase in current prices tends to induce an expectation of further price appreciations from housing market participants. With regard to commercial banks, property prices influence its capital conditions and thus the credit lending capacities change either directly, viz., the market valuations of bank holdings of real estate assets, or indirectly, viz., the changes in the volume of non-performing loans (Gerlach and Peng, 2005). Thus, given a rising housing price, credit supply to housing buyers will be expanded due to 'wealth effects' as banks are expecting lower mortgage default risk and higher profitability. In the meantime, due to an expectation of future price appreciation as well as an intention of maximizing perceived wealth with a smaller borrowing cost, credit demand of housing buyers will also be boosted to meet their current high housing demand. In turn, housing prices will be further lifted by the increase of housing demand.

On the other hand, through the channel of 'collateral effects', the rise of collateralized asset prices will induce a credit demand boom given that lending margins are exogenously constant (Ling et al., 2016), and encourage the individuals to borrow and spend more money, for example in the housing market transaction, due to the improvement of their borrowing capacity (Goodhart and Hofmann, 2008). On the contrary, the dip of collateralized assets decreases the debt capacity and investment (Campello and Giambona, 2013; Chaney et al., 2012). In addition, Cooper (2013) also finds a positive impact of house price appreciation on household consumption and argues that it is due to the 'collateral effect' rather than the 'wealth effect'. The heightened value of housing (collateral) can directly raise the spending of households who face borrowing constraints, while the effect is negligible to other households who face little financing constraints. Thus, changes in housing prices could theoretically lead to variations of both demand and supply of bank credit in the same direction through the perspective of the housing demand.

The next question is what specific mechanism can lend a robust explanation of the effects of credit on the housing market dynamics? Through the lens of a demand-supply channel, a simple example can be given. We know that greater/less access to bank credit can affect housing prices by shifting housing demand. First, through the perspective of credit demand, the increase of credit demand will indeed stimulate individuals to spend money in buying properties due to 'wealth effects' (Muellbauer and Murphy, 2008). Given the fixed housing supply in the short-run (because there is a relative long-time period for the provisions of new property), both housing demand and housing prices will subsequently increase. With time moves forward in the long run, although housing suppliers are able to adjust by increasing housing inventories, housing prices will still keep boosting due to the assumption of the disequilibrium market (the high level demand versus the relatively insufficient supply) and the sticky housing price, so that it is reluctant to dwindle even in face of a signal of the increasing housing supply (Oikarinen, 2009).[5]

Second, many researchers argue that an increase of housing prices should be ultimately attributed to the expansion of credit supply instead of credit demand (Duca et al., 2011; Favara and Imbs, 2015; Justiniano et al., 2015; Ling et al., 2016; Mian and Sufi, 2009). The liberalization of credit markets implied by the credit supply expansion stimulates the increase of housing prices. On one hand, lower collateral requirements due possibly to the implementation of quantitative easing (QE) monetary policies can boost credit demand of households by loosening their borrowing limits (constraints) against the value of the collateral (i.e. the residential real estate) given that the households are borrowing-constrained (Kiyotaki and Moore, 1997). It then accelerates housing demand and housing prices following the mechanism discussed above. On the other hand, the expansion of bank credit supply (liquidity) can lower the levels of loan interest rates and increase current values of the mortgage properties (the discounted future cash flows of property returns) by influencing the discount rate.

On the whole, prior research has analyzed the central role of bank credit on determining housing prices via the demand aspect of housing. The conceptual underpinning is presented in Figure 3.1 (positive: blue-colored effects). However, it surprisingly ignores the supply side aspects of the effects of bank credit, which is another crucial channel for the dynamics of credit and housing prices interaction. Hence, it will be meaningful if we segregate credit aggregates via both demand and supply sides of housing, and separately investigate the real impacts of both the disaggregate credit. The following subsections presents such arguments.

3.2.2 Does segregation of credit unravel the true effects?

The idea of 'disaggregation' of credit can be attributed to Keynes (1930). He notes that credit/money should be split into 'industrial' and 'financial' circulations to offer insights into how credit really impacts on output growth and the appreciation of financial

[5]In the chapter, we theoretically define both short-run and long-run to describe specific time periods when a target variable reacts at first and later given an exogenous shock, respectively. These definitions do not involve and consider formations of the equilibrium status of the housing market. They are estimated and tested through the impulse response function technique in our empirical analysis.

assets. It is also worth noting that the simultaneous upward trends of both booming financial markets and increasing asset prices in the 1980s can be regarded as a good demonstration for the post-Keynesian quantity theory of credit. The above motivate us to segregate bank credit into *credit to the real economy* and *credit to the asset markets* so that suitable inferences on their impacts on the asset markets/real economy can be made.

The channel of disaggregate credit (in various forms but with limited implications for housing prices) has been used in some recent studies. For instance, Jordà et al. (2016) undertake cross-country analysis and use division of credit to show that *mortgage credit* possesses significant implications for business cycles and financial stability risks, whereas *non-mortgage credit* only plays a negligible role. In another empirical contribution, Unger (2017) investigates the interrelationship between domestic credit and the current account balance in European countries. By disaggregating credit into *financial* and *non-financial private sectors*, an increase in bank credit to the non-financial private sectors (i.e. non-financial firms and households) is found to be one of the main reasons for growing current account imbalances. To the best of our knowledge, only a few studies explore the role of disaggregate bank credit in economic growth and macroeconomic contexts, and there appears to be little contribution to the context of housing price variations. With these limitations in the literature in mind, we propose the 'disaggregation' of bank credit - following the Keynesian tradition - in more inclusive terms viz., *credit to the real economy* and *credit to the asset markets* to study if credit (and so, how and which component of credit) interacts with housing price dynamics. In the following subsection, we introduce each type of disaggregate credit in detail, and discuss their individual impacts on housing prices.

3.2.3 A framework for disaggregate credit-asset market interactions

While the existing research has stressed that credit is an important determinant of housing prices on the demand side of the housing market as earlier discussed in Subsection 3.2.1, its role on the housing supply side has been less clear. This is possibly one of the reasons why the components of credit have been overlooked in the study of the real effects of credit on housing price dynamics. It is well-known that the availability of credit to housing developers is also a powerful instrument that determines housing prices; greater access to finance encourages developers to supply more houses, thereby potentially influencing the direction of housing prices. One way to understand how credit supply to developers determines the housing market is to actually *segregate* aggregate credit lending into *(i) credit lending to the real economy,* cr and *(ii) credit lending to the asset markets,* cf. It is the latter form of credit, which can demonstrate whether bank credit provided to housing developers can affect housing prices through the housing supply side. Indeed, credit in the aggregate form can mask the heterogeneous impacts of its components (cr and cf), which determine the level of housing prices through different channels, viz. housing demand and housing supply, respectively.

Hence, another important question arises: how can we define *credit to the real economy* (cr) and *credit to the asset markets* (cf) to make them good proxies for credit to housing demand and supply, respectively? In the following section, we describe a channel through which these two components of credit are directly related to the demand and supply aspects of a housing market.

3.2.3.1 Disaggregate credit and identification of demand and supply channels of housing market

(a) cr and housing demand

Conventionally, cr denotes credit that is associated with all GDP transactions, and its holders include all the non-financial sector such as households, non-profit institutions serving households and private-/public-owned businesses, etc. However, this conventional definition of cr is not a good proxy for credit to housing demand as it contains not only credit to the house buyers or individuals, but also credit to the house developers in the primary real estate market, viz. the residential construction industry. Thus, to serve as a qualified approximation for the credit to housing demand and distinguish against credit to the asset markets (a proxy for credit to housing supply), our chapter only uses credit to the households and non-profit institutions serving households to represent cr. In theory, cr and housing prices should depict a positive relationship.

(b) cf and housing supply

Similarly, cf denotes credit for non-GDP transactions, viz. credit to other financial corporations especially including the real estate holding companies, who mainly purchase the real estate in primary housing markets and then operate the rental and sales businesses as the housing supplier in secondary markets. Moreover, it is well-known that most of the properties purchased especially in industrialized countries occur in the secondary markets, viz. the second-hand purchases (See, among others, Arestis and Howells, 1999; Best and Kleven, 2018; Palley, 1995).[6] Thus, in our study, cf presents a convenient way to measure the amount of credit lent to housing suppliers in the secondary market such as the real estate holding companies.

[6] Based on our calculation from the National Association of Realtors and the US Bureau of the Census, the ratio of numbers of existing/second-hand home sales to the numbers of total home sales for the US between March 2017 and March 2018 is 99.05%. For the UK, this ratio is 90.25% between January 2007 and December 2016 (Data source: Office for National Statistics). Moreover, the ratio of the amount of existing home transactions to the total amount of home transactions in 2018 is 98.31% (Data source: HM Land Registry Open Data).

On the whole, we eventually conclude two motivations to segregate credit aggregates as cr and cf. First, by doing this, we are able to unravel and gauge the distinct impacts of credit shocks from both the housing demand and supply sides on housing price dynamics, respectively, and vice versa. In particular, our argued dual roles of credit shocks in separately affecting housing prices through the demand and supply perspectives can be clearly identified. Second, we are also able to conveniently examine the rationale of the *post-Keynesian quantity theory of credit* by studying if the components of credit aggregates for GDP and non-GDP transactions contribute differently to the movements of housing prices and economic growth.

(c) Discussions of effects

In terms of cr, as earlier explained in Subsection 3.2.1, cr tends to have a positive interaction with housing prices. Their interaction can be intuitively seen in Figure 3.1 (see the effect of cr on housing prices in the blue color; the effect of housing prices on cr in the green color). Moreover, the interaction that will be mainly discussed in this subsection is between cf and housing prices. Although important, little existing literature nevertheless focuses on the relationship between them. Overall, cf depicts a theoretically expected positive relationship with housing prices due to the following two reasons. First, based on the post-Keynesian quantity theory of credit, it argues that only money used for GDP transactions (cr) drives economic growth, while the specific part of money used for non-GDP transactions (cf) induces the appreciation of asset prices including housing prices.

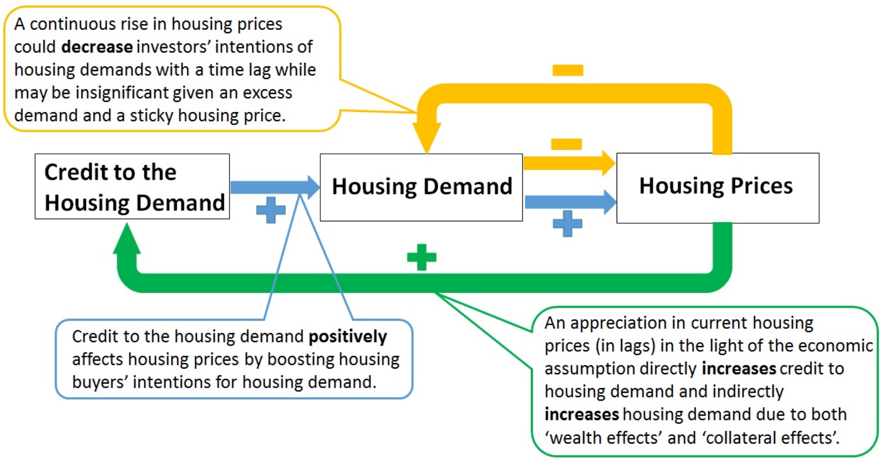
Second, based on the theory of market equilibrium, cf (a proxy for credit to housing supply) also depicts a positive effect on housing prices although through a more complex mechanism. Figure 3.2 presents and describes such a relationship (effects of cf on housing prices: blue colour; effects of housing prices on cf: green colour). Specifically, the disequilibrium condition of the real estate market presents as an insufficient housing supply and relevantly excess housing demand, especially in the short-run period. It implies that housing supply is less elastic relative to the housing demand.[7] In other words, the response of housing supply is smaller and slower than that of housing

[7] Recent phenomena provide strong support in this regard as we find a rapid growth in housing prices largely dominated by a continuous boom in housing demand in many developed and emerging economies (See empirical examples, Cameron et al., 2006; Kuenzel and Bjornbak, 2008; Muellbauer and Murphy, 1997). In contrast, housing supply is more inelastic in those regions, which appears to be unresponsive and ineffective in the face of a fast rising housing price (Glaeser et al., 2012; Glaeser and Saiz, 2004). Because housing is so durable that the market cannot quickly adjust the housing supply downward (DiPasquale, 1999; Green et al., 2005). Instead, the provision of new housing supply needs a considerably long duration of preparation including the planning process and the construction period, whereas the response of housing demand is relatively faster and greater. On the other hand, limited land availability and high land values could be another reason why housing supply is more inelastic (Saiz, 2010). In addition, a forward-looking behaviour of housing suppliers could also lead to a strong reducing effect on the supply elasticity, especially in housing booms (Murphy, 2018).

demand when there is a unit percent change of housing prices. In light of the disequilibrium behavior in the housing market, an increase in credit to housing supply (cf) may not immediately raise the housing supply, indicating that an increase in cf leaves a negligible effect on the increase of housing supply and the deflation of housing prices. Hence, in the short-run, housing prices may witness a slump (complying with theoretical expectations) and can be insignificant.

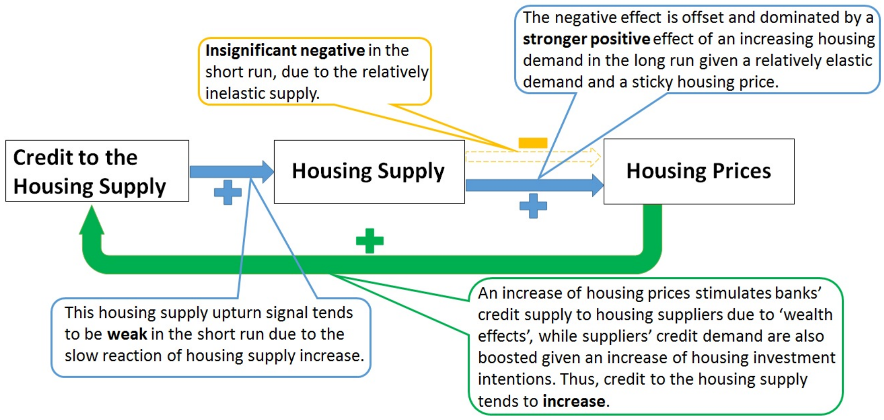
In the long-run, although housing suppliers can enlarge the housing supply by providing more housing units, appropriate adjustments of the housing demand will be made as well. Perceiving the aforementioned decline in housing prices, the housing demand tends to also increase, while its positive effect on raising housing prices is stronger than the corresponding negative effect of an increasing housing supply. This is mainly due to the relatively elastic housing demand against supply and the sticky housing prices that incline to sustain in a high-level dominated by the existing excess housing demand in the market. Thus, in the face of an increase in the credit to the housing supply, a 'housing price puzzle' will be derived that it will eventually rise instead of a suggested decline from the conventional market equilibrium theory. To summarize, *effect of credit-to-the-housing supply* on housing prices is theoretically negative but negligible and can be a short-run phenomenon. However, such an impact will be offset/dominated by an increasing housing demand, eventually becoming positive and significant in the long-run (Arestis and Gonzalez-Martinez, 2016).

Figure 3.1: **Housing Prices - Credit: Housing Demand Channel**



On the whole, it is not surprising to observe - in the face of a housing market disequilibrium - an insignificant negative effect of cf on housing prices in the short-run, and a significant positive effect in the long-run. This gives rise to an interesting phenomenon: *housing prices can keep rising regardless of the simultaneous increase of credit availability to housing supply*. The theoretical mechanism behind such a complex interaction is summarized in Figure 3.2 (the significant positive effect of cf on housing prices: blue colour; its insignificant negative effect: yellow colour in a dotted line). This diagram can explain the phenomenon of overvalued housing prices and expanded housing stocks in

Figure 3.2: **Housing Prices - Credit: Housing Supply Channel**



Note: Figures 3.1 and 3.2 *summarize how disaggregate credit interacts with housing prices through both housing demand and supply channels after we control for variations in the macroeconomic fundamentals.*

the US (Muellbauer and Murphy, 2008). A similar positive relation between them has also been reported in Jordà et al. (2016). Moreover, it is also consistent with Barker (2004, 2006), suggesting that a housing supply shortage in the face of excess housing demand is found to be a root cause of overvalued housing prices in the UK.

With regard to the effect of housing prices on credit to the housing supply (cf), similar with its effect on credit to the housing demand (cr) as earlier discussed in Subsection 3.2.1, an increase in housing prices will stimulate banks' credit supply to housing suppliers due to what is known as 'wealth effects'. At the same time, housing suppliers will also be inclined to enlarge their housing inventories by borrowing more credit from the banks. Hence, the credit demand of housing suppliers will eventually get a boost.

Overall, since the majority of extant relevant research for the credit-housing price interaction relies on either credit in the aggregate format, or alternatively, an over-emphasis on the housing demand side, the important credit circulation channel through the housing supply side is surprisingly under-researched, which gives rise to the root cause of inconclusive results regarding both signs and directions of the interaction. Hence, to fill in this gap, this chapter applies an innovative credit disaggregation strategy to the housing market to investigate how credit exerts impacts on housing price dynamics through not only the housing demand but also the housing supply credit circulations. To build a solid theoretical foundation for the following empirical analysis, this section conducts detailed and specific discussions on effect transmission mechanisms between housing prices and credit to the housing demand side (cr) (See in Subsection 3.2.1), and credit to the housing supply side (cf) (See in Subsections 3.2.2 and 3.2.3), respectively.

To summarize, cr and housing prices could behave a mutually positive reinforcing relationship; the effect of cf on housing prices tends to be more complex. Given the existence of the market disequilibrium as a representation of the excess housing demand (elastic demand) and the relatively insufficient housing supply (inelastic supply), cf could exert an insignificant and negative effect on housing prices in the short-run, while its impact becomes significant and positive in the long-run. Particularly, it is noteworthy that the above explanation of the impact of cf on housing prices from the market equilibrium theory are also in line with the post-Keynesian quantity theory of credit in favour of a more differentiated quantity equation for the real economy and the asset markets, respectively. Moreover, as the main research focus of this chapter is the investigation of the credit-housing price interaction at the macroeconomic perspective, for convenience, this section accordingly builds the theoretical framework by setting the research environment as a 'common and uniform market' type. However, the naturally-existing idiosyncratic characteristics and heterogeneity possessed by different countries should not be neglected, given that our empirical research employs an international panel dataset covering nine industrialized countries. Thus, to account for the existence of cross-country variation within our dataset, in the following empirical analysis, country/panel-specific effects are well-controlled by using a panel vector autoregressive (PVAR) model.

3.3 Methodology and Estimation

3.3.1 Panel VAR estimation of a reduced form representation

Noting that our empirical objective is to use a data involving observations in time-country domain, to capture and model dynamic interdependence between credit, housing prices, and macroeconomic variables, we estimate a reduced form representation of our conceptual model and undertake estimation using a panel vector autoregressive (VAR). As commonly used in the macroeconomic studies as well as recently embraced in real estate related literature (Hollifield et al., 2017; Lengyel and Eriksson, 2017; Saffi and Vergara-Alert, 2014), this approach will help us in estimating how temporal lags of incorporated variables affect their corresponding contemporaneous counterparts across countries over a period of time. Following Abrigo and Love (2016), the general specification of an order p panel vector autoregressive (PVAR) model with panel-specific fixed effects is presented as

$$Y_{it} = \sum_{p=1}^{P} Y_{it-p}\alpha_p + u_i + \epsilon_{it} \tag{3.1}$$

$i = 1, \dots, N; t = 1, \dots, T; p = 1, \dots, P.$

Where Y_{it} stands for a $(1 \times K)$ row vector of dependent variables where K is the number of endogenous variables included in the model system, u_i is a $(1 \times K)$ row vector of panel-specific fixed effects and ϵ_{it} is a row vector of the error terms $(1 \times K)$, where $\epsilon_{it} \sim iidN(0, \sigma^2)$. α is a $K \times K$ coefficient matrix, viz. $\alpha_1, \alpha_2, ..., \alpha_p$, and p is the order of time lags included on the right hand side of (3.1). In line with the idea of Holtz-Eakin et al. (1988), we assume that cross-sectional units follow a same data generation process, denoting that the coefficients matrix α is homogeneous for different panels. Moreover, the corresponding heterogeneous parts are modeled and captured by the panel-specific fixed effects (u_i). In terms of the PVAR model specification in our empirical exercise, we use six variables in the estimation (details in Section 3.4), viz. consumer price index (cpi), credit to the real economy (cr), credit to the asset markets (cf), nominal GDP ($ngdp$), nominal house prices (hpi), and interest rates ($irate$). By setting lag order $p = 1$, we describe:

$$\underset{(1\times 6)}{\begin{pmatrix} dlcpi_{it} \\ dlcr_{it} \\ dlcf_{it} \\ dlngdp_{it} \\ dlhpi_{it} \\ dirate_{it} \end{pmatrix}'} = \underset{(1\times 6)}{\begin{pmatrix} dlcpi_{it-1} \\ dlcr_{it-1} \\ dlcf_{it-1} \\ dlngdp_{it-1} \\ dlhpi_{it-1} \\ dirate_{it-1} \end{pmatrix}'} \underset{(6\times 6)}{\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{16} \\ a_{21} & a_{22} & \cdots & a_{26} \\ a_{31} & a_{32} & \cdots & a_{36} \\ a_{41} & a_{42} & \cdots & a_{46} \\ a_{51} & a_{52} & \cdots & a_{56} \\ a_{61} & a_{62} & \cdots & a_{66} \end{pmatrix}} + \underset{(1\times 6)}{\begin{pmatrix} u_{1i} \\ u_{2i} \\ u_{3i} \\ u_{4i} \\ u_{5i} \\ u_{6i} \end{pmatrix}'} + \underset{(1\times 6)}{\begin{pmatrix} \epsilon_{1it} \\ \epsilon_{2it} \\ \epsilon_{3it} \\ \epsilon_{4it} \\ \epsilon_{5it} \\ \epsilon_{6it} \end{pmatrix}'} \tag{3.2}$$

We use (3.2) as our benchmark model. The panel VAR equation in (3.1) is thus expressed in compact form, where $Y_{it} = \begin{bmatrix} dlcpi_{it} & dlcr_{it} & dlcf_{it} & dlngdp_{it} & dlhpi_{it} & dirate_{it} \end{bmatrix}$; α is a 6×6 coefficient matrix of Y_{it-1}; $u_i = \begin{bmatrix} u_{1i} & u_{2i} & u_{3i} & u_{4i} & u_{5i} & u_{6i} \end{bmatrix}$ and $\epsilon_{it} = \begin{bmatrix} \epsilon_{1i} & \epsilon_{2i} & \epsilon_{3i} & \epsilon_{4i} & \epsilon_{5i} & \epsilon_{6i} \end{bmatrix}$ are the panel specific fixed effects and error terms of each endogenous variable in Y_{it}, respectively. The panel VAR model can capture the potential multiple dynamic interactions among the target economic variables (Muellbauer and Murphy, 2008) and depict a *system-wide* effect rather than individual country-specific effect that 'shuns the intra/inter-country movements of shocks'. In addition, identifying the fixed effects help us account for the idiosyncratic effects from each individual country and capture the heterogeneity in the panel data. However, the panel VAR model cannot be estimated using OLS (even after eliminating fixed effects) because the OLS estimator cannot account for the endogeneity problem due to the presence of the lagged dependent variables on the right hand side (RHS) of (3.1) (Judson and Owen, 1999; Nickell, 1981). Thus, in light of this, we employ the generalized method of moments (GMM) to avoid potential endogeneity problems.

3.3.2 Endogeneity issues

It is well known that GMM estimators of the PVAR model result in consistent estimates and mitigate endogeneity problems due to the presence of lagged variables in the model (Abrigo and Love, 2016). There are two different data transformation methods available in the GMM estimation, viz., first difference (FD) and forward orthogonal deviation (FOD), respectively to remove the time-invariant effects (panel-specific fixed effects) from the PVAR model. The first difference method transforms each variable in (3.1) by using its first time-differenced value (Anderson and Hsiao, 1982).

The transformed variables are instrumented by the differences and levels of untransformed variables in Y_{it} from earlier time periods. However, the first difference (FD) transformation would widen the time-period gap, especially in the context of the unbalanced panel dataset, while its minimum required time period is larger than that required by the forward orthogonal deviation (FOD) transformation for the same PVAR model (Abrigo and Love, 2016). Indeed, the FOD method enables us to avoid the weaknesses of the FD method (Arellano and Bover, 1995). Rather than using the observations in the earlier periods to undertake transformation, the FOD method subtracts the average value of all available future observations from each untransformed variable. Hence, the loss of data points can be minimized. Moreover, the instruments for each FOD transformed variable on the RHS of (3.1) can even include its untransformed variable at the same time period because the past observations are not involved during the transformation, therefore it remains as a valid instrument.

In addition, the efficiency of the GMM estimation can be improved by using more time-lagged dependent variables as instrumental variables. However, this would give rise to the problem of missing observations, while selecting a reasonable set of instruments based on data availability and then substituting corresponding missing observations by zeros could be a remedy (Holtz-Eakin et al., 1988). Moreover, GMM estimators based on FD or FOD transformations are well designed for panel datasets with small time periods (T) and large cross-sections (N), and also perform well even when T is large (Judson and Owen, 1999). In particular, GMM estimators based on the FOD transformation are consistent given that the fraction N/T is a positive constant, which is less than or equal to 2 (Alvarez and Arellano, 2003). Our dataset conforms to the above requirement of GMM estimators. It is also consistent with existing empirical applications of GMM estimators in the panel VAR model (See for instance, Alecke et al., 2010; Mäki-Arvela, 2003).

Fitting the PVAR model as an equation system can improve the efficiency of GMM estimation in contrast to the separate and equation-by-equation GMM estimations, although both give rise to consistent estimates. Based on the PVAR model specification with untransformed variables shown in (3.1), we provide below, for ease of understanding, the steps to obtain a transformed PVAR model (see equation (3.3)) and to study how the GMM estimator can explicitly control for the endogeneity problem.

$$Y_{it}^* = \widetilde{Y}_{it}^* A + \epsilon_{it}^* \tag{3.3}$$

Each variable and parameter in (3.3) can be explicitly presented in a matrix form.

$$Y_{it}^* = \begin{bmatrix} y_{1it}^* & y_{2it}^* & \cdots & y_{K-1it}^* & y_{Kit}^* \end{bmatrix} \tag{3.4}$$

$$\widetilde{Y}_{it}^* = \begin{bmatrix} Y_{it-1}^* & Y_{it-2}^* & \cdots & Y_{it-P+1}^* & Y_{it-P}^* \end{bmatrix} \tag{3.5}$$

$$A' = \begin{bmatrix} A_1' & A_2' & \cdots & A_{P-1}' & A_P' \end{bmatrix} \tag{3.6}$$

$$\epsilon_{it}^* = \begin{bmatrix} \epsilon_{1it}^* & \epsilon_{2it}^* & \cdots & \epsilon_{K-1it}^* & \epsilon_{Kit}^* \end{bmatrix} \tag{3.7}$$

Where Y_{it}^* on the left hand side (LHS) of (3.3) is a $(1 \times K)$ row vector to represent transformed Y_{it} in (3.1); $\widetilde{Y}_{it}^*$ on the right hand side (RHS) of (3.3) is the $(1 \times KP)$ row vector of transformed $\sum_{p=1}^{P} Y_{it-p}$ in (3.1); A is the $(KP \times K)$ coefficient matrix, which needs to be estimated; ϵ_{it}^* is the $(1 \times K)$ row vector of the transformed error terms (ϵ_{it}). Overall, variables with an asterisk superscript in (3.3) are the transformed version of the corresponding variables in (3.1) by using either the FD or the FOD transformation. For our empirical exercise, FOD transformation is preferred and any transformed variable, h_{it}^* in (3.3) can be expressed as

$$h_{it}^* = (h_{it} - \overline{h}_{it})\sqrt{\frac{O_{it}}{O_{it}+1}} \tag{3.8}$$

Where h_{it}^* is the transformed variable and h_{it} is its untransformed counterpart; $\overline{h}_{it}$ is the average value of all available future observations for cross-section i at time t; O_{it} is the total number of future observations. Hence, (3.3) can be expanded and re-formulated in algebraic form as

$$Y_{it}^* = Y_{it-1}^* A_1 + Y_{it-2}^* A_2 + \cdots + Y_{it-P}^* A_P + \epsilon_{it}^* \tag{3.9}$$

$$Q = \begin{bmatrix} Y_{it-1} & Y_{it-2} & \cdots & Y_{it-P+1} & Y_{it-P} \end{bmatrix} \tag{3.10}$$

Where M instruments of variables on the RHS of (3.9) are included in the common instrument set (Q); Q is a $1 \times M$ row vector and $M \geq KP$. [8] By assuming that target

[8] $M = KP$, if and only if the instrument of each transformed variable is it's untransformed variable at the same time period.

variables are predetermined variables, viz. weakly exogenous, in the PVAR system, the set of instrumental variables of $Y^*_{it-\alpha}$ is: $Q_\alpha = \begin{bmatrix} Y_{it-\alpha} & Y_{it-\alpha-1} & \cdots & Y_{it-P+1} & Y_{it-P} \end{bmatrix}$; $\alpha = 1, \ldots, P$, implying an important inference that the untransformed variable can still be a valid instrument of its transformed form in the same time period, viz. $Y_{it-\alpha}$ is a valid instrument of $Y^*_{it-\alpha}$; $cov(Q'_\alpha, \epsilon^*_{it}) = 0$. It further indicates that there is no correlation between the instrumental variables and the error terms in (3.9). Overall, the GMM estimator can indeed eliminate the endogeneity problem in the transformed PVAR model as presented in (3.9).

Furthermore, following a *'general to specific'* strategy, we now introduce a specific case to further explain the mechanisms of the FOD transformation and the corresponding instrument selection in the GMM estimation. Assume that there are only four time periods ($T = 4$ and $P = 2$), which are $t+1, t, t-1$ and $t-2$, and one variable in Y^*_{it} ($K = 1$). Thus, the FOD transformed PVAR of (3.9) can be re-expressed as

$$Y^*_{it} = Y^*_{it-1}A_1 + Y^*_{it-2}A_2 + \epsilon^*_{it} \tag{3.11}$$

Where Y^*_{t+1} is not presented in (3.11) and it will be used in the FOD transformation. In detail, for each $i = 1, \ldots, N$, these transformed variables are formulated based on (3.8) as

$$Y^*_{it} = Y_{it} - [(Y_{it+1})/1] \times \sqrt{\frac{1}{2}} \tag{3.12}$$

$$Y^*_{it-1} = Y_{it-1} - [(Y_{it} + Y_{it+1})/2] \times \sqrt{\frac{2}{3}} \tag{3.13}$$

$$Y^*_{it-2} = Y_{it-2} - [(Y_{it-1} + Y_{it} + Y_{it+1})/3] \times \sqrt{\frac{3}{4}} \tag{3.14}$$

$$\epsilon^*_{it} = \epsilon_{it} - [(\epsilon_{it+1})/1] \times \sqrt{\frac{1}{2}} \tag{3.15}$$

Thus, the instrument set (Q) of all variables on the RHS of (3.11), viz. both Y^*_{it-1} and Y^*_{it-2}, is shown in the following matrix form

$$Q = \begin{bmatrix} \underbrace{Y_{it-1} \quad Y_{it-2}}_{Y^*_{it-1}} & \underbrace{Y_{it-2}}_{Y^*_{it-2}} \end{bmatrix} \tag{3.16}$$

Where, in Q, the instruments of Y^*_{it-1} are Y_{it-1} and Y_{it-2}, and the instrument of Y^*_{it-2} is Y_{it-2}. The number of elements in Q is 3, which is greater than $KP = 2$. In addition, we can also clearly confirm that Y_{it-1} and Y_{it-2} are the valid instruments to Y^*_{it-1} and Y^*_{it-2}, respectively, due to $cov(Y_{it-1}, \epsilon^*_{it})$=$cov(Y_{it-2}, \epsilon^*_{it})$ = 0. Overall, the mechanism of this specific and simplified case is exactly consistent with the aforementioned general one regarding the model transformation and the instrument selection.

Finally, with regard to the the GMM estimator in the FOD-transformed PVAR presented in (3.9), suppose observations in the data are stacked over panels and then over time. The GMM estimator is consistent if $\mathrm{E}\,(Q'\epsilon^*_{it}) = 0$ and rank $(\mathrm{E}\,(\widetilde{Y^*}'_{it}Q))$=$KP$ (Abrigo and Love, 2016). Thus, the specification of the GMM estimator can be eventually presented in the following matrix form.

$$A = (\widetilde{Y^*}'Q\widehat{W}Q'\widetilde{Y^*})^{-1}(\widetilde{Y^*}'Q\widehat{W}Q'\widetilde{Y^*}) \tag{3.17}$$

Where $\widehat{W}$ is a $(M \times M)$ weighted matrix, which is assumed to be nonsingular, symmetric, and positive semidefinite. The weighted matrix $\widehat{W}$ is chosen so as to maximize efficiency of the GMM estimation (Hansen, 1982).

3.3.3 Identification strategies

Our identification strategy is based on four commonly-used analytical tools associated with the panel VAR model, viz., optimal lag order selection process, Granger causality test, generalized impulse response function (IRF) and forecasting error variance decomposition (FEVD). To determine the optimal lag order of the panel VAR model and the moment condition, we follow Andrews and Lu (2001) and apply their proposed Model and Moment Selection (MMSC) criteria to the GMM estimators of our PVAR model. The MMSC is constructed based on the Hansen's J statistic regarding overidentifying restrictions (Hansen, 1982), and is similar to the widely-used information criteria system based on the maximum likelihood technique, such as Akaike information criteria (AIC), Bayesian information criteria (BIC) and Hannan-Quinn information criteria (HQIC). Overall, the optimal lag order can be chosen as the one that has the minimized MMSC statistics.

In terms of a Granger causality test, given that the equation system of the PVAR model is jointly estimated by the GMM method, we can use Wald test to perform hypothesis for any a given specific parameter (Abrigo and Love, 2016). The hypothesis here is that coefficients/effects of the temporal lags of a given variable y_1 from all equations on a specific variable y_2 are jointly equal to zero. In order to gauge how our target variables respond after receiving an isolated unit shock to a specific variable, a generalized impulse response function (IRF) plot summarizes the responses. Moreover, instead of obtaining averaged estimates in the PVAR estimation, the IRF plot enables us to explicitly observe the predictive behavior of each target variable in both the short- and long-runs. The fourth tool we employ is to forecast the error variance decomposition (FEVD). It summarizes the contribution of a specific variable to the error variance forecast of other variables in a predefined-period ahead.

3.4 Data and Preliminary Observations

3.4.1 Data

In terms of the selection of target variables in this chapter, as discussed in detail in previous Section 3.2, through a credit disaggregation strategy, this chapter aims to study the interactions between housing prices and different credit components flowing to the demand and supply sides of a housing market, respectively. At the same time, we are also interested in examining how credit flowing to the real economy and to the financial markets distinctly impact economic growth and the appreciation of asset prices, i.e. housing prices, respectively. Hence, rather than including the aggregate credit, we segregate total credit as *credit to the real economy* (cr) and *credit to the asset markets* (cf), both of which can also depict the components of credit flowing into the housing demand and supply sides, respectively. Nominal GDP ($ngdp$) is selected to represent economic growth in a given country. Moreover, in addition to 'the quantities of money' (i.e. cr and cf), as another important component of the monetary transmission mechanism, interest rate ($irate$) also plays a crucial role that it describes 'the price of money', which changes can ultimately affect the provision of credit lending to various different markets across the broad economy in general, and the demand and supply sides of a housing market in particular. In addition, it is also noteworthy that the role of the nationwide price level, i.e. inflation (cpi), cannot be ignored. It could impact the determination of credit lending levels and macroeconomic variables, such as housing prices and economic growth, as well as their interactions.

Hence, this chapter employs a quarterly panel dataset for nine industrialized countries, including Australia, Belgium, Canada, France, Germany, Japan, Spain, Switzerland, and United Kingdom, over the period from 1990Q1 to 2014Q2.[9] We use six economic variables in our estimation: consumer price index (cpi), credit to the real economy (cr), credit to the asset markets (cf), nominal GDP ($ngdp$), nominal house prices (hpi), and interest rates ($irate$).[10] In addition, both variable descriptions and corresponding data sources can be seen in Table 3.1. Note further that each variable is transformed in logarithms except interest rates ($irate$), which is described in levels, to express as the rate of growth and avoid any domestic currency effect. Moreover, all variables, except interest rates, are seasonally adjusted through using X-12-ARIMA method. For interest

[9] Due to data unavailability on disaggregate bank credit, our empirical research is restricted to these nine countries.

[10] The interest rate used in this study is *short-term* instead of a *long-term* interest rate due to the following reasons. First, the short-term interest rate is a classical approach to describe 'the price of money' (Arestis, 2011; Clarida et al., 1999; Woodford, 2011). Indeed, both 'the price of money' and 'the quantities of money', viz. cr and cf, together form the monetary transmission mechanism of a given economy. Second, short-term interest is more suitable to our research focus: the role of credit in housing price dynamics. Because it is able to impact housing prices by directly affecting the credit constraints on both housing demand and supply sides. While the long-term interest rate can also represent the monetary policy by regulating the liquidity through the investors' asset portfolio rebalancing, it has been out of the scope of our research.

rates we could not detect any seasonal peaks in its spectrum. Nominal GDP ($ngdp$) and nominal housing prices (hpi) are our main variables, where their interactions with disaggregate bank credit (both cr and cf) will be studied. Other macroeconomic variables are used as various predictors but are assumed to endogenously determine housing prices, for instance, through the lead-lag effects of bank credit and income.

Particularly in terms of housing prices, in order to ensure a large sample size of observed housing values while comprehensively representing housing price changes considering different types of residential properties, this chapter decides to employ the series of nominal house price index retrieved from the Bank of International Settlements (BIS). As one of our key target variables, nominal housing prices reported by the above series can well track movements of the price index nationwide for different types of dwellings while comprehensively covering both new and existing dwellings in each given country. As original data of the series built by the BIS are from various sources, the employed methodology and types of covered geographical areas and dwellings for calculation of the series may vary over different target countries. Detailed related data descriptions can be seen through Scatigna and Szemere (2015). In addition, specific discussions regarding different approaches to the measurement of the housing price index are provided in Chapter 4.

Table 3.1: **Data Description**

Variable	Definition	Data Source
Consumer price index (cpi)	The price changes of a basket of goods and services overtime required by a reference population	OECD Main Economic Indicators (MEI)
Credit to the real economy (cr)	Nominal bank credit lending to the real economy (the households and the non-profit institutions serving households) (Millions of national currency)	Central Bank data on Monetary Financial Institutions' assets
Credit to the asset markets (cf)	Nominal bank credit lending to the asset markets, e.g., real estate markets and financial markets (Millions of national currency)	Central Bank data on Monetary Financial Institutions' assets
Nominal GDP ($ngdp$)	Nominal Gross Domestic Product (Millions of national currency)	OECD Main Economic Indicators (MEI)
Nominal housing prices (hpi)	Nominal price index of different types of dwellings at different geographical locations	The Bank of International Settlements (BIS)
Interest rates ($irate$)	Nominal three-month or 90-day interbank rates	OECD Main Economic Indicators (MEI)

3.4.2 Understanding trend

In Figures 3.3 and 3.4, we present the movement patterns of all variables. The sub-figure (a) of Figure 3.3 demonstrates the moving tendency regarding the growth rates of disaggregated credit (both (cr) and (cf)), nominal GDP ($ngdp$), and housing prices (hpi). It can be observed that the growth rates of both cr and cf demonstrate an increasing movement over time and are roughly similar to that of $ngdp$ and hpi. The sub-figure (b) of Figure 3.3 depicts the movements in growth rates of consumer price index (cpi), nominal GDP ($ngdp$), housing prices (hpi), and changes of interest rates ($irate$) over time.

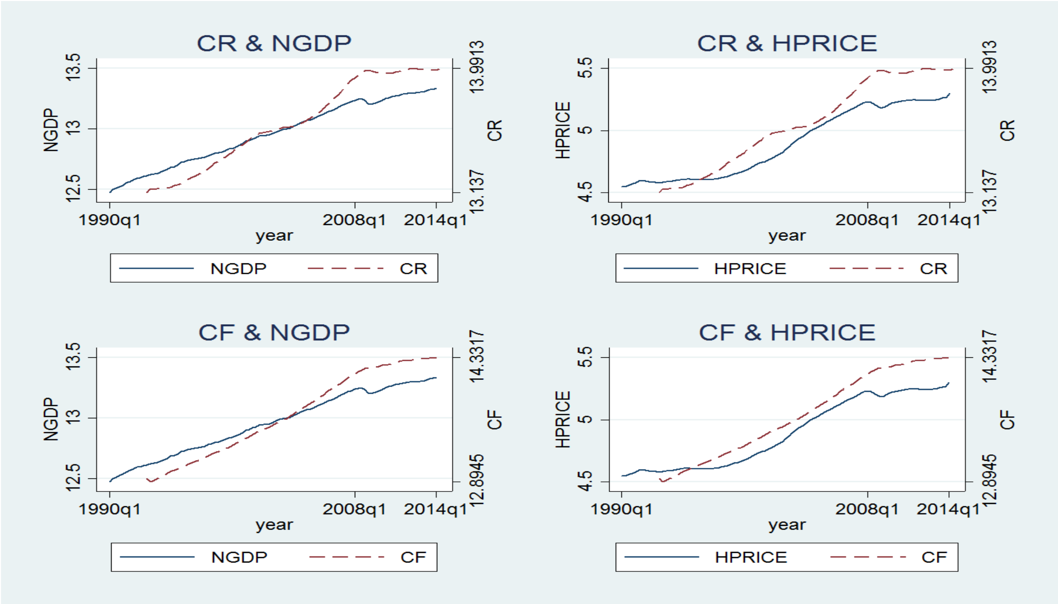
The rates of growth of both cpi and $ngdp$ exhibit a similar growth pattern. Although $irate$ had an increasing momentum in 2008, it experienced a decline after 2009 and approached a zero lower bound shortly thereafter. This might be due to the pro-growth monetary policy during the 'Great Moderation (1995-2006)' and followed by the more prudential monetary policy during the 'Great Recession (2007-2009)'. In addition, except for $irate$, the outbreak of a global financial crisis in 2008 resulted in a marked negative impact on the dynamics of all variables. In the aftermath, the growth rates of all variables except cf show a significant decline, while the growth rate of cf gradually levels out.

Furthermore, the movements of corresponding standard deviations of all variables as shown in Figure 3.4 present interesting patterns. The dispersions of the growths of disaggregate credit (both (cr) and (cf)), nominal GDP ($ngdp$), and CPI (cpi) present a declining tendency, implying a receding volatility, whereas the growth of housing prices (hpi) conversely become more volatile (higher standard deviation) over time. To summarize, we conclude that the growth rates of both disaggregate credit (cr and cf) and CPI (cpi) demonstrate a positive co-movement with the growths of both nominal GDP ($ngdp$) and housing prices (hpi), while the changes in interest rates ($irate$) depict a negative relation. In particular, the strong co-movements between both the disaggregate credit (cr and cf) and hpi provide preliminary supports to our theoretical arguments (in Section 3.2), viz. the positive impacts of both credit to the housing demand and to the housing supply on housing prices, although through different mechanisms.

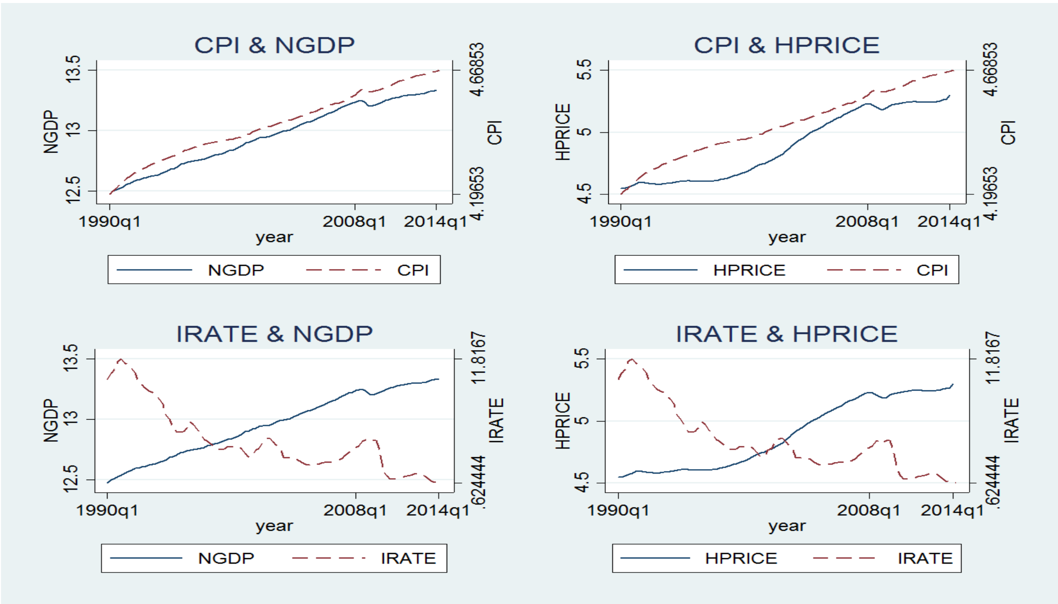
3.4.3 Identifying non-stationarity

The presence of a unit root in the included variables can cause problems of weak instrumentation in the GMM estimation for the PVAR model (Blundell and Bond, 1998). To ensure the stationarity of all variables before estimating the PVAR, we perform a series of unit root tests for our panel dataset, viz., IPS test (Im et al., 2003) and PESCADF test (Pesaran, 2004). Table B.1 in Appendix B presents these results. We find that except for interest rates ($irate$), other variables in levels are not stationary as we fail to reject the null hypothesis of a unit root. Moreover, after first difference, all variables turn out to be stationary. Therefore, all variables are first-differenced to meet the stationarity requirements and measure the impacts of variables in increments in the PVAR estimation.

Figure 3.3: **The Cross-country Mean**



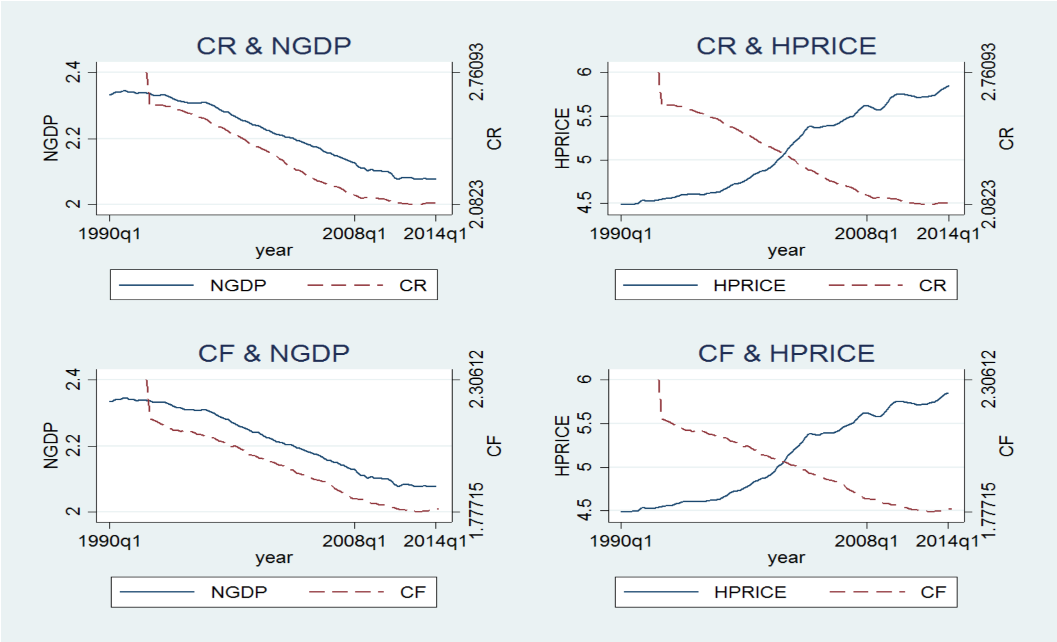
(a) Disaggregate credit, Nominal GDP, and Housing prices



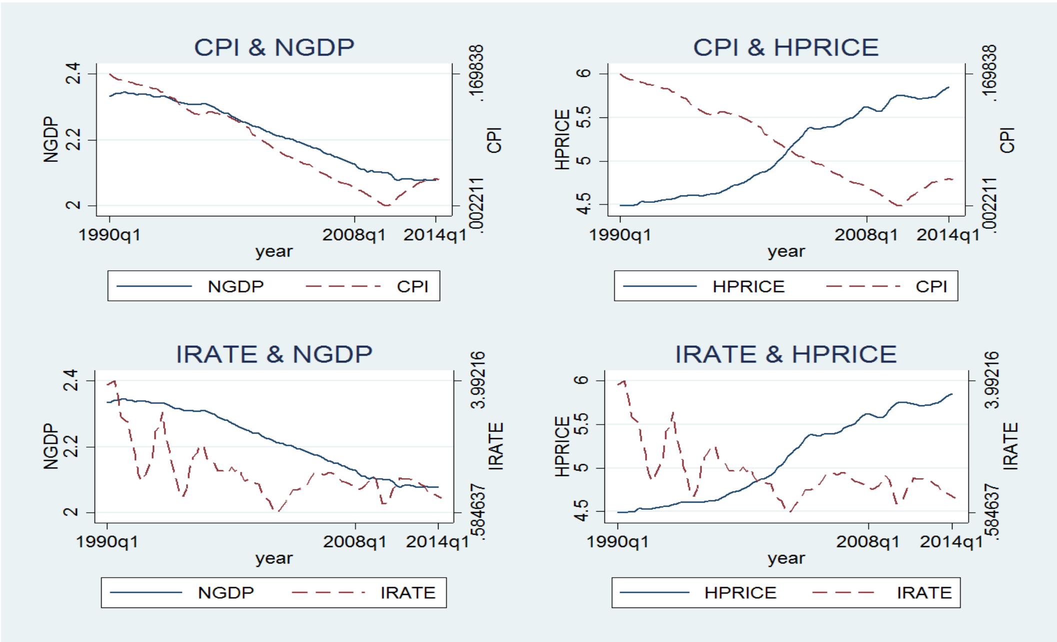
(b) CPI, Interest rate, Nominal GDP, and Housing prices

Note: (i) the variables except interest rates are transformed in logarithms and are cross-country averaged overtime; (ii) cross-country logarithmic variables ($AveLog(X)$) in each time period in each sub-figure are calculated through the following formula:$AveLog(X_t) = \left(\sum_{i=1}^{N} Log(X_{it})\right)/N$; (iii) the quarterly data time period is from 1990Q1 to 2014Q2; (iv) data sources can be seen in Table 3.1.

Figure 3.4: **Standard Deviation**



(a) Disaggregate credit, Nominal GDP, and Housing prices



(b) CPI, Interest rate, Nominal GDP, and Housing prices

Note: (i) the values shown in each sub-figure are standard deviations for each variable presented in Figure 3.3; (ii) the quarterly data time period is from 1990Q1 to 2014Q2; (iii) data sources can be seen in Table 3.1.

3.5 Main Results

In this section, we present the results from panel VAR estimation for both the benchmark model and the robustness exercises. Our benchmark results comprise of estimations with business cycles and without business cycles. For the latter, we employ the

Hamilton filter and perform the estimation on the de-cycled series. A series of robustness checks are then undertaken to study the sensitivity of our benchmark results.

3.5.1 Benchmark results

3.5.1.1 Untreated data: Estimation in the presence of business cycles

In this section, we present results from a panel VAR estimation for the untreated data, i.e., the data with business cycle features (this is basically the original data without employing the Hamilton filter for business cycles removal). To identify the VAR structure, we begin with the optimal lag order selection of the model. We use the order selection criteria for the purpose (see Table 3.2). The validity of up to five lags in the PVAR model, including four quarters given the quarterly frequency of our sample plus an extra lag for the instrumentation, is examined, in order to both maximize the estimation efficiency and minimize the data loss simultaneously (Abrigo and Love, 2016). Hence, as shown in Table 3.2, the first-order panel VAR is preferable over others due to its smallest values of the modified BIC, QIC, and AIC. Moreover, since large degrees of freedom can be lost for enlarging more lags as instrumental variables, we follow Holtz-Eakin et al. (1988) to substitute those missing observations with zeros to ensure the efficiency of GMM estimators.

Table 3.2: **Model and moment selection criteria**

No.lag	CD	J statistic	J p-value	MBIC	MAIC	MQIC
1	0.8695122	228.7439	8.84E-06	-729.0825	-59.25614	-316.9739
2	0.9052584	154.3506	0.0022986	-564.0192	-61.64942	-254.9377
3	0.9260017	101.7399	0.012061	-377.1732	-42.26006	-171.1189
4	0.9228213	61.79143	0.0047538	-177.6652	-10.20857	-74.638

(a) Main findings from the PVAR estimation

Overall, Table 3.3 presents the results of the first order PVAR estimation by using original data in the presence of business cycles. The key findings are summarized as follows. First, all six variables display - as expected - significant positive autoregression, implying temporal dependence of the current value of each variable on the past. Second, in line with the quantity theory of credit (the post-Keynesian school of thought), credit to the real economy ($dlcr$) significantly boosts economic growth ($dlngdp$). A 1% increase in credit to the real economy (cr) in the previous period exerts an approximately 0.112% increase in nominal GDP ($ngdp$), whereas the effect of credit to the asset markets ($dlcf$) on nominal GDP ($dlngdp$) is found to be negligible.

Table 3.3: **The Benchmark Estimations (Without Business Cycles Removal)**

$dlcpi$		$dlngdp$		$dlhpi$		$dlcf$		$dlcr$		$dirate$	
L.$dlcpi$	0.599***	L.$dlcpi$	0.384***	L.$dlcpi$	0.198	L.$dlcpi$	0.158	L.$dlcpi$	0.034	L.$dlcpi$	-0.291***
	(0.058)		(0.104)		(1.321)		(0.109)		(0.097)		-0.081
L.$dlngdp$	-0.01	L.$dlngdp$	0.223***	L.$dlngdp$	0.821	L.$dlngdp$	0.225***	L.$dlngdp$	0.103**	L.$dlngdp$	0.014
	(0.016)		(0.048)		(0.533)		(0.053)		(0.04)		(0.026)
L.$dlhpi$	0.001	L.$dlhpi$	0.014***	L.$dlhpi$	0.578***	L.$dlhpi$	0.008**	L.$dlhpi$	0.008***	L.$dlhpi$	-0.002
	(0.001)		(0.002)		(0.045)		(0.004)		(0.003)		(0.001)
L.$dlcf$	0.025**	L.$dlcf$	0.029	L.$dlcf$	-0.173	L.$dlcf$	0.413***	L.$dlcf$	0.197***	L.$dlcf$	-0.008
	(0.011)		(0.024)		(0.408)		(0.044)		(0.033)		(0.014)
L.$dlcr$	0.002	L.$dlcr$	0.112***	L.$dlcr$	1.735***	L.$dlcr$	0.280***	L.$dlcr$	0.627***	L.$dlcr$	0.054***
	(0.009)		(0.025)		(0.351)		(0.034)		(0.034)		(0.013)
L.$dirate$	-0.005	L.$dirate$	-0.392***	L.$dirate$	-6.841***	L.$dirate$	-0.373***	L.$dirate$	0.215***	L.$dirate$	0.530***
	(0.022)		(0.075)		(1.65)		(0.085)		(0.066)		(0.058)

Note: (i) *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; (ii) cpi for consumer price index, $ngdp$ for nominal GDP, hpi for nominal house prices, cr for bank credit to the real economy, cf for bank credit to the asset markets, and $irate$ for interest rates; (iii) the signal 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix '*dl*'.

Third, in terms of the effects of disaggregate credit ($dlcr$ and $dlcf$) on housing prices ($dlhpi$), credit to the real economy ($dlcr$) exerts a positive impact where its elasticity of housing prices is 1.735, which is significantly greater than its elasticity of nominal GDP ($dlngdp$) (0.112). This positive effect supports our theoretical arguments (in Section 3.2) that the increase of credit availability to house buyers can boost both housing demand and then housing prices. It is also in line with many existing studies such as Ling et al. (2016) that a reduction of credit constraints has a significant effect on increasing housing prices in the real estate market. Moreover, credit to the asset markets ($dlcf$) has a negative effect on housing prices ($dlhpi$) although insignificant. However, as theoretically expected, it may only have an insignificant and negative impact on housing prices in the short-run because of the existence of housing market disequilibrium, while its impact tends to be significant and positive in the long run, and corresponding empirical evidence will be presented later in this section. In addition, it also may be due to the disturbances of short-run periodic (cyclical) fluctuations induced by business cycles in the original data.[11] On the whole, we conclude that credit to the real economy and housing prices are mutually positive reinforcing in both the short- and long-runs. The effect of credit to the asset markets on housing prices is insignificant and negative in the short run, while it becomes positive and significant in the long run.

Fourth, both housing prices ($dlhpi$) and nominal GDP ($dlngdp$) depict significant and positive interactions with credit to the real economy ($dlcr$); the elasticities are positive and are 0.008 and 0.103, respectively. However, both nominal GDP and housing prices evince a unidirectional effect on credit to the asset markets ($dlcf$) with positive elasticities 0.225 and 0.008, respectively. Following our arguments in Section 3.2, the boom of credit is attributed to both economic (GDP) growth and housing price appreciations. It results in the growing optimism about economic conditions from (housing) market buyers/sellers, banks and other market participants. Eventually, this leads to expansions of both credit demand and supply in the real estate market (Gerlach and Peng, 2005; Muellbauer and Murphy, 2008). Fifth, the appreciation of inflation ($dlcpi$) can also be regarded as a driving force of nominal GDP ($dlngdp$), viz., a 1% increase of CPI leads to a 0.384% increase of nominal GDP, while CPI only exerts an insignificant impact on housing prices. Furthermore, interest rates negatively affects both nominal GDP and housing prices, and the corresponding semi-elasticities are -0.392 and -6.841 respectively.

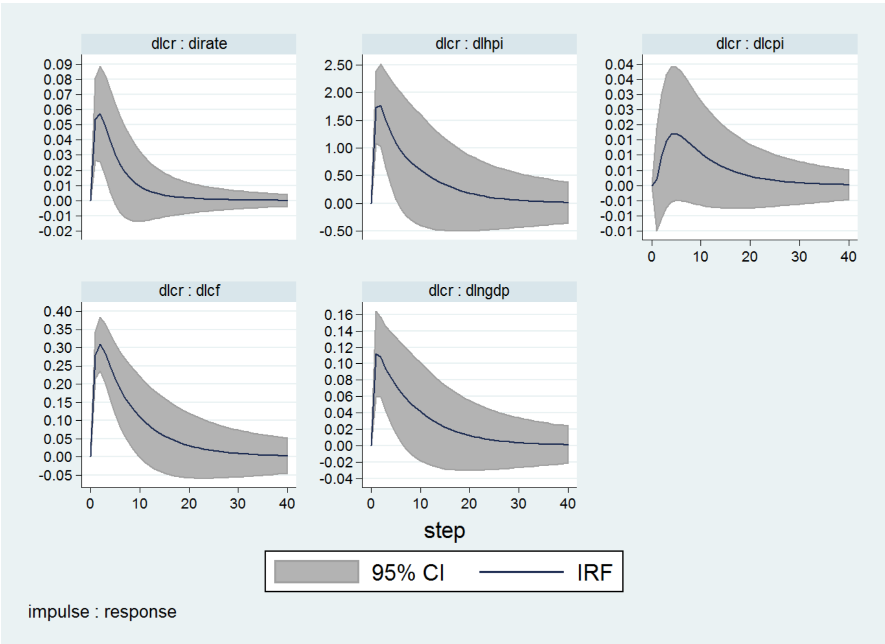
(b) Response to shocks

We now present the results from impulse-response function (IRF) analysis where we study the response of each variable to a unit shock to other variables in the system. A

[11] In Section 3.5.1.2, we demonstrate - after removing business cycles - that the effect of $dlcf$ becomes significant and positive.

generalized IRF mechanism is suitable in our case as the responses are invariant to the ordering of the variables in the panel VAR system. The corresponding IRF plots are presented in Figure 3.5 to 3.8. The IRF analysis enables us to go beyond the average estimates shown in Table 3.3 and forecast the future behaviors of response variables both in the short- and long-runs. For instance, with regard to the relationship between credit to the asset markets ($dlcf$) and housing prices ($dlhpi$), from Figure 3.6 it is clear that due to a unit shock in $dlcf$, the response of $dlhpi$ depicts a pattern of decline in a very short-run period before witnessing a rise throughout the rest of the periods. It is also worth noting that the theoretically expected positive impact of $dlcf$ on $dlhpi$ in the long-run becomes more significant, while its insignificant negative impact at the beginning periods disappears once we remove business cycles from the raw series, account for the effects of economic policy uncertainty and the global financial crisis, respectively. Corresponding IRF plots in support of this inference will be presented shortly in Figures 3.10, 3.14, and 3.19. Indeed, these empirical results can strongly support our theoretical expectations discussed in Section 3.2 that the effect of $dlcf$ on $dlhpi$ tends to be insignificant and negative in the very short run while being significant and positive in the long run.

Figure 3.5: **Generalized IRF of** $dlcr$



Moreover, in Figure 3.5, a unit shock of credit to the real economy ($dlcr$) impacts significantly and positively on all variables lasting for around 10 periods (except for CPI ($dlcpi$) which has an insignificant effect). In particular, a unit shock to $dlcr$ impacts both housing prices ($dlhpi$) and nominal GDP ($dlngdp$) positively; the effect on $dlhpi$ peaks at 1.7, which is much greater than that for $dlngdp$ (0.11). Interestingly, in terms of the IRF plots, as theoretically expected, the effect of credit to the asset markets ($dlcf$) on nominal GDP ($dlngdp$) is insignificant in most of the 40-periods (see Figure 3.6), whereas

Figure 3.6: **Generalized IRF of** $dlcf$

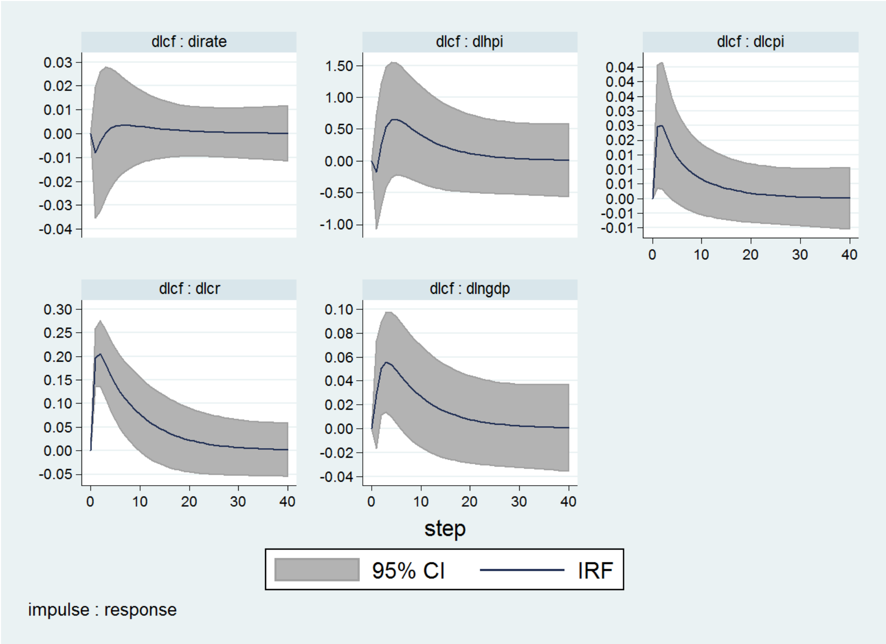
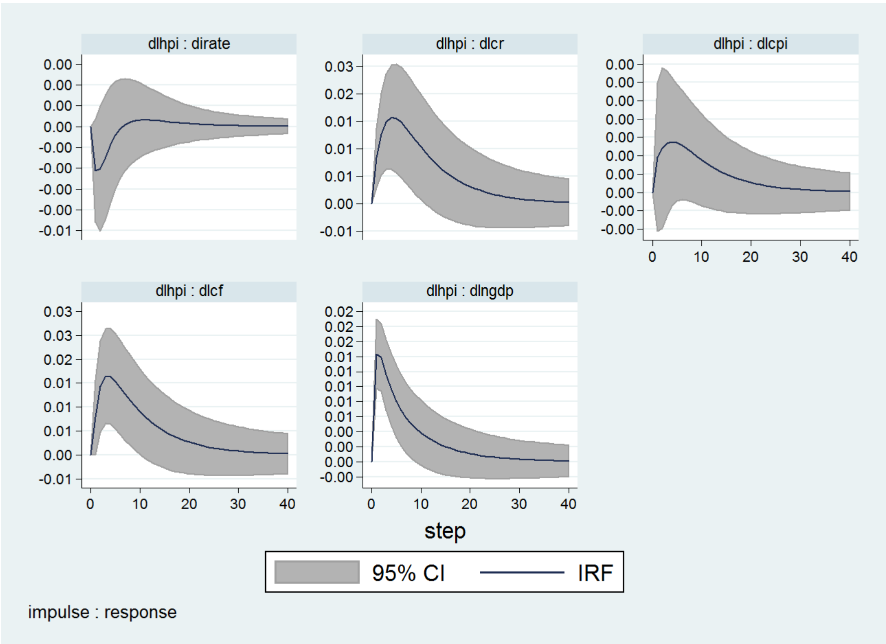
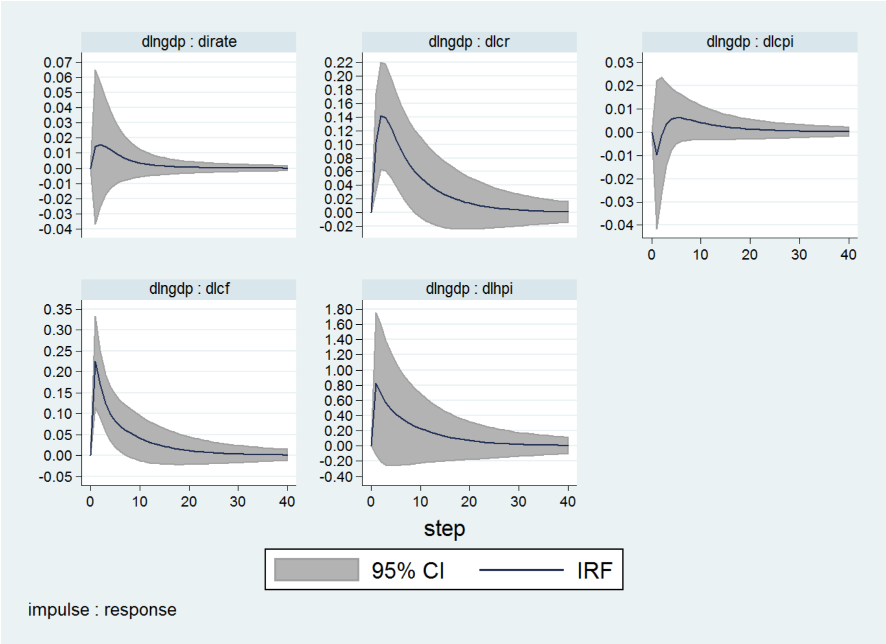


Figure 3.7: **Generalized IRF of** $dlhpi$



it turns to be significant over a short period from the 5th to 8th period. In addition, the impacts of housing prices ($dlhpi$) and nominal GDP ($dlngdp$) on other variables, including disaggregate credit (both $dlcr$ and $dlcf$), are presented in Figures 3.7 and 3.8. A unit current isolated shock to either $dlhpi$ or $dlngdp$ gives rise to a positive effect on disaggregate credit. Furthermore, $dlhpi$ exhibit a significant positive effect on $dlngdp$, while the latter only has a negligible effect on the former.

Figure 3.8: **Generalized IRF of** $dlngdp$



(c) Causality

We now determine the direction of causality among the variables. By employing Granger causality test, we find that the results are broadly consistent with the average estimates (see Table B.2 in Appendix B). Using the error variance decomposition (FEVD) technique, we also forecast how the error variance of each variable is determined by other variables including itself. The results are presented in Table B.3 in Appendix B. We find that the previous lags of each variable contribute in large part to its error variance. In particular, the contributions of credit to the real economy ($dlcr$) and credit to the asset markets ($dlcf$) to the error variance of nominal GDP ($dlngdp$) are 2.70% and 4.54%, respectively, while their contributions to housing prices ($dlhpi$) are 1.7% and 4.6%, respectively. Furthermore, $dlhpi$ explains 10.26% and 8.10% of the error variance of $dlcr$ and $dlcf$, which are all greater than the corresponding contributions of $dlngdp$.

To summarize, the panel VAR estimation of our 'untreated' data provides evidence that credit to the real economy offers a significant positive impact on nominal GDP in contrast to the insignificant impact of credit to the asset markets. It also performs a mutually positive reinforcing relationship with housing prices. Moreover, as clearly and explicitly observed from the IRF plot, credit to the asset markets first shows a negative effect on housing prices in the very short-run, and it then exerts an expected positive effect in the long-run. While the overall results hold significance in light of the theory, we also know that potential periodic fluctuations induced by business cycles could contaminate the real effects of credit, and therefore there is a necessity to remove those periodic fluctuations from the raw data preceding with the panel VAR estimation.

In the next section, we further conduct an PVAR estimation with the same variables, but now after applying the Hamilton's filer for business cycles removal.

3.5.1.2 Estimation after treatment: The effects of business cycles removal

Indeed, it is well-established that macroeconomic variables and housing prices often suffer from business cycle fluctuations, i.e., periodic fluctuations, that occur repeatedly throughout the trajectory of the growth of these variables.[12] To accurately model the dynamic interdependence among target variables, it is necessary to control for these periodic movements, a failure of which may give rise to biased inferences in interpreting the lead-lag relationship between them. The Hodrick-Prescott (H-P) filter (Hodrick and Prescott, 1997) is one of the most popular methods used to minimize these fluctuations. However, very recently Hamilton (2017) criticizes the H-P filter method on its underlying assumption to generate the smoothly-varying trend component. The author shows that the H-P method measures trend and cyclical components by artificially altering the original features of the raw series, which cannot truly replicate the dynamics of its Data Generating Process (DGP).

To avoid these fundamental weaknesses, Hamilton (2017) develops a new filtering method, which is known to be a better replication of the real Data Generation Process (DGP). It is able to decompose any a given non-stationary series by extracting a stationary part as its cyclical component, while the remaining part is defined as the trend component.[13] Thus, we remove periodic fluctuations from our data using Hamilton's filter and re-estimate the panel VAR for the benchmark model. Following Hamilton (2017), a two-year horizon is set to recognize business cycles in the raw series. The corresponding results, including coefficient estimates, Granger causality test and variance decompositions, are presented in Tables 3.4, B.4, and B.5, respectively. Impulse response function (IRF) plots of selected variables are reported in Figures 3.9 to 3.12.[14]

[12] There can be many sources of these fluctuations, and important ones are technological changes, changes in policy regime and/or financial regulations.

[13] Tian (2018) and López-Salido et al. (2017) are some of the most recent applications of the newly developed Hamilton filter.

[14] Note that the variables used in this estimation are *treated/de-cycled* as we have filtered out cyclical components from the raw series.

Table 3.4: **The Benchmark Estimations (Business Cycles Removal)**

dlcpi		*dlngdp*		*dlhpi*		*dlcf*		*dlcr*		*dirate*	
L.*dlcpi*	0.418***	L.*dlcpi*	0.464***	L.*dlcpi*	-0.032	L.*dlcpi*	0.997***	L.*dlcpi*	0.416**	L.*dlcpi*	0.052
	(0.051)		(0.125)		(0.101)		(0.214)		(0.168)		(0.041)
L.*dlngdp*	0.023**	L.*dlngdp*	0.143***	L.*dlngdp*	-0.014	L.*dlngdp*	0.184***	L.*dlngdp*	0.180***	L.*dlngdp*	-0.012
	(0.011)		(0.037)		(0.026)		(0.054)		(0.067)		(0.011)
L.*dlhpi*	0.003	L.*dlhpi*	0.213***	L.*dlhpi*	0.692***	L.*dlhpi*	0.271***	L.*dlhpi*	0.202***	L.*dlhpi*	-0.001
	(0.009)		(0.025)		(0.037)		(0.048)		(0.043)		(0.011)
L.*dlcf*	0.027***	L.*dlcf*	0.05	L.*dlcf*	0.062***	L.*dlcf*	0.206***	L.*dlcf*	0.170***	L.*dlcf*	-0.003
	(0.007)		(0.035)		(0.022)		(0.058)		(0.036)		(0.007)
L.*dlcr*	-0.002	L.*dlcr*	0.077***	L.*dlcr*	0.037**	L.*dlcr*	0.074*	L.*dlcr*	0.251***	L.*dlcr*	0.022***
	(0.007)		(0.026)		(0.017)		(0.043)		(0.040)		(0.007)
L.*dirate*	0.007	L.*dirate*	-0.137**	L.*dirate*	0.175**	L.*dirate*	-0.024	L.*dirate*	0.739***	L.*dirate*	0.556***
	(0.021)		(0.064)		(0.078)		(0.109)		(0.117)		(0.046)

Note: (i) *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; (ii) *cpi* for consumer price index, *ngdp* for nominal GDP, *hpi* for nominal house prices, *cr* for bank credit to the real economy, *cf* for bank credit to the asset markets, and *irate* for interest rates; (iii) the signal 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix '*dl*'.

Overall, the results of this re-estimation using the treated/de-cycled data are broadly consistent with the benchmark estimation from the untreated data. On top of that, two main findings emerge. First, in terms of the impacts of credit to the real economy ($dlcr$) on nominal GDP ($dlngdp$), we find that only $dlcr$ presents a significant positive effect on $dlngdp$, which is 0.077, in contrast to the insignificant effect of credit to the asset markets ($dlcf$). These results are consistent with *the post-Keynesian school of thought*. As expected, $dlcr$ also exerts a significant positive impact on housing prices ($dlhpi$). Conversely, both $dlngdp$ and $dlhpi$ impact $dlcr$ positively. In addition, it is worth noting that interactions between $dlcr$, $dlngdp$, and $dlhpi$ obtained in this benchmark re-estimation with business cycles removal (Table 3.4) are comparatively smaller than the ones obtained without business cycles removal (Table 3.3).

Second, the effect of credit to the financial markets ($dlcf$) on housing prices ($dlhpi$) is significantly positive after de-cycling the data, in contrast to insignificant and negative in the benchmark estimation (without business cycles removal) in Table 3.3. Specifically, as shown in Table 3.4, a 1% unit change of cf induces a 0.062% change of hpi in the same direction, while its effect is nearly twice as larger as that of cr. Furthermore, the corresponding IRF plots (Figure 3.10) and Granger Causality test (Table B.4) provide further supporting evidence for our proposition. In particular, through Figure 3.10, we obtain a theoretically expected effect of credit to the asset markets on housing prices in the long-run, viz. significant and positive. It is because that the negative and insignificant result obtained earlier in the benchmark model (without cycles removal) could be due to the contamination of short-run periodic disturbances in the original data. These are clearly seen to underestimate the real impacts of components of credit on housing prices in the long-run. Indeed, the 'treated' data present the theoretically expected sign and significance in contrast to the 'untreated' data.

To summarize, the removal of business cycles from the raw data appears to have helped in eliminating the periodic disturbances in the short-run. The panel VAR estimation using de-cycled data thus produces sharp and distinct effects of long-term interactions among variables. In addition, the confidence intervals of IRF plots in this sense become more narrow in contrast to the ones using the original data, implying a more accurate result. From a broader perspective, the benchmark estimates without business cycles are consistent with the ones with business cycles. Together, they lend solid empirical supports to our theoretical construct regarding the complex dynamics of housing-macroeconomy-credit interactions.

Figure 3.9: **Generalized IRF of** $dlcr$

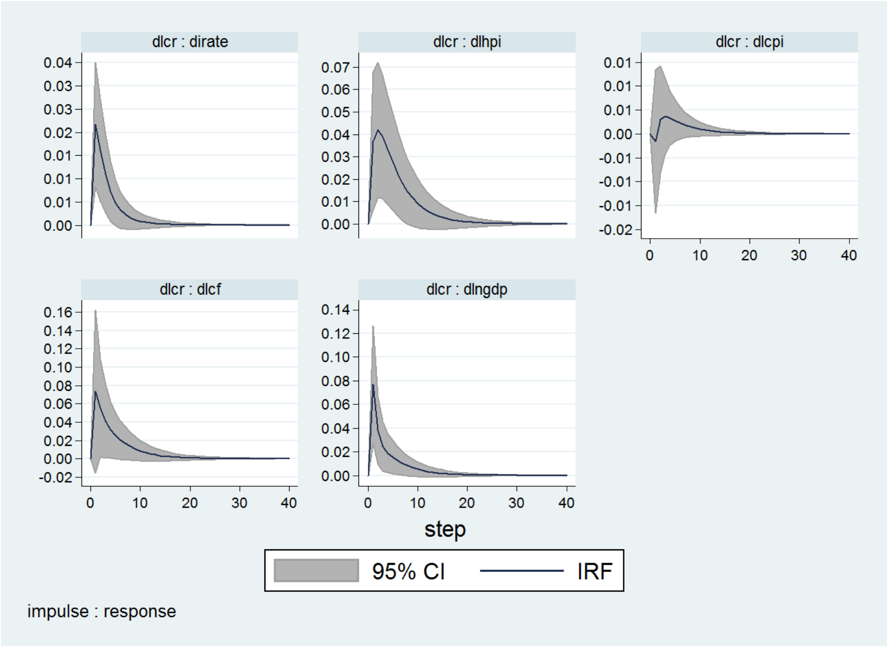


Figure 3.10: **Generalized IRF of** $dlcf$

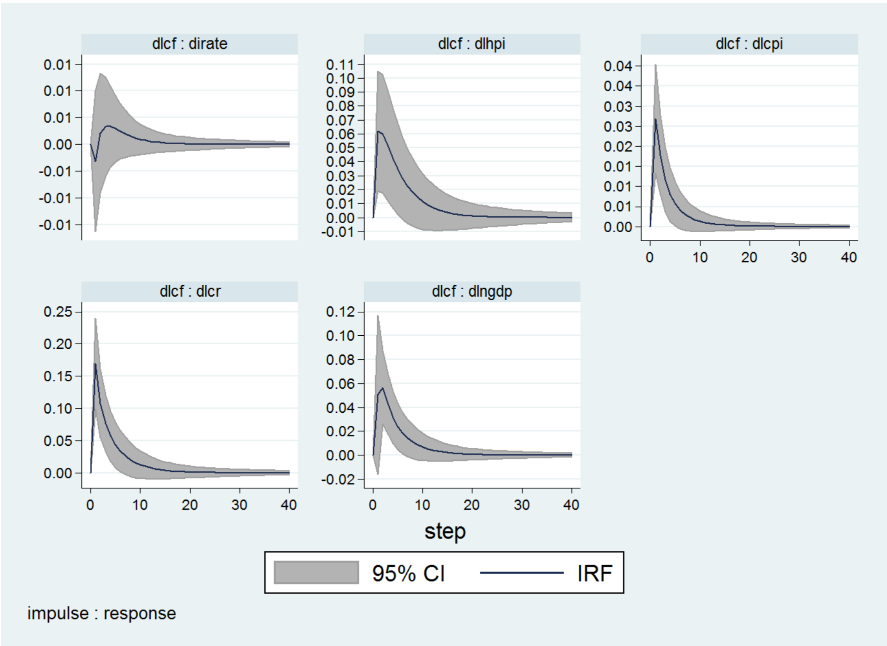


Figure 3.11: **Generalized IRF of** $dlhpi$

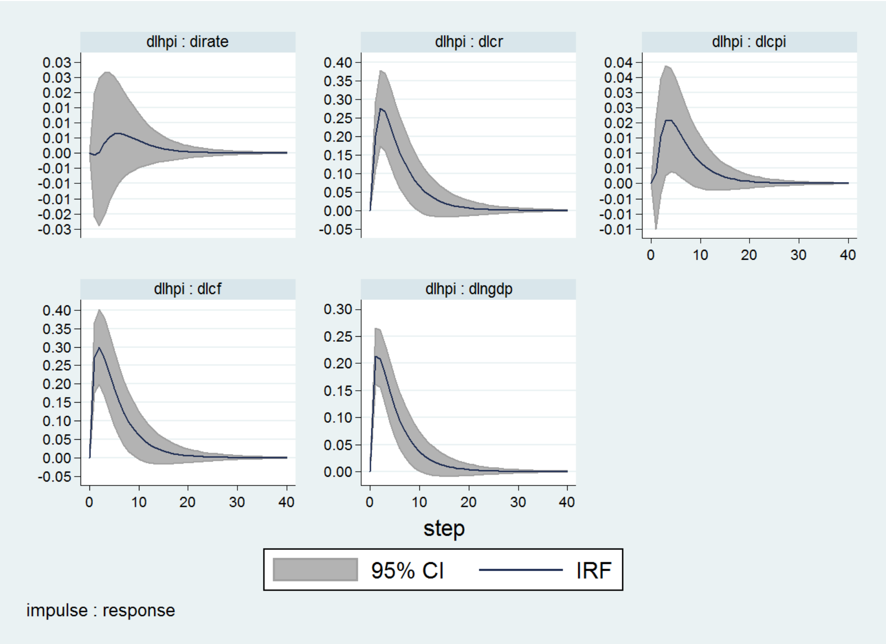
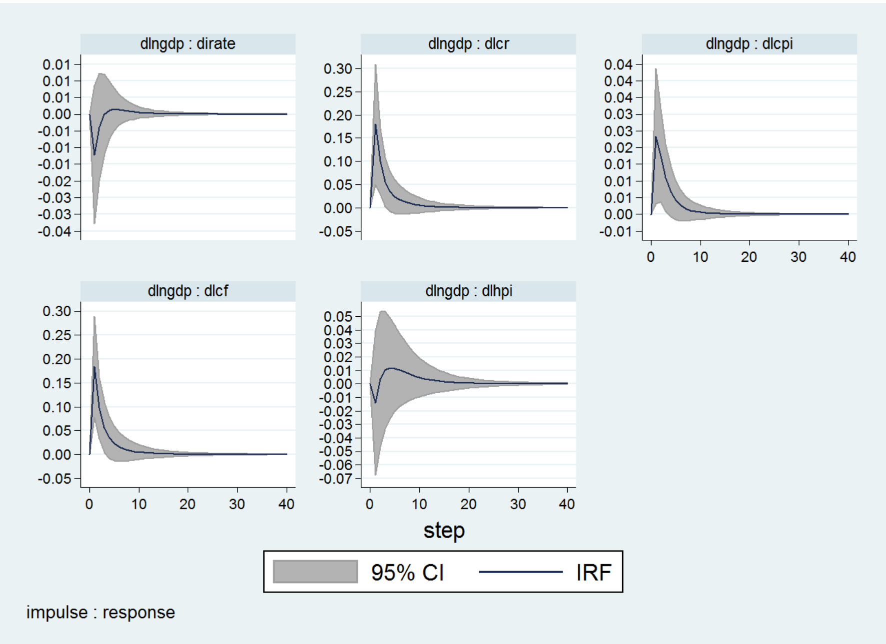


Figure 3.12: **Generalized IRF of** $dlngdp$



3.5.2 Robustness checks

How robust are our benchmark estimates in the presence of economic policy uncertainty (EPU) and global financial crisis (GFC)? The EPU is known to limit free movements of credit in the asset markets and in the real economy, while GFC can serve as a structural break point. Hence, the uncertainty and the structural break may alter the dynamic interdependence among our target variables. We examine their impacts below.

3.5.2.1 Accounting for the effects of economic policy uncertainty

Baker et al. (2016), among others, show that economic policy uncertainty significantly impacts real economic fluctuations. Researchers have argued that a heightened uncertainty gives rise to periods of sustained volatility, which invariably manifest negative psychological effects among investors. Due to the robust empirical evidence and sound theoretical foundations of the role of uncertainty in real economic variations, it is reasonable to assume that persistent uncertainty can produce the asymmetric information in the economic system. The significant rise of global economic policy uncertainty (see Figure B.1 in Appendix B) implies that credit to both the real economy and the asset markets may be trapped under the asymmetric information leading to a suboptimal flow than would be expected under a stable economic environment. Using the EPU index of Baker et al. (2016) at the global level, we find that the EPU has experienced an average annual growth of 6.51%. Thus, how much credit should be supplied to the real economy and the financial markets also becomes a policy question. Due to this rising uncertainty, real-estate investors may not be willing to invest a big amount in the property market, while the buyers' perception is also negative.

To examine the impact of uncertainty, we add the EPU index[15] to our data set and re-estimate panel VAR.[16] We aim to condition the dynamic interdependence among variables to the movements of uncertainty and particularly shed light on the true effects that disaggregate credit might have on macroeconomic fluctuations. The results are summarized in Tables 3.5, B.6, and B.7 respectively. From Table 3.5, we find that the addition of uncertainty does not alter the main conclusions from the benchmark estimations (see Table 3.4), while obtained results are also consistent with our theoretical expectations. Specifically, credit to the real economy ($dlcr$) exerts significant positive effects on both nominal GDP ($dlngdp$) and housing prices ($dlhpi$), which are 0.098 and 0.050 respectively, while such positive effects are also bidirectional.

Moreover, credit to the asset markets ($dlcf$) exerts no significant effect on $dlngdp$, while its impact on $dlhpi$ is significant and positive. In addition to the averaged estimates, the IRF plot in Figure 3.14 demonstrates that $dlhpi$ witnesses an significant increasing movement for around 10 periods after a current unit shock to $dlcf$. Its positive movement only decays to zero after the 20th period, which particularly indicates that the

[15]For each country except Switzerland, the EPU index is available from http://www.policyuncertainty.com. The Swiss EPU index can be downloaded from KOF Swiss Economic Institute through https://www.kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-uncertainty-indicator.html. Moreover, we have to exclude Belgium as its EPU index is currently not available.

[16]Given the superiority of the de-cycled data to the raw data, we present results from the data after removing business cycles. The results for the raw data are also consistent with the counterparts in the benchmark estimation.

effect of cf tends to be deepened after considering uncertainty compared with the one reported in the benchmark (See in Figure 3.10). It also speaks in favor of our early arguments that the insignificant and negative effect of $dlcf$ on $dlhpi$ reported in Table 3.3 is contaminated by the existence of business cycles. Overall, all the above results support our theoretical discussions in Section 3.2.3 regarding the interaction between disaggregate credit (cr and cf) and hpi.

Furthermore, as demonstrated in Tables 3.5, nominal GDP ($dlngdp$) and housing prices ($dlhpi$) depict significant positive effects on disaggregate credit ($dlcr$ and $dlcf$); the corresponding magnitudes are similar both in direction and in size with the ones in the benchmark estimation with cycles removal (See in Table 3.4). In addition, the EPU index ($dluncer$) imparts a significant negative effect on key macroeconomic variables, such as nominal GDP and housing prices. This result might indicate that an increasing uncertainty would depress economic activities due to a fall in the level of confidence among investors and the asymmetric information it manifests within an economy. A rise in uncertainty can also negatively affect bank credit (both cf and cr) although insignificant.

In terms of impulse response functions (IRF) (see Figures 3.13 to 3.16), predictive movements of $dlcr$, $dlcf$, $dlhpi$, and $dngdp$ are consistent with their corresponding impulses at the benchmark estimation. In particular, it is worth noting that after comparing both coefficient estimates and IRF plots from models with and without uncertainty ($dluncer$), the interactions between both components of aggregated credit ($dlcr$ and $dlcf$) and $dlhpi$ become more pronounced once controlling for the uncertainty ($dluncer$). Moreover, as theoretically expected, the IRF plot of uncertainty ($dluncer$) shown in Figure 3.17 provides evidence of the significant negative effect on key macroeconomic variables, including nominal GDP and housing prices. However, although it does not significantly affect both $dlcr$ and $dlcf$ until the 10th period, this could help explain why the averaged negative effect of $dluner$ on $dlcr$ and $dlcf$ presented Table 3.5 is insignificant.

Furthermore, the corresponding results of the Granger causality test (in Table B.6) are also consistent with the averaged estimated coefficients in Table 3.5. At the 5% significant level, $dlcr$ Granger causes both $dlngdp$ and $dlhpi$ respectively, and such causal relationships appear to be bidirectional; $dlcf$ does not Granger cause $dlngdp$ but $dlhpi$; $dluncer$ Granger causes $dlngdp$ and $dlhpi$. Regarding the results of variance decomposition (FEVD) shown in Table B.7, we find that they broadly mimic the results of FEVD in the benchmark. In particular, although significant, the contributions of uncertainty ($dluncer$) to the changes of error variance of key economic variables are relatively small.

Overall, it is concluded that adding uncertainty to our benchmark model does not alter the broad conclusions from the benchmark estimation. Rather, we found that inclusion of economic policy uncertainty in the benchmark model enriches our inferences on the exact impacts of components of credit on housing prices and nominal GDP.

3.5.2.2 The effect of the global financial crisis

The intervention of the Global Financial Crisis (GFC) is known to slow the growth of key economic fundamentals across countries. Arguably the largest impact has been felt in the housing market as it was measurably affected by information cascades and weak lending restrictions. Furthermore, a visual inspection of Figure 3.3 also reveals the negative impacts of the outbreak of the global financial crisis on our economic variables. All the above motivate us to study GFC's real impacts in our empirical exercise. Thus, to gauge its impacts on the interdependence among target variables in our estimation, we follow National Bureau of Economic Research (2010) and introduce a time dummy variable (fc) to capture the outbreak of GFC, where its value equals to 1 from 2008Q1 to 2009Q2 depicting the presence of a break point, and 0 otherwise. To begin with, we perform the Chow test to confirm this structural break. The null hypothesis of time stability for the outbreak of GFC in housing prices is rejected at 5% level of significance, since the χ^2 statistic is 12.91.[17]

The results of the re-estimation of the PVAR regression after accounting for the effect of the crisis are reported in Tables 3.6, B.8, and B.9. Corresponding IRF plots of key variables are presented in Figures 3.18 to 3.22. It is evident that our conclusions remain consistent with our theoretical expectations discussed in Section 3.2.3 as well as the benchmark estimates (See in Table 3.4); there is no significant difference between the estimations before and after the intervention of the global financial crisis (GFC). In other words, adding such a time dummy does not considerably alter our conclusions of the effects of credit shocks on housing prices and other economic variables. One notable conclusion emerges from this regression though; the global financial crisis tends to dampen the dynamics of key economic variables, including nominal GDP and housing prices, producing significant negative effects on $dlngdp$ and $dlhpi$, which are -0.400 and -0.153, respectively in Table 3.6.

As expected from our main estimates, $dlcr$ presents bidirectional positive interactions with both $dlngdp$ and $dlhpi$. $dlcf$ exerts a significant positive effect on $dlhpi$ while has no significant effect on $dlngdp$. In particular, consistent with the benchmark estimates and presented in Figure 3.19, after a current unit shock to $dlcf$, $dlhpi$ experiences a positive and significant movement lasting for 10 periods, while returns to zero after 20 periods. In addition, similar moving patterns of response variables (in face of a current unit shock to $dlcr$, $dlhpi$, and $dlngdp$) to the ones in the benchmark estimates

[17] In addition to imposing an exogenous/certain break point, we also performed a sequential break point test or Sup-Wald test following Andrews (1993). The estimated value in the first iteration was found to be larger than the critical value at 5% significance level provided by Andrews (2003), but lower than in the second iteration, hence we concluded that there was only one structural break at year 2008.

are obtained and presented in Figures 3.18, 3.20, and 3.21, respectively. Examining the IRF plot in Figure 3.22 in particular, we find that apart from the negative influences of the outbreak of GFC on $dlhpi$ and $dlngdp$, the GFC exerts a positive effect on $dlcr$ rather than $dlcf$, which tends to be in line with the extensively implemented quantitative easing policy in the real economy to stimulate economic growth after the outbreak of GFC.

Overall, by studying the averaged estimates (in Table 3.6), Granger causality test (in Table B.8) and variance decomposition (in Table B.9) along with the impulse response function plots from Figures 3.18 to 3.22, we conclude that the results are consistent with our benchmark estimations.

3.6 Conclusions and Implications

In line with Keynesian arguments on the quantity theory of credit, we propose a conceptual construct to demonstrate that *disaggregated* credit possesses quantitatively important information regarding their impacts on the demand-supply interactions in the housing market and on the real economy. We show that the two defined components of credit exert distinct policy-relevant impacts on housing demand and housing supply. The effects are shown to be robust and exactly identifiable. We also shed light on a likely bias in the estimation with cycle-unadjusted data because the latter often displays varied convergence processes and non-synchronized paths of co-movements of the temporal variables within a system. In addition, asymmetric information arising from persistence in economic policy uncertainty, can also significantly determine the magnitude and dynamics of credit distribution within a real economic and financial system. Our three-pronged strategy, viz., disaggregation of credit, cyclical adjustment of all variables, and explicit treatment of economic policy uncertainty unravels the true effects of credit in the short-run and long-run movements of housing prices and macroeconomic variables.

Consistent with our theoretical expectations, the main conclusion of the chapter is that *credit-to-the-real-economy* engages in a dynamic and mutually reinforcing relationship with housing prices, whereas *credit-to-the-asset-markets* and housing prices tend to be intertwined and appear to affect each other through a complex mechanism. Specifically, *credit-to-the-asset-markets* is found to leave a negligible negative effect on housing prices in the very short-run and a strong positive effect in the long-run. Only *credit to the real economy* rather than *credit to the asset markets* is found to significantly contribute towards economic growth. The introduction of economic policy uncertainty into the interplay of credit-housing market-real economy fluctuations further supports our results. In particular, the interactions between both components of credit and housing prices tend to become more pronounced once we have controlled for the effects of economic policy uncertainty. Moreover, consistent with the literature, both uncertainty and the global financial crisis give rise to significant negative effects on the key macroeconomic variables including housing prices and nominal GDP.

Our results possess valuable insights for policy. First, since *aggregate* credit presents only 'averaged out' real effects of its *components*, policy makers may like to minimize significant loss of microlevel information by using *disaggregate* credit so that an optimal allocation of credit to the real economy and the financial markets is made. Second, economic policy uncertainty is a persistent phenomenon in modern economic and financial systems and its detrimental role cannot be overlooked while modeling dynamic interactions among macro-financial variables and the asset markets/real economy in general, and the credit market and the housing market/real economy, in particular. Third, ours is a cross-country study and in a way, our findings of the various effects of credit are more representative than the ones from single country studies. An appropriate policy intervention is necessary to accelerate/decelerate money supply depending on our insights into the *distinct influences of different money circulation channels* on various markets. Such a knowledge can help policy makers implement a balancing strategy to limit risks of 'overheating in the housing market and the real economy'.

Table 3.5: **The Estimations: Robustness Check (Adding Uncertainty Index)**

$dlcpi$		$dlngdp$		$dlhpi$		$dlcf$		$dlcr$		$dirate$		$dluncer$	
L.$dlcpi$	0.389***	L.$dlcpi$	0.407***	L.$dlcpi$	-0.196*	L.$dlcpi$	1.134***	L.$dlcpi$	0.687***	L.$dlcpi$	0.137***	L.$dlcpi$	1.301***
	(0.047)		(0.113)		(0.111)		(0.222)		(0.152)		(0.033)		(0.227)
L.$dlngdp$	0.007	L.$dlngdp$	0.012	L.$dlngdp$	-0.037*	L.$dlngdp$	0.270***	L.$dlngdp$	0.161***	L.$dlngdp$	-0.007	L.$dlngdp$	0.067
	(0.010)		(0.025)		(0.019)		(0.055)		(0.062)		(0.008)		(0.062)
L.$dlhpi$	0.008	L.$dlhpi$	0.234***	L.$dlhpi$	0.745***	L.$dlhpi$	0.339***	L.$dlhpi$	0.291***	L.$dlhpi$	0	L.$dlhpi$	-0.009
	(0.008)		(0.021)		(0.031)		(0.042)		(0.033)		(0.008)		(0.058)
L.$dlcf$	0.022***	L.$dlcf$	0.036	L.$dlcf$	0.065***	L.$dlcf$	0.209***	L.$dlcf$	0.206***	L.$dlcf$	0.005	L.$dlcf$	-0.115***
	(0.005)		(0.022)		(0.018)		(0.053)		(0.029)		(0.005)		(0.042)
L.$dlcr$	0.005	L.$dlcr$	0.098***	L.$dlcr$	0.050***	L.$dlcr$	0.052	L.$dlcr$	0.167***	L.$dlcr$	0.023***	L.$dlcr$	0.012
	(0.006)		(0.022)		(0.013)		(0.041)		(0.033)		(0.006)		(0.050)
L.$dirate$	-0.002	L.$dirate$	-0.328***	L.$dirate$	0.323***	L.$dirate$	0.689***	L.$dirate$	0.766***	L.$dirate$	0.468***	L.$dirate$	-0.941***
	(0.021)		(0.056)		(0.075)		(0.132)		(0.110)		(0.036)		(0.155)
L.$dluncer$	0.006	L.$dluncer$	-0.036***	L.$dluncer$	-0.046***	L.$dluncer$	-0.021	L.$dluncer$	-0.012	L.$dluncer$	0.001	L.$dluncer$	-0.107***
	(0.004)		(0.011)		(0.012)		(0.022)		(0.019)		(0.003)		(0.031)

Note: (i) *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; (ii) cpi for consumer price index, $ngdp$ for nominal GDP, hpi for nominal house prices, cr for bank credit to the real economy, cf for bank credit to the asset markets, $irate$ for interest rates, and $uncer$ for EPU index; (iii) the signal 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix 'dl'.

Figure 3.13: **Generalized IRF of** $dlcr$

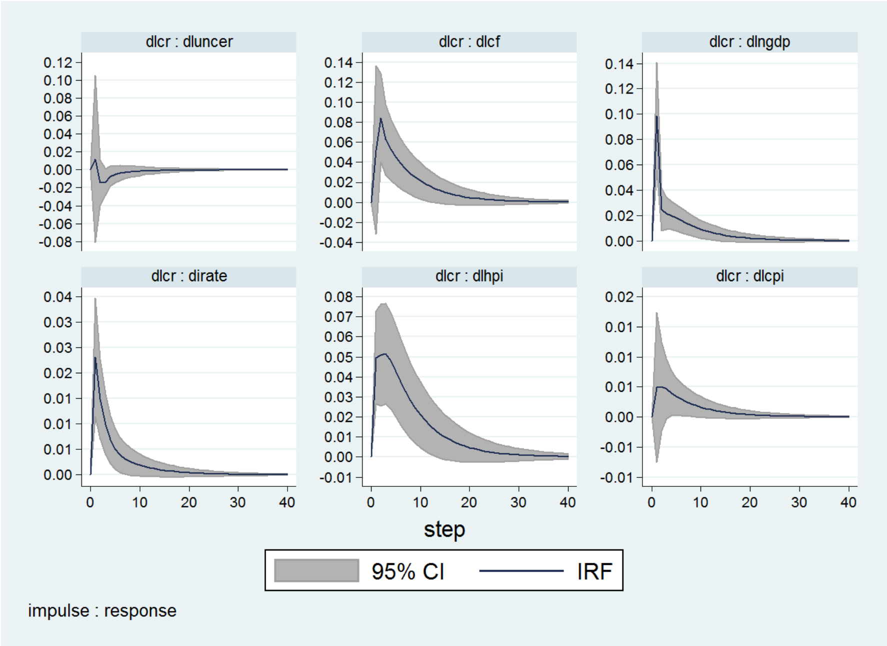


Figure 3.14: **Generalized IRF of** $dlcf$

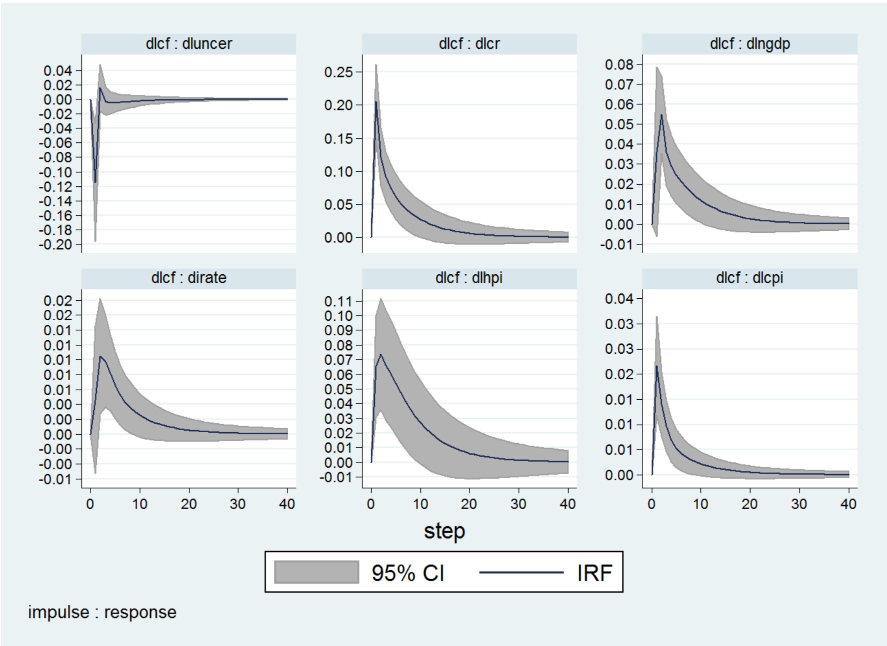


Figure 3.15: **Generalized IRF of** $dhpi$

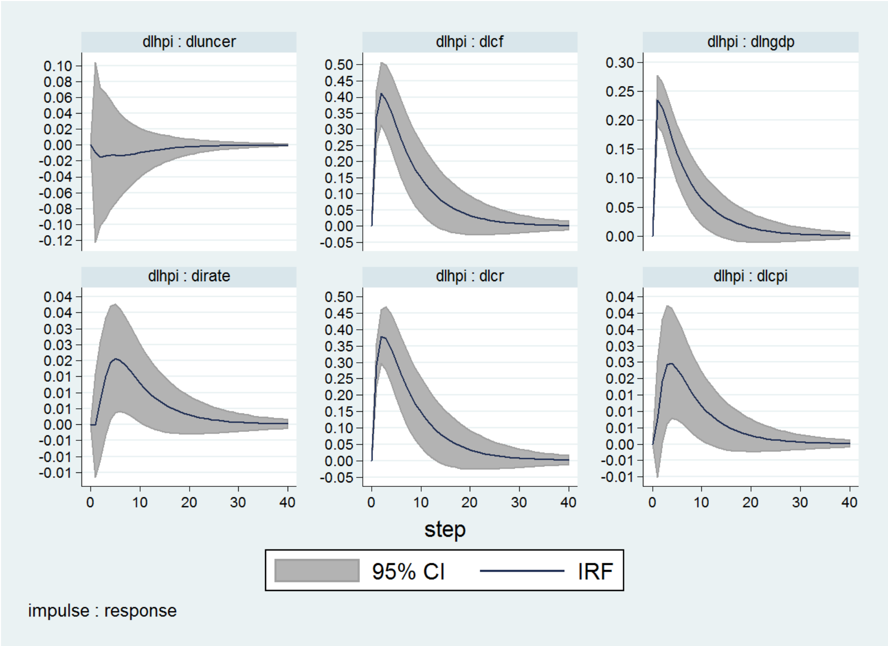


Figure 3.16: **Generalized IRF of** $dlngdp$

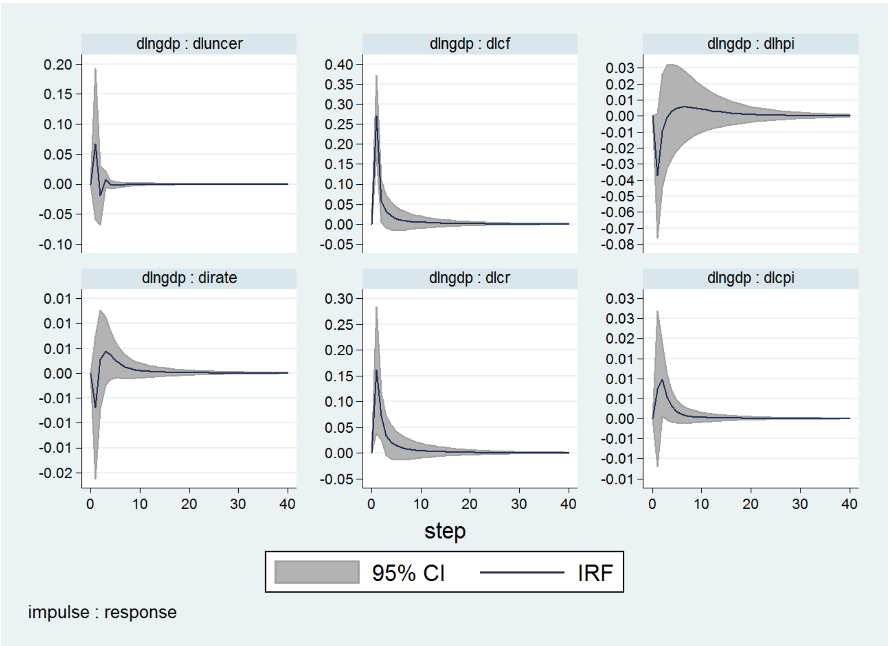


Figure 3.17: **Generalized IRF of** $dluncert$

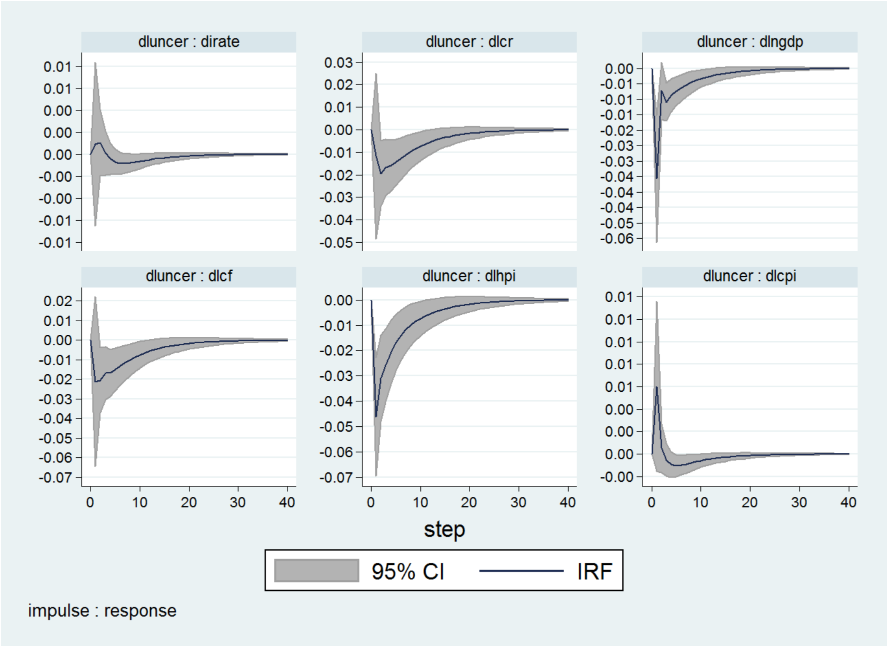


Table 3.6: **The Estimations: Robustness Check (Considering Global Financial Crisis)**

$dlcpi$		$dlngdp$		$dlhpi$		$dlcf$		$dlcr$		$dirate$		fc	
L.$dlcpi$	0.561***	L.$dlcpi$	0.888***	L.$dlcpi$	-0.259***	L.$dlcpi$	1.207***	L.$dlcpi$	1.007***	L.$dlcpi$	0.041	L.$dlcpi$	0.008***
	(0.038)		(0.089)		(0.083)		(0.153)		(0.133)		(0.028)		(0.003)
L.$dlngdp$	0.009	L.$dlngdp$	0.028	L.$dlngdp$	0.006	L.$dlngdp$	0.181***	L.$dlngdp$	0.081	L.$dlngdp$	-0.005	L.$dlngdp$	0.001
	(0.010)		(0.029)		(0.021)		(0.044)		(0.057)		(0.008)		(0.001)
L.$dlhpi$	0.001	L.$dlhpi$	0.227***	L.$dlhpi$	0.696***	L.$dlhpi$	0.276***	L.$dlhpi$	0.258***	L.$dlhpi$	0.016**	L.$dlhpi$	0.001
	(0.007)		(0.019)		(0.030)		(0.041)		(0.035)		(0.008)		(0.001)
L.$dlcf$	0.019***	L.$dlcf$	0.016	L.$dlcf$	0.064***	L.$dlcf$	0.197***	L.$dlcf$	0.193***	L.$dlcf$	-0.007	L.$dlcf$	-0.001
	(0.005)		(0.018)		(0.017)		(0.043)		(0.025)		(0.005)		(0.001)
L.$dlcr$	0.007	L.$dlcr$	0.118***	L.$dlcr$	0.048***	L.$dlcr$	0.062*	L.$dlcr$	0.201***	L.$dlcr$	0.020***	L.$dlcr$	0.003***
	(0.006)		(0.021)		(0.013)		(0.037)		(0.033)		(0.006)		(0.001)
L.$dirate$	0.023	L.$dirate$	-0.178***	L.$dirate$	0.328***	L.$dirate$	0.059	L.$dirate$	0.824***	L.$dirate$	0.614***	L.$dirate$	0.001
	(0.020)		(0.052)		(0.074)		(0.088)		(0.095)		(0.032)		(0.001)
L.fc	-0.152***	L.fc	-0.400***	L.fc	-0.153*	L.fc	0.088	L.fc	1.665***	L.fc	0.021	L.fc	0.897***
	(0.027)		(0.079)		(0.093)		(0.189)		(0.181)		(0.015)		(0.012)

Note: (i) *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; (ii) cpi for consumer price index, $ngdp$ for nominal GDP, hpi for nominal house prices, cr for bank credit to the real economy, cf for bank credit to the asset markets, $irate$ for interest rates, and fc for the global financial crisis; (iii) the signal 'L.' denotes the first temporal lag of the variable, and variables in the first-differenced logarithms begin with a prefix 'dl'.

Figure 3.18: **Generalized IRF of** $dlcr$

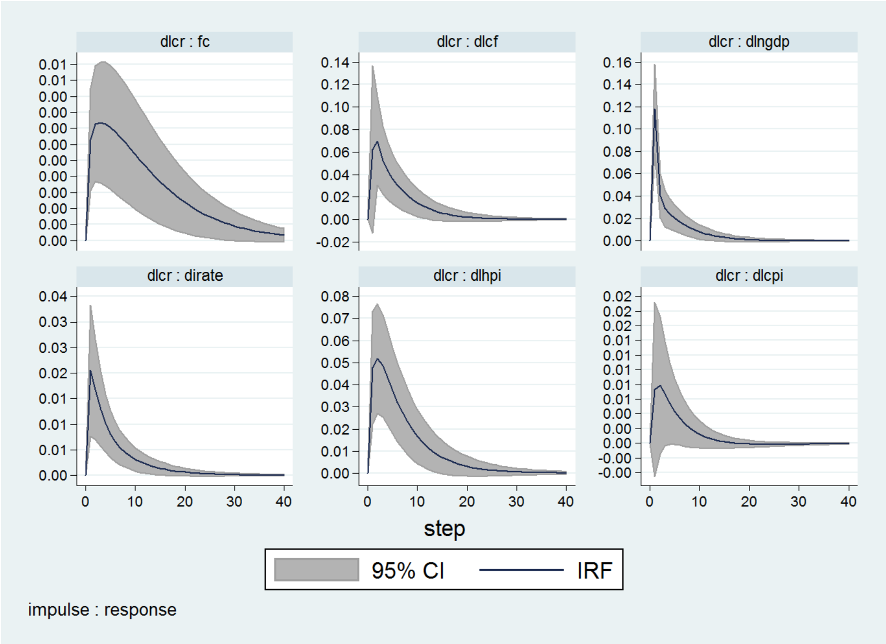


Figure 3.19: **Generalized IRF of** $dlcf$

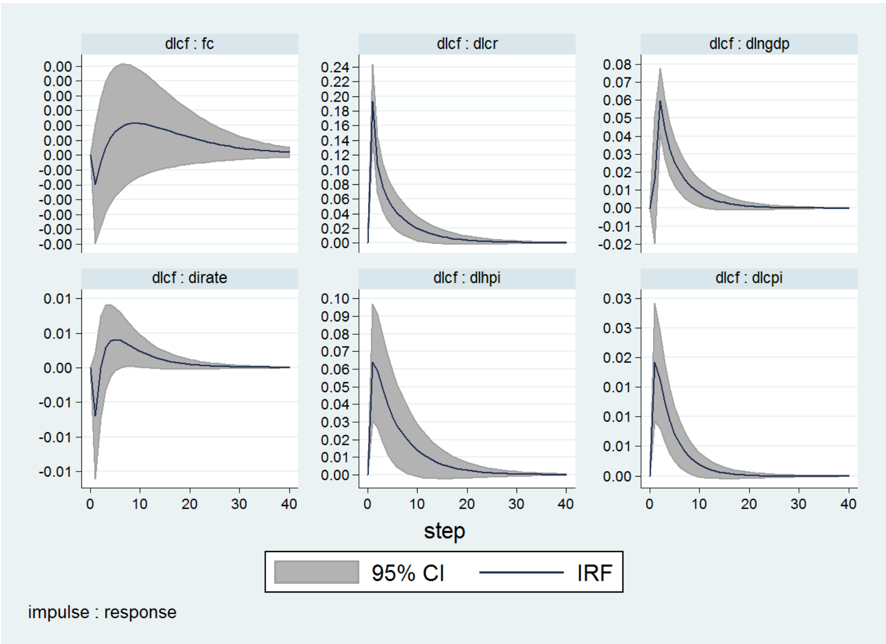


Figure 3.20: **Generalized IRF of** $dlhpi$

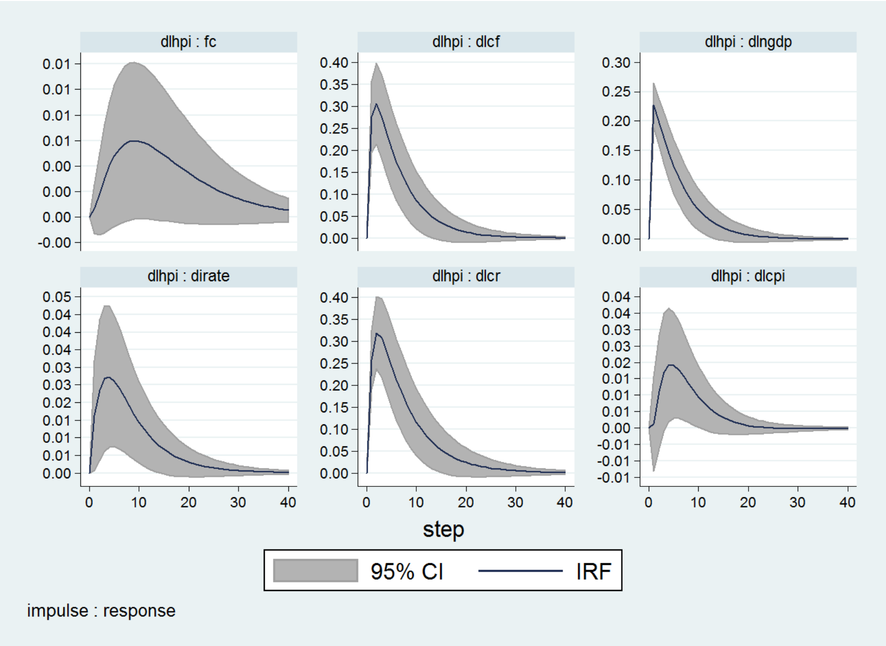


Figure 3.21: **Generalized IRF of** $dlngdp$

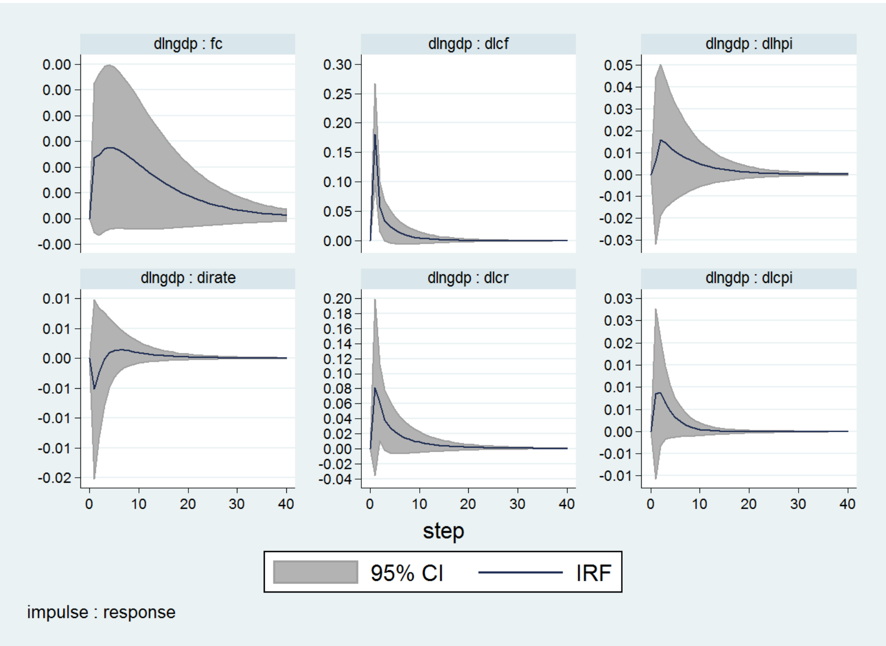
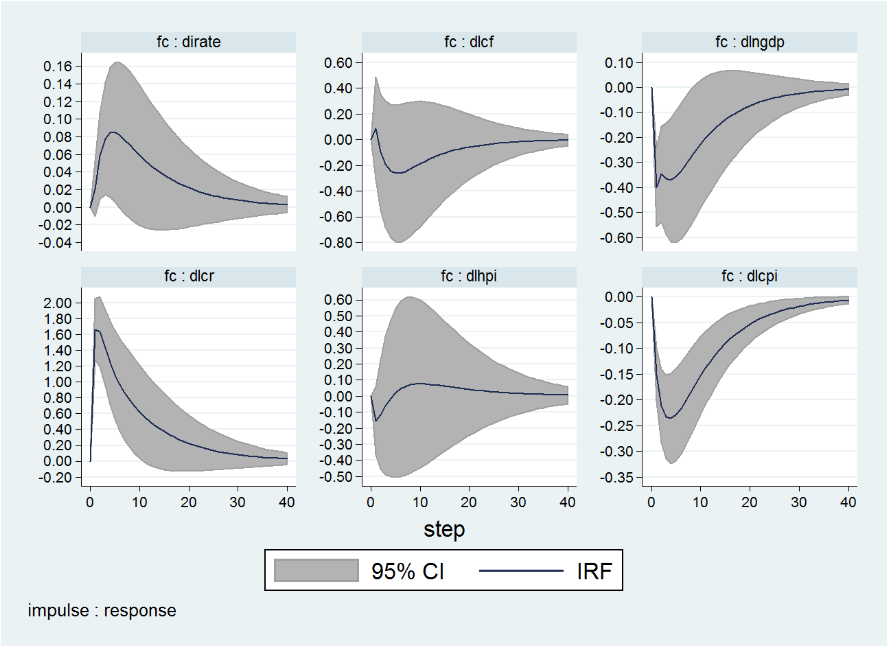


Figure 3.22: **Generalized IRF of** fc



Chapter 4

Memory and Dynamic Co-movements in Housing Prices and Macroeconomic Fundamentals: A Fractionally Cointegrated VAR Approach

4.1 Introduction

The extant literature finds that macroeconomic conditions can significantly affect asset price movements (see for instance, Arestis and Gonzalez-Martinez, 2016; Duan et al., 2018a,b). A deep understanding of asset price dynamics can help policymakers design rational macroeconomic policies in achieving stable long-run economic conditions (Carstensen, 2006). It is well-known that a macroeconomic determinant could impact housing prices either exclusively through housing demand or supply functions or simultaneously through both functions, while the equilibrium price level tends to be a trade-off between determinants from these two functions. Thus, quantifying impacts of macroeconomic fundamentals on housing prices requires a clear identification of distinct effect-transmission channels in the macroeconomy-housing market interactive system. Simply building a combined housing price determination equation including both demand- and supply-driven factors would intertwine the real impacts of macroeconomic variables and therefore induce inconclusive results.

Indeed, some prior literature reports a 'puzzled' housing price behaviour in the face of a macroeconomic shock. It could be as a result of dual and distinct impacts of the shock on shifting both housing demand and supply curves, respectively. For example, McCarthy and Peach (2002) observe that housing prices first rise over a short period and then fall given a positive shock to federal funds rate.[1] Moreover, given a fixed housing demand, a rising economic policy uncertainty could induce a more cautious response of housing supply due to an intrinsic irreversibility of residential fixed investment (Tsatsaronis and Zhu, 2004), while it also tends to depress individuals' house purchase intentions given its large transaction-to-whole-wealth ratio and an increasing role of risk aversion. Thus, we argue that a clear identification of the transmission channels is of key importance to measure the true impacts of demand- and supply-driven factors on housing price movements.

Moreover, as stochastic shocks could taper-off slowly towards the long-run mean, without considering that, it is very challenging to identify a stable co-movement structure between housing prices and macroeconomic variables. In addition, there exists compelling evidence of a gradual price adjustment towards the market equilibrium rather than an instant market clearing as conventionally assumed (DiPasquale and Wheaton, 1994). Thus, controlling for both the slowly-converged shocks with a long-memory decay and the gradual price adjustment are very important to a precise identification and estimation of the dynamic co-movements in the macroeconomy-housing market interaction. To the best of our knowledge, this still has not been encapsulated by literature either from a theoretical or from an empirical perspective.

[1] A more detailed discussion is provided in Section 4.2.

Our chapter aims to fill this gap by disentangling the dynamic interaction, and quantifying the extent to how macroeconomic fundamentals precisely determine equilibrium housing prices through the distinct transmission channels in a long-memory cointegration framework. To do that, we first build a conceptual framework in which equilibrium housing price determinations can be explained through both housing demand and supply functions, respectively. This way, we are able to gauge explanatory powers of the macroeconomic variables that exclusively impact on either the demand or the supply sides. More importantly, we can also unravel the dual roles of specific variables which affect housing prices simultaneously on both sides. Unlike much existing literature which neglects the role of housing production factors, we investigate how behaviours of both housing buyers and developers affect housing price dynamics.

Employing a fractional cointegration vector autoregression (FCVAR) method with a quarterly dataset for the US over the period 1975Q1-2016Q1, we relax the conventional assumption of a unit root to capture long-memory shocks implied in target series, and model our theoretical construct in a long-memory cointegration framework. Preceding with that, we follow a rigorous econometrics procedure for data transformation (seasonal adjustment and business cycle removal) and identification of fractional integration order in each target series (through various techniques). Moreover, both short-run disequilibrium corrections and long-run cointegration relationship(s) of the macroeconomy-housing market interaction are measured in both the housing demand and supply functions, respectively. In addition, a five-year-ahead forecasting technique has also been applied in both the functions to predict future movements of the target series and obtained cointegrating relationship(s). Finally, by solving simultaneous demand and supply functions, we derive the aggregate impacts of macroeconomic fundamentals on housing prices in a stationary equilibrium condition. Robustness checkes are then conducted by executing rational restricted FCVAR models to examine the accuracy of our unrestricted FCVAR estimates of both the functions.

The rest of chapter is structured as follows. Section 4.2 reviews existing literature regarding the role of macroeconomic fundamentals on housing prices. Section 4.3 presents a conceptual framework in housing price determination through both demand and supply channels. Section 4.4 introduces the methodology and discusses estimation issues. Section 4.5 provides variable descriptions and corresponding data sources. Section 4.6 describes procedures of data transformation and preliminary observations. Section 4.7 contains detailed discussions of our empirical estimations and, finally, Section 4.8 summarizes main findings of the chapter.

4.2 Literature Review

Although the co-movement pattern between housing prices and macroeconomic fundamentals has been highly recognized (Arestis and Gonzalez-Martinez, 2016; Duan et al., 2018a,b), macroeconomic factors can exert distinct impacts on housing price dynamics via demand and/or supply effect channels with regard to both magnitude and sign. A failure to disentangle the real macroeconomic impacts from these different channels would not precisely model housing price movements. Existing literature, although thin, has started realizing its importance.

McCarthy and Peach (2002) find 'puzzled' housing price behaviours in the face of a monetary policy shock in the US: after restructuring the housing finance system since the mid 1980s, tightening monetary policy (a positive shock to the federal funds rate) first heightens housing prices in the short-run, and then declines in the long-run. They attribute such a short-run increase of housing prices to sellers' willingness to sustain a high housing price to minimize loss particularly in a downturn, which suggests a decreasing housing supply given a rising cost of construction finance. On the other hand, buyers tend to expect a further fall in interest rates given a current monetary tightening policy, thanks to an extensive availability of adjustable-rate mortgages, and therefore retain a relatively strong housing demand, which also induces an increase of housing prices in the short-run. However, in the long-run, housing prices will witness a gradual dip due to an overwhelmingly negative impact of a slump of housing demand given an increasing mortgage financing expenditure.

4.2.1 Housing demand effect channel

Undoubtedly, housing prices are determined by many demand-driven factors. Representative research can be tracked back to the 1980s. Muellbauer and Murphy (1997) focus on studying the dynamics of housing prices in the UK through an inverted housing demand function, and point out a dominant role of housing demand factors in the boom (in the late 1980s) and bust (in the 1990s) eras of housing prices. This chapter reports some key findings summarised as follows. First, along with many existing studies (DiPasquale and Wheaton, 1994; Meen, 1996, 1990, 1993), they find an important role of individuals' financial constraints, which dampens both housing demand and housing prices. A failure to account for it would disregard credit borrowing/down-payment limitations in reality, and therefore could not precisely describe both the behaviour of housing buyers and the shifts of housing demand curve. Moreover, the study of Muellbauer and Murphy (1997) is also consistent with Poterba (1984) who points out that a negative shock of user financing costs raises housing prices given fixed housing stocks in the short-run; then housing prices will experience a gradual decline in a market adjustment period with increasing housing stocks until a new steady state is reached.[2]

Second, macroeconomic factors demonstrate impacts on determining housing prices. Muellbauer and Murphy (1997) point out that income level exerts a positive effect on housing prices by boosting the housing demand. They also find that available housing stocks reveal the level of housing demand in the market and assume that the latter is proportional to the former. Indeed, the new housing unit completion reflects a specific component of buyers' house needs that has already been converted to the effective housing demand, while it also implies the market's effective supply ability to meet the demand although there exists a gap between them called 'demand gap' (Heath, 2014). Thus, through the demand perspective, current high housing stocks could indicate a singal of high housing demand. Then housing prices tend to subsequently experience an increase given a strong demand.

Moreover, McCarthy and Peach (2002) echo the above discussions and also recognize the role of housing stocks in determining the equilibrium housing prices through both demand and supply channels. In addition to that, recent studies, such as Arestis and Gonzalez-Martinez (2016); Duan et al. (2018a,b), build a conceptual framework to attribute housing price dynamics to factors from both demand and supply sides. They particularly find that demand factors involving personal disposable income, interest rate and credit availability contribute theoretically expected effects to housing price changes. Other relevant studies including Fitzpatrick and McQuinn (2007); Gerlach and Peng (2005); Hwang and Quigley (2006); Senhadji and Collyns (2002) also discuss the determination of housing prices through the demand channel. Third, the effect of uncertainty also cannot be neglected (Baker et al., 2016; Muellbauer and Murphy, 1997). Along with Meen (1990, 1993), the existence of housing market uncertainty can dampen individuals' intentions of property purchase and then depress housing prices (through the housing demand side).

In summary, there potentially exist the following flaws in existing demand-related research. First, although a gradual/slow price adjustment to market equilibrium has been recognized (DiPasquale and Wheaton, 1994), relaxing the traditional assumption of a rapid housing market clearing still has not been extensively valued, which is far from replicating reality. Second, much literature regarding the conventional two-equation stock-flow model does not account for the extent to how supply-driven (production) factors affect housing prices. Instead, only total housing stock is included to represent the housing supply in the price determination function. However, important explanatory powers of housing production factors on the supply side cannot be

[2]See Tables B.10 and B.11 in Chapter 3, the importance of credit on housing price movements has also been embraced by much of the recent literature (See representative studies among others, Abdallah and Lastrapes, 2013; Favara and Imbs, 2015; Gerlach and Peng, 2005; Ling et al., 2016; Mian and Sufi, 2009).

ignored. Furthermore, although some research indeed considers housing price determinants from both demand and supply sides, they are nevertheless imposed in a combined determination function, instead of being modelled separately. As a consequence, impacts of these driven factors from different sides would be intertwined, therefore the law of housing price movements still fails to be unlocked. In the next subsection, we discuss relevant literature focusing on the supply side of the housing market.

4.2.2 Housing supply effect channel

Although there exist much literature modelling housing price determinations through the housing demand function, little focuses on studying impacts of the supply-driven/housing production factors. Some prior research has realized this and summarized corresponding reasons why the housing supply is hard to model. Quigley (1979) points out that considerable quality variations of each housing unit and indefinite dimensions of the housing quality evaluation inhibit accurate measurement of the total housing supply and outputs. Second, available housing stocks in the market are provided by different housing suppliers such as new housing builders and existing housing owners. It is nevertheless difficult to capture their individual behaviours due to the paucity of such micro-level data. Third, in addition to private sectors, the government can also exert a marked impact on shifting the supply curve by its implementation of public housing provision and property tax levy, further raising uncertainty and fluctuations of the housing supply (DiPasquale, 1999).

As mentioned in Section 4.2.1, one popular approach to model the equilibrium housing prices using demand-driven factors and housing stocks is the stock-flow model. A representative prior study regarding this model is from DiPasquale and Wheaton (1994). Introducing an error correction structure, they enhance the traditional model by allowing a slow price adjustment towards a market clearing. Features of housing market operations are summarized in their paper as follows. First, housing prices exert a strong positive autocorrelation, denoting that future prices are moved with backward-looking expectations. This finding is qualitatively consistent with the feature of 'lagged appreciation of current housing prices' proposed by Abraham and Hendershott (1996) and Muellbauer and Murphy (2008) and the feature of 'forward-looking' of housing builders regarding current prices (Murphy, 2018). Second, the housing market appears to behave as a serious disequilibrium given the excess demand and insufficient supply in reality. Given a price shock, the demand reacts more quickly and on a greater scale compared to the supply, which tends to be unresponsive, particularly in the short-run. This is also in line with Poterba (1984) and Mankiw and Weil (1989).

Third, consistent with DiPasquale (1999), impacts of various (housing production) factor markets, particularly the land market, on the housing constructions are still elusive due to the data limitation. Poterba (1984) suggests that a buoyant demand of production factors is able to heighten the equilibrium housing prices due to a downward shift of supply curve induced by a rising supply expenditure. The author recognizes the importance of land, although it is neglected in the paper due to data constraints. This is also embraced by Knoll et al. (2017), in which the land price is found to be a key factor to determine the long-run housing price dynamics. In addition, DiPasquale and Wheaton (1994) also provide an explanation about the impact of land value on housing prices on the supply side. Given an initial housing price increase, it stimulates the rise of housing stocks, which implies an increase of housing supply and a decline of land availability for construction. Land value will then rise as a consequence, which tends to cause the housing supply to further falter by absorbing excess returns generated from the initial housing price increase, and further raise housing prices. Recent studies echo this viewpoint and find that the supply-driven factors such as construction cost and land value demonstrate marked impacts on housing prices (Glaeser et al., 2008; Green et al., 2005; Knoll et al., 2017; Saiz, 2010).

Although housing price is deemed to determine housing stocks in the 'stock-flow model' related literature, the latter in turn can indeed exert an impact on the former. In addition to its impact through the housing demand channel as discussed in Section 4.2.1, it is also able to affect housing prices through the supply perspective. Muellbauer and Murphy (1997) point out that an increase of available housing stocks is found to drive a slump in housing prices by positively shifting the supply curve. Furthermore, studies using one aggregated housing price determination function can indeed involve both demand and supply factors (Arestis and Gonzalez-Martinez, 2016; Duan et al., 2018a,b). However, although described theoretically, they nevertheless could not empirically disentangle explanatory powers of specific variables, which have dual impacts through both demand and supply functions, respectively. Instead, only aggregate effects of these factors are reported, which could still give rise to confusing conclusions. For example, through a financing perspective in the housing market, it is possible that a positive shock to interest rates decreases housing prices by depressing housing demand, while it can also raise housing prices by a falling housing supply simultaneously. A similar mechanism is expected from other variables with the dual roles such as credit, housing stocks and uncertainty.

Overall, we do not apply the traditional stock-flow model in this chapter for the following reasons. First, the model fails to account for impacts of supply-driven factors on housing prices although these factors can contribute to important explanatory powers. Second, there is no precise way to quantify the housing stock. Its conventional proxy is the aggregate housing supply, regardless of possible heterogeneous housing qualities and types (See, among others, DiPasquale and Wheaton, 1994; Hwang and Quigley, 2006; Muellbauer and Murphy, 1997), which is far from reality. Moreover, as explained in Section 4.2.1, the approach of an aggregate determination equation is also not applicable to our research focus. Thus, to avoid these obstacles, we construct simultaneous housing demand and supply function systems to separately model how housing prices are determined through those two channels, and subsequently quantify which one dominates the equilibrium housing price determination.

4.3 Theoretical Underpinning

To direct our empirical analyses and in light of market equilibrium theory, we build a theoretical construct to describe the ways that macroeconomic fundamentals contribute to equilibrium housing prices. This incorporates both demand and supply functions, both of which consider a gradual price adjustment process towards a market clearing within a long-memory framework. Following McCarthy and Peach (2002), we formulate the long-run equilibrium housing price levels through both the functions, respectively [3]

In terms of the variable selection, this chapter constructs both the housing demand and supply functions accordingly in light of the selection approaches employed in Chapters 2 and 3. Specifically, based on the credit disaggregation strategy, rather than using the aggregate credit, credit lending to housing buyers (CD) and housing suppliers (CS) are separately considered in this chapter, both of which form an important tool of monetary policy to represent 'the quantities of money'. Their roles in the equilibrium housing price determinations can be measured in our built housing demand and supply functions, respectively. At the same time, as another important monetary policy instrument, interest rate (LIR) can demonstrate 'the price of money' and direct housing prices by separately affecting the borrowing costs of housing buyers and suppliers. In addition, both the nationwide price level (DEF) and economic policy uncertainty (EPU) are also included in the analysis, having well examined their significant impacts on housing prices, as well as the interaction between housing prices and macroeconomic fundamentals, in Chapter 3.

Moreover, since both variables of *housing prices* and *housing stocks* are the two important and significant indicators to define the housing equilibrium through perspectives of price and quantity, respectively, the research framework in this chapter includes both of them to well demonstrate the equilibrium conditions of the housing market. It has been well-established that housing stocks can not only describe the market ability for housing provisions through the housing supply side, but also demonstrate the housing buyers' current house needs through the housing demand side. Thus, as the common explanatory variable, housing price (RHP) is included in both the demand and supply functions. In addition to RHP, the variable of housing stocks (HUC) is also considered

[3]Detailed explanations of signs of all incorporated demand- and supply-driven factors have been discussed in Arestis and Gonzalez-Martinez (2016); Duan et al. (2018b).

in both the functions simultaneously. In addition, as one of the most important and representative housing production factors, compelling evidence shows the significant impacts of land market value (RLV) on housing price dynamics. Indeed, an increase in RLV can raise the housing production costs, subsequently decline the housing supply, and ultimately increase housing prices. Thus, RLV is included in the supply function to represent the impacts of housing production factors on directing the equilibrium housing price levels.

Through the housing demand side, the demand function drives the equilibrium housing prices (RHP^{D*}) that will clear the current stock of housing (HUC). It in turn depends upon variables involving individuals' house purchase abilities (CD), purchase financing cost (LIR), the price level of the economy (DEF), the current stock of housing (HUC), and economic policy uncertainty (EPC). In the demand-driven equilibrium, DEF, LIR, and EPU are all expected to demonstrate a negative effect on RHP^{D*}, while HUC and CD are expected to exert a positive effect.

$$RHP^{D*} = \alpha_1 \underset{(+)}{HUC} + \alpha_2 \underset{(-)}{DEF} + \alpha_3 \underset{(-)}{LIR} + \alpha_4 \underset{(-)}{EPU} + \alpha_5 \underset{(+)}{CD} \tag{4.1}$$

Through the housing supply side, assuming that there is a perfect competitive environment in which housing suppliers make a zero profit in the long-run, the supply function determines the equilibrium housing prices (RHP^{S}) that equate the supplied housing stock (HUC) to the real buyers' housing demand in the market. It in turn depends upon suppliers' financing levels (CS), land market value (RLV), suppliers' financing cost (LIR), the current stock of housing (HUC), and economic policy uncertainty (EPU). In the supply-driven equilibrium, HUC and CS are expected to negatively affect RHP^{S*}, while EPU, LIR, and RLV exert a positive effect. Proxies for each demand- and supply-driven variable, detailed definitions and corresponding data sources are summarized in Table 4.2 in Section 4.5.

$$RHP^{S*} = \alpha_1 \underset{(-)}{HUC} + \alpha_2 \underset{(+)}{EPU} + \alpha_3 \underset{(+)}{LIR} + \alpha_4 \underset{(+)}{RLV} + \alpha_5 \underset{(-)}{CS} \tag{4.2}$$

Indeed, as already highlighted in both Chapters 2 and 3, the housing supply is also an important component of the housing market in addition to the housing demand, while the housing supply along with the housing demand form the naturally-existing effect transmission channels through which housing prices and macroeconomic fundamentals co-move in the equilibrium condition. Thus, simply imposing the strict assumption of the constant housing supply in extant housing-related literature could be far from reality especially when the long-term dynamics of housing markets are focused on. Overall, following both Chapters 2 and 3, this chapter identifies the effect transmission channels in the macroeconomy-housing market interactive system through not only the conventional housing demand side but also the supply side. The above mentioned variable selection process in this section specifically discusses the mechanism through which macroeconomic variables impact housing price dynamics by shifting the housing supply and demand curves, respectively. Particularly, based on our selected housing supply factors from the above selection process, the housing supply function can be accordingly constructed and shown as (4.2).

If a housing market clears promptly, we can directly estimate these above two simultaneous equations and then solve an overall housing determination function in equilibrium, viz. $RHP^{*} = RHP^{D*} = RHP^{S*}$. However, it is well known that house prices adjust towards the equilibrium level slowly given shocks to either the demand side or the supply side (see McCarthy and Peach, 2002, for a summary of related literature). Moreover, there exists overwhelming evidence in supporting the disequilibrium status in the housing market particularly in the short-run due to aforementioned shocks. Thus, we explicitly consider such slow adjustments by employing an error correction framework in both (4.1) and (4.2). Specifically, we identify that a given shock to the equilibrium housing prices will generate wedges between current price level and RHP^{D*} as well as RHP^{S*}. Such a disequilibrium status in a housing market implied by these wedges will dissipate slowly towards the equilibrium level if there are no other shocks in the system through the housing demand and supply sides, respectively.

Furthermore, there is compelling evidence in favour of persistent and slowly-converged shocks in the macroeconomy-housing market interaction instead of a unit root process as conventionally assumed. Thus, we identify a slow decay pattern (e.g. long-memory) of shocks in each target series in demand and supply functions by allowing for the existence of fractional integration.[4] Thus, demand- and supply-driven housing price determination functions are constructed as follows:

$$\begin{aligned}\Delta RHP_t = \Pi_D L_{d1}(RHP_t - RHP_t^{D*}) + \beta_1 \Delta HUC_t + \beta_2 \Delta DEF_t + \beta_3 \Delta LIR_t \\ + \beta_4 \Delta EPU_t + \beta_5 \Delta CD_t + \varepsilon_D\end{aligned} \tag{4.3}$$

$$\begin{aligned}\Delta RHP_t = \Pi_S L_{d2}(RHP_t - RHP_t^{S*}) + \gamma_1 \Delta HUC_t + \gamma_2 \Delta EPU_t + \gamma_3 \Delta LIR_t \\ + \gamma_4 \Delta RLV_t + \gamma_5 \Delta CS_t + \varepsilon_S\end{aligned} \tag{4.4}$$

where $L_{d1}(RHP_t - RHP_t^{D*})$ and $L_{d2}(RHP_t - RHP_t^{S*})$ represented in (4.3) and (4.4) denote error correction processes towards the equilibrium housing prices through demand and supply effect-transmission channels, respectively. L_d denotes the difference operator with an order d while d can be any real number. Furthermore, both short-run disequilibrium corrections and long-run equilibrium relationships in the macroeconomy-housing market interaction system can be explicitly investigated separately from both the channels, respectively. Although our research emphasis is the determination of housing prices as modelled by (4.3) and (4.4), we also recognize and allow for potential multi-directional interactions among target variables. Moreover, as earlier noted in

[4]Detailed mathematical explanations are elaborated on in Section 4.4.

Section 4.1, this theoretical setting enables us to quantify effects of factors that impact exclusively through demand or supply functions, for instance, DEF and CD on the demand function; and RLV and CS on the supply function.

More importantly, it also disentangles possible dual roles of specific factors, for instance, HUC, LIR, and EPU, which can affect housing prices through both the functions. It is well known that these specific variables can demonstrate two distinct effects on housing prices simultaneously by shifting demand and supply curves, respectively. Thus, simply measuring their aggregate effects in a single equation can not precisely investigate their real roles. Instead, through a micro perspective, our theoretical construct provides an effective way to separately gauge their dual impacts and further study which one demonstrates a dominant role in determining housing prices. After separately estimating both (4.3) and (4.4), we can eventually derive the overall equilibrium housing price determination function. In the next section, we will focus on discussing how to gauge the fractional integration order implied in a target series, and how to identify the cointegrating relationship(s) in both demand and supply functions in a long-memory framework.

4.4 Methodology

Rather than using the conventional methodology, which imposes an implausible assumption that orders of integration and cointegration should be integer numbers (Engle and Granger, 1987), we relax this assumption and employ the fractionally cointegrated vector autoregressive (FCVAR) model. Following Johansen (2008) and Johansen and Nielsen (2012), the FCVAR model is able to identify potential long-memory properties in our target series by allowing for fractional integration orders, while it can further model both disequilibrium error corrections and cointegrating relationship(s) among target variables in a long-memory context. In particular, a clear identification of the long-memory shocks by using the FCVAR model is an innovative contribution in studying interactions between housing prices and macroeconomic fundamentals. Discussions surrounding both fractional integration and the FCVAR model are presented in this section.

4.4.1 Fractional integration

Given any time series, we start from a conventional expression of an integrated process of order d as follows given that $t = 1, \ldots, T$.

$$(1-L)^d y_t = \psi(L)\varepsilon_t \tag{4.5}$$

where $(1-L)^d$ is the difference operator of order d. For example, if $d=1$, $(1-L)^1 y_t = y_t - y_{t-1} = \Delta y_t$. $\psi(L^j)$ is the coefficient of the error term (ε) at each specific time period $t-j$ with $\sum_{j=0}^{\infty} |\psi(L^j)| < \infty$, $j = 0, 1, 2, \ldots$, and the error term (ε_t) is a white noise process with zero mean and constant variance, viz. $\varepsilon_t \sim iid(0, \sigma^2)$. Following Hamilton (1994), instead of abiding by the conventional assumption that order d should be an integer, a fractional integrated process allows a fractional value of d. Given that the inverse value of $(1-L)^d$ exists subject to $d < 1/2$, (4.5) can be transformed into the following form.[5]

$$y_t = (1-L)^{-d} \psi(L) \varepsilon_t \tag{4.6}$$

Based on the technique of power series expansion, the operator $(1-L)^{-d}$ is suggested to be demonstrated as

$$(1-L)^{-d} = \sum_{j=0}^{\infty} \gamma_j L^j \tag{4.7}$$

where $\gamma_0 \equiv 1$ and

$$\gamma_j = \frac{(d+j-1)(d+j-2)\cdots(d+2)(d+1)(d)}{j!} \tag{4.8}$$

where $\gamma_j \cong (j+1)^{d-1}$ given that $d < 1$ and j is large. Thus, the fractionally integrated process (4.6) can be re-formulated subject to (4.7) as a following moving average (MA(∞)) representation.[6]

$$y_t = (1-L)^{-d} \varepsilon_t = \gamma_0 \varepsilon_t + \gamma_1 \varepsilon_{t-1} + \gamma_2 \varepsilon_{t-2} + \cdots \tag{4.9}$$

where impulse response coefficients of y_t, γ_j, imply a slow decay pattern of shocks to the error terms of y_t. It indeed captures the potential 'long-memory' property of a time series (Granger and Joyeux, 1980). In contrast, impulse response coefficients of a 'short-memory' time series decay more quickly. For example, impulse response coefficients (ρ^i) of a covariance-stationary AR(1) process, $y_t = \sum_{i=0}^{\infty} \rho^i \varepsilon_{t-i}$, decay geometrically.

To study the stationary property of (4.9), given that $d \neq 0$, y_t is covariance-stationary only when $d < 1/2$ due to a constant mean and a square summable γ_j. In particular, the proof of the latter is demonstrated as follows based on the idea of Hamilton (1994).

[5] As explained by Hamilton (1994), if $d > 1/2$, y_t will no longer be stationary as the inverse of $(1-L)^d$ approaches infinity.

[6] We remove ψ_L in (4.9) and the coefficient of each $L^j \varepsilon_t$ is now depicted by γ_j as defined in (4.8).

$$\begin{aligned}\sum_{j=0}^{N-1}\gamma_j^2 &= \sum_{j=0}^{N-1}(j+1)^{2(d-1)} \\ &= \sum_{j=1}^{N} j^{2(d-1)} \\ &< 1 + \int_1^N x^{2(d-1)}dx \\ &= 1 + [1/(2d-1)]x^{2d-1}|_{x=1}^{N} \\ &= 1 + [1/(2d-1)][N^{2d-1} - 1]\end{aligned} \tag{4.10}$$

where the sum of square values of γ_j converges to $1 - 1/(2d-1)$ only when $2d - 1 < 0$, i.e., $d < 1/2$ given that N approaches to infinity, $N \to \infty$. That is to say, $\sum_{j=0}^{\infty}\gamma_j^2 < \infty$ conditional on $d < 1/2$. Thus, in light of the stationary requirements of a MA (∞) process, y_t is covariance-stationary when $d < 1/2$. However, if $d \geq 1/2$, y_t will not be covariance-stationary, and it is supposed to be differenced until $d < 1/2$ to become stationary. For example, if $d = 0.8$, the integrated process (4.5) can be re-written as $(1-L)^{-0.2}(1-L)y_t = \psi(L)\varepsilon_t$. We can therefore conclude that $\Delta y_t = (1-L)y_t$ is a stationary process, which is fractionally integrated with an new order of $d_1 = -0.2 < 0.5$. Moreover, in terms of a stationary ARMA process, it has a mean-reversion property and a finite variance. In terms of a non-stationary ARMA process, there is no mean-reversion while its variance is infinite.

In general, regarding a fractional integrated process y_t as expressed in (4.9), it can be a mean-reverting process as long as the superscript $d-1$ in $\gamma_j \cong (j+1)^{d-1}$ is less than 0, i.e., $d < 1$. This indicates that the shocks of error terms, i.e., $\varepsilon_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_1$, as well as previous values of y, i.e., $y_{t-1}, y_{t-2}, \ldots, y_1$, will demonstrate a gradually diminishing influence on affecting y_t with the increase of time lags given that $t \geq 1$. Otherwise, it will not be a mean-reverting process if $d \geq 1$. Furthermore, y_t can have a finite variance only when $d < 1/2$, implying a square-summable error term coefficients as indicated by (4.10), while its variance will be infinite if $d \geq 1/2$.

Properties of fractionally integrated series

In this section, we further discuss conditions under which a given time series, y_t, depicted in (4.5) is a long-memory or short-memory process and under which condition it is covariance-stationary.

If $d < 0$,

$$(1-L)^d y_t = \psi(L)\varepsilon_t \tag{4.11}$$

We can then re-express (4.11) by multiplying the fractional lag operator $(1-L)^{-d}$ on both sides as

$$y_t = (1-L)^{-d}\psi(L)\varepsilon_t \tag{4.12}$$

where $-d > 0$ and $(1-L)^{-d}\psi(L)$ is the coefficient of ε in different time periods. For example, if $d = -2$, $(1-L)^2\psi(L)\varepsilon_t = \psi(L^0)\varepsilon_t + \psi(L^1)\varepsilon_{t-1} + \psi(L^2)\varepsilon_{t-2}$. Based on (4.8) and (4.10), y_t is a covariance-stationary long-memory series, which is fractionally integrated with order d. In addition, given that y_t is stationary and $d < 0$, it is known that y_t has been 'over-differencing', which would mask the true dynamics of target series (Cochrane, 2012). Overall, under the condition that $d < 0$, the mean value of y_t will be convergent to a constant, implied by (4.8) and (4.9), while its variance will be finite implied by (4.10) in the long-run, all of which suggest a long-memory stationary property of y_t.

If d is an integer and $d = 0$,

$$(1-L)^0 y_t = \psi(L)\varepsilon_t \tag{4.13}$$

As $(1-L)^0 = 1$, the above formula can be re-written as

$$y_t = \psi(L)\varepsilon_t \tag{4.14}$$

where y_t is a covariance-stationary short-memory time-series. Under this condition, the integration order of y_t is 0, $y_t \sim I(0)$. It has a reverting mean achieved in the short-run and a finite variance.

If $0 < d < 0.5$,

$$(1-L)^d y_t = \psi(L)\varepsilon_t \tag{4.15}$$

where y_t depicts a long-memory property and is fractionally integrated with order d, viz. $y_t \sim I(d)$. It is also covariance-stationary due to a convergent constant mean and a finite variance as suggested by $d < 1/2$. In addition, the required time length that converges the mean value of a long-memory process ($d < 1$ and $d \neq 0$) is much longer than that of a short-memory process ($d = 0$).

If $0.5 \leq d < 1$,

$$(1-L)^{d-1}(1-L)^1 y_t = \psi(L)\varepsilon_t \tag{4.16}$$

where y_t is not covariance-stationary while still having a long memory property; and Δy_t is covariance-stationary and fractionally integrated with order $d-1$. In this case, the mean value of y_t is still convergent to a constant, while its variance is no longer finite as suggested by $d \geq 1/2$.

If d is an integer and $d = 1$,

$$(1-L)^1 y_t = \psi(L)\varepsilon_t \tag{4.17}$$

Hence, we can re-express it as

$$\Delta y_t = y_t - y_{t-1} = \psi(L)\varepsilon_t \tag{4.18}$$

where y_t is not covariance-stationary and is defined as a unit root process. It indicates that there exists one character root in the character function of y_t lying on the unit circle. In this case, y_t does not have a converged mean and a finite variance. The first-difference transformation is convenient to convert it to be stationary. In addition, instead of short-lived or long-lived shock durations implied when $d = 0$ or $d < 1$ and $d \neq 0$, respectively, shocks to error terms of a unit root process appear to be infinite.[7] Qualitatively the same conclusions are also applicable to a ARMA process.

Finally, *if* $d > 1$,

then, indeed, the series y_t will not be covariance stationary and have a long-memory property. Similar to the case when $d = 1$, its mean diverges instead of a mean-reversion, and it does not have a finite variance. In addition, shocks to its error terms follow an explosive pattern, through which shocks will increase with the increase of time lags (Tkacz, 2001). Overall, Table 4.1 summarizes 'memory properties' of a specific time series with different integration orders.

Table 4.1: **Memory Properties of y_t with Different d Values**

d Value	Memory	Stationarity	Mean	Variance	Shock Duration
$d < 0$	Long	Stationary	Mean-reversion	Finite	Long-lived
$d = 0$	Short	Stationary	Mean-reversion	Finite	Short-lived
$0 < d < 0.5$	Long	Stationary	Mean-reversion	Finite	Long-lived
$0.5 \leq d < 1$	Long	Non-stationary	Mean-reversion	Infinite	Long-lived
$d = 1$	Permanent	Non-stationary, unit root process	No Mean-Reversion	Infinite	Permanent
$d > 1$	Permanent	Non-stationary	No Mean-Reversion	Infinite	Permanent, the effects increase over time

4.4.2 Fractional cointegrated VAR model

It is widely recognized that a fractional integration order of a series is able to demonstrate its long-memory property, while also providing an essential foundation when examining whether a specific group of variables are fractionally cointegrated or not. To estimate the long-memory in a system, we employ the fractionally cointegrated vector autoregressive (FCVAR) model developed by Johansen (2008) and Johansen and

[7] For example, in terms of the MA (∞) specification of a unit root AR(1) process, effects of error terms from previous periods on the current value of the series are permanently equal to one.

Nielsen (2012). It enables us to capture both error corrections and equilibrium relationship(s) in a system including specific target variables in a long-memory cointegration framework.

The FCVAR model is derived from the cointegrated vector autoregressive (CVAR) model, which only allows for an integer integration order, proposed by Johansen (1995). Assuming X_t is a K-dimensional $I(1)$ time series with $t = 1, 2, \ldots, T$, the CVAR model with p lags can be expressed as

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \varepsilon_t = \alpha\beta' L X_t + \sum_{i=1}^{p} \Gamma_i \Delta L^i X_t + \varepsilon_t \tag{4.19}$$

Based on (4.19), the FCVAR can be derived by replacing the difference operator (Δ) and the lag operator ($L = 1 - \Delta$) by their fractional counterparts, which are $\Delta^b = 1 - L_b = (1 - L)^b$ and $L_b = 1 - \Delta^b$, respectively. L_b can be also re-expressed as: $L_b = 1 - \Delta^b = 1 - (1 - L)^b$. In addition, b should be positive to ensure that the order of target time series should not be affected by applying the fractional lag operator (L_b) (Tschernig et al., 2013). Thus, the FCVAR model specification is formulated as follows.

$$\Delta^b X_t = \alpha\beta' L_b X_t + \sum_{i=1}^{p} \Gamma_i \Delta^b L_b^i X_t + \varepsilon_t \tag{4.20}$$

where the error term (ε_t) is a K-dimensional independent identically distributed time series with a zero mean and a constant variance-covariance matrix ($\varepsilon_t \sim iid(0, \Omega)$). Indeed, the FCVAR model allows multiple time series integrated with fractional order d to be cointegrated to order $d - b$. We now assume that X_t is fractionally integrated with an order b: $(1 - L)^b X_t = \varepsilon_t$. When we apply $X_t = \Delta^{d-b} Y_t$, then $(1 - L)^b X_t$ = $(1 - L)^b \Delta^{d-b} Y_t$ = $(1 - L)^b (1 - L)^{d-b} Y_t$ = $(1 - L)^d Y_t$ = ε_t. Thus, the FCVAR model shown in (4.20) can be re-formulated as

$$\Delta^d Y_t = \alpha\beta' L_b \Delta^{d-b} Y_t + \sum_{i=1}^{p} \Gamma_i \Delta^d L_b^i Y_t + \varepsilon_t \tag{4.21}$$

Model parameters in the FCVAR have the same interpretations as those in the CVAR model. Specifically, Π is a parameter that defines the cointegration relationship(s) and it can be further identified as two sub-parameters, viz. $\Pi = \alpha\beta'$. α and β are $K \times r$ matrices given that r is the rank of Y_t and $0 \leq r \leq K$. In addition, the value of r indicates the number of cointegration(s) in the model. β identifies the cointegrating relationship(s) among variables in Y_t, and α defines the adjustment speed towards the long-run equilibrium of each variable in Y_t. Γ_i describes the short-run dynamics of target variables. Overall, (4.21) implies that elements of Y_t are fractionally integrated to order d, and the model system is cointegrated to order $d - b$. The FCVAR model enables us to capture the long-run equilibrium relationship, viz. $\beta' L_b \Delta^{d-b} Y_t$, the short-run adjustment processes to deviations towards the equilibrium, and the short-run dynamics among variables in the system. Moreover, the FCVAR model also allows us to evaluate the model fit (viz., if the asymptotic distribution assumption of the model parameters is achieved) by testing the residuals. In our empirical research, we concentrate on the case when $d = b$ to ensure that a linear combination of variables depicted in cointegrating relationship(s) with a constant term δ tends to be stationary. The FCVAR can be further expressed as

$$\Delta^d Y_t = \alpha(\beta' L_d Y_t + \delta') + \sum_{i=1}^{p} \Gamma_i \Delta^d L_d^i Y_t + \varepsilon_t \tag{4.22}$$

Our defined fractional integration is based on an infinite time series as shown in (4.9), while it cannot be realised in the real world as the number of any observed observations is finite. Although an assumption that values of any a given time series are zero before the start of data sample allows us to measure the fractional difference, it is nevertheless too strict to be rational in reality and will cause an estimation bias (Johansen and Nielsen, 2016). They point out that such bias can be corrected by introducing a drift term (ρ) that shifts each time series in Y_t by a constant value. Thus, the updated FCVAR model can be eventually shown as

$$\Delta^d (Y_t - \rho) = \alpha\beta' L_d (Y_t - \rho) + \sum_{i=1}^{p} \Gamma_i \Delta^d L_d^i (Y_t - \rho) + \varepsilon_t \tag{4.23}$$

where $\beta' \rho = -\delta'$ represents the constant mean value of stationary cointegrating relationships. (4.23) is the FCVAR model specification that we will employ in the empirical section. In terms of the estimation technique, we follow Johansen and Nielsen (2012) and estimate the FCVAR model by using the maximum likelihood (ML) estimation. They find that the ML estimators of model parameters, such as $\hat{d}, \hat{\alpha}$ and $\hat{\Gamma}_i$, follow a asymptotically normal distribution, while the ML estimators of other model parameters, viz. $\hat{\beta}$ and $\hat{\delta}$, still follow a asymptotically normal distribution when $d < 1/2$ and a asymptotically mixed normal distribution when $d > 1/2$.

Importantly, these above properties imply that the asymptotic χ^2 inference can be applied to test the significance of parameters through the likelihood ratio (LR) tests. Although the asymptotic distribution of the drift parameter, $\hat{\rho}$, is still unknown, it is not that crucial for the estimation as $\hat{\rho}$ is only used to correct for the fact that all initial values of Y_t are not observed (Jones et al., 2014). In addition, the determination of the FCVAR model specification, its model estimation and its forecasting exercise to be discussed below are executed using a Matlab program proposed by Nielsen and Popiel (2018), viz. FCVAR version 1.4.0a. It is also worth noting that identification problems of the FCVAR system raised in Johansen and Nielsen (2010) and Carlini and de Magistris (2017) have been considered and alleviated in the program.

Similar to the hypothesis testing in the CVAR model, the FCVAR model can also conduct a series of hypothesis tests on model parameters (Jones et al., 2014). In particular, the theoretical framework of hypothesis tests on β and α can be formulated below respectively.

$$\beta = \omega\lambda \tag{4.24}$$

$$\alpha = \tau\theta \tag{4.25}$$

In terms of the hypothesis test on β as shown in (4.24), ω is a $K \times q$ matrix identifying imposed restriction(s) on cointegrating relationship(s), and λ is a $q \times r$ matrix defining free varying parameter(s). K is the number of variables within the FCVAR system; q is the number of restriction(s) associated with β-related hypothesis tests; and r denotes the number of rank(s) of Y_t. In the case that each cointegrating relationship is imposed with the same restriction, the degree of freedom of the hypothesis test is equal to $(K - q)r$. If the number of cointegrating relationships is greater than one, viz. $r > 1$, different restrictions could be imposed on different columns of β. β can be then re-expressed as a row vector, i.e., $\beta = (\omega_1\lambda_1, \omega_2\lambda_2, \ldots, \omega_r\lambda_r)$. Each column of β is the product between ω_i and λ_i, where ω_i is a $K \times q_i$ matrix and defines the imposed restriction on the column i of β; and λ_i is a $q_i \times 1$ matrix and defines the free varying parameter on the column i of β. In that case, the degree of freedom of the hypothesis test is $\sum_{i=1}^{r}(K - r - q_i + 1)$.

In terms of the hypothesis test on α as shown in (4.25), τ is a $K \times l$ matrix that defines restriction(s) on error corrections towards equilibrium of target variables, while θ is a $l \times r$ matrix representing free varying parameter(s) with $l \geq r$ where l stands for the number of restriction(s) associated with α-related hypothesis tests. Its degree of freedom is equal to $(K - l)r$.

4.4.3 Test of fractional cointegration

We now discuss how numbers of fractional cointegration ranks are tested through the likelihood ratio (LR) test statistic, which enables us to build the trace test of the null hypothesis (H_0): rank(Π) = r against the alternative hypothesis (H_1): rank(Π) = K. Based on the FCVAR model specified in (4.23), let θ = (d, b, ρ) denote the model parameters set that numerically maximizes the likelihood of making the given observations. Let $L(d, b, \rho, r)$ be the profile likelihood function given a specified rank r, where other model parameters, viz. α, β and Γ, have been concentrated out by regression and reduced rank regression (Johansen and Nielsen, 2012). The LR test statistic can be calculated when the profile likelihood function is maximized under both hypotheses H_0 and H_1 as

$$LR_T(\tau) = 2log(\frac{L(\hat{\theta}_K, K)}{L(\hat{\theta}_r, r)}) \tag{4.26}$$

where $\tau = K - r$, $L(\hat{\theta}_K, K) = max(L(\theta_K, K))$ and $L(\hat{\theta}_r, r) = max(L(\theta_r, r))$. The asymptotic distribution of $LR_T(\tau)$ depends upon the parameter b. Thus, the cointegration is defined as 'weak' when $0 < b < 1/2$ and $LR_T(\tau)$ follows a standard asymptotic distribution (Johansen and Nielsen, 2012).

$$LR_T(\tau) \to \chi^2(\tau^2) \tag{4.27}$$

Moreover, when $1/2 < b \leq d$, the cointegration is defined as 'strong', while the asymptotic distribution is not standard (Nielsen and Popiel, 2018). It is then formulated as

$$LR_T(\tau) \to Tr\{\int_0^1 dW(s)F(s)^{'}(\int_0^1 F(s)F(s)^{'}ds)^{-1})\int_0^1 F(s)dw(s)^{'}\} \tag{4.28}$$

Following Nielsen and Popiel (2018), the vector process dW denotes the increment of ordinary vector standard Brownian motion of dimension $\tau = K - r$, and the vector process F relies on the deterministics, which is similar to the mechanism in CVAR model discussed in Johansen (1995). Building the above LR cointegration rank test when $d = b$ involves calculations of both asymptotic critical values and corresponding P values. In our case, we measure both of them by employing computer programs provided by MacKinnon and Nielsen (2014) in the empirical section.

4.4.4 Forecasting from the FCVAR model

Following Nielsen and Shibaev (2018), we now focus on how to forecast our target series (Y_t) and obtained cointegrating relationships from the FCVAR model by using the best (minimum mean-squared error) linear predictor. First, regarding an one-step-ahead forecast of Y_{t+1}, we note that

$$\Delta^d(Y_{t+1} - \rho) = Y_{t+1} - \rho - (Y_{t+1} - \rho) + \Delta^d(Y_{t+1} - \rho) = Y_{t+1} - \rho - L_d(Y_{t+1} - \rho) \tag{4.29}$$

Based on (4.29), since $L_d = 1 - \Delta^d$ and $d = b$ as earlier defined, the FCVAR model, (4.23), is then re-formulated as

$$Y_{t+1} = \rho + L_d(Y_{t+1} - \rho) + \alpha\beta^{'} L_d(Y_{t+1} - \rho) + \sum_{i=1}^{p} \Gamma_i \Delta^d L_d^i (Y_{t+1} - \rho) + \varepsilon_{t+1} \tag{4.30}$$

This is the foundation of the FCVAR forecasting. Each item on the right hand side (RHS) of (4.30) is known at time t for $d > 0$ and $i \geq 1$. A conditional expectation of any variable Y_{t+1} given an available information set at time t can be defined as: $\hat{Y}_{t+1|t} = E_t(Y_{t+1})$. Similarly, a conditional expectation of the residuals ε_{t+1} given available information at time t is $\hat{\varepsilon}_{t+1|t} = E_t(\varepsilon_{t+1})$. Hence, by substituting the estimated values of FCVAR model coefficients, viz. $\hat{d}, \hat{\rho}, \hat{\alpha}, \hat{\beta}, \hat{\Gamma}_i$, which have been obtained through the ML method, we re-express (4.30) as

$$\hat{Y}_{t+1|t} = \hat{\rho} + L_{\hat{d}}(Y_{t+1} - \hat{\rho}) + \hat{\alpha}\hat{\beta}' L_{\hat{d}}(Y_{t+1} - \hat{\rho}) + \sum_{i=1}^{p} \hat{\Gamma}_i \Delta^{\hat{d}} L^i_{\hat{d}}(Y_{t+1} - \hat{\rho}) \tag{4.31}$$

where (4.31) defines the model specification of a one-step-ahead forecasting of Y_{t+1} given available information at time t. Then, a multi-period forecasting can be simply derived based on that. We can similarly define a conditional expectation of Y_{t+j} given an available information set at time t as $\hat{Y}_{t+j|t} = E_t(Y_{t+j})$. Thus, a j-step ahead FCVAR forecasting can be formulated as

$$\hat{Y}_{t+j|t} = \hat{\rho} + L_{\hat{d}}(\hat{Y}_{t+j|t} - \hat{\rho}) + \hat{\alpha}\hat{\beta}' L_{\hat{d}}(\hat{Y}_{t+j|t} - \hat{\rho}) + \sum_{i=1}^{p} \hat{\Gamma}_i \Delta^{\hat{d}} L^i_{\hat{d}}(\hat{Y}_{t+j|t} - \hat{\rho}) \tag{4.32}$$

where $\hat{Y}_{z|t} = Y_z$ if $z \leq t$. Recursively, a j-step-ahead forecasting, $Y_{t+j|t}$, are calculated from (4.32) for any a given $j \geq 1$. As examined by Nielsen and Shibaev (2018), the FCVAR model performs a minimised root-mean-squared forecast error, while its forecasting performance is superior to both the univariate fractional model and the cointegrated VAR model. We will apply its j-step-ahead forecasting in both demand- and supply-driven determination functions in our forthcoming empirical analysis.

Model forecasting performance evaluations

To evaluate the model forecasting performance and measure the improvement of forecasting accuracy of the FCVAR model over other model specifications, for instance, the CVAR model (a special case of the FCVAR model when $d = b = 1$), we follow Nielsen and Shibaev (2018) and examine the target model's forecasting performance by calculating its root mean squared forecasting errors (RMSFE). The specification of the RMSFE calculation is shown in (4.33).

$$RMSFE = \left\{ \frac{1}{K} \sum_{i=1}^{K} (\hat{Y}_{i,t+h|t} - Y_{i,t+h|t})^2 \right\}^{1/2} \tag{4.33}$$

where $\hat{Y}_{i,t+h|t}$ denotes forecasting values of variable Y_i over the time period $t+1$ to $t+h$ given that an information set of Y_i at time t is available. i indicates specific included variables in the target model system, and i=1,$\cdots$,K. h denotes specified forecasting horizons. Overall, the above formula can measure the RMSFE of the target multivariate model system, which is calculated as the averaged value of the RMSFE for each incorporated series in the system. It can report magnitudes of forecasting errors produced by the whole model system.

4.5 Data

Our empirical study uses a quarterly dataset for the US spanning more than four decades (1975-2016). Overall, a summarized data description of our target variables involving housing prices and macroeconomic fundamentals is reported in Table 4.2 below. In this section, we introduce each of them in detail. Sequentially starting from the variable of bank credit, we discuss issues surrounding what each variable's definition is and how we choose a rational proxy to represent each of them in the empirical analysis.

Table 4.2: **Data Description**

Variable Name and Abbreviation	Detailed Series	Time Period	Data Source
Credit to the Housing Demand (CD)	Mortgage debt outstanding for the residence purchase	1951Q3-2017Q2	Board of Governors of the Federal Reserve System (US)
Credit to the Housing Supply (CS)	Private residential fixed investment	1946Q4-2017Q2	US Bureau of Economic Analysis
Residential Land Value (RLV)	Aggregate market value of residential land	1975Q1-2016Q1	Lincoln Institute of Land Policy
Long-term Interest Rate (LIR)	10-year treasury constant maturity rate	1954Q2-2017Q3	Board of Governors of the Federal Reserve System
Inflation (DEF)	GDP deflator	1946Q4Q1-2017Q3	US Bureau of Economic Analysis
Residential Housing Stocks (HUC)	New privately-owned housing units completed	1967Q4-2017Q4	US Bureau of Census & US Department of Housing and Urban Development
Economic Policy Uncertainty (EPU)	US historical news-based policy index	1900Q1-2017Q4	Baker et al. (2016)
Residential Housing Prices (RHP)	S&P/Case-Shiller US National Home Price Index	1975Q1-2017Q3	S&P Dow Jones Indices LLC

Bank credit is defined as the net lending that is claimed by money issuers, while it also denotes the outstanding amounts that money borrowers are liable to repay. Money-issuing sectors are formed by monetary financial institutions (MFIs) altogether, while bank credit can be obtained from the asset side of MFIs' consolidated balance sheet (Docker and Willoughby, 1999). MFIs are financial institutions whose businesses are to receive deposits and grant credit on their own account to entities other than MFIs (non-MFIs), such as households, nonprofit institutions serving households, private non-financial corporations and other financial corporations (OFCs).[8] On the basis of definitions from the European Central Bank (ECB), the Bank of England (BOE), and the International Monetary Fund (IMF), under the conceptual framework of the 2018 SNA (United Nations, 2008), MFIs stand for depository corporations including central bank and other deposit-taking corporations, such as commercial banks, credit unions, saving institutions and money market mutual funds, at the broadest level. In light of the definition of credit, we segregate bank credit to separately gauge how much credit is provided to the demand side (CD) and the supply side (CS), respectively, in the residential real estate market.

In our chapter, the amount of CD is represented by outstanding mortgage debts for the home purchase (e.g. one- to four- family, and multifamily residences). It explicitly measures the amount of money/credit used to finance the housing demand in a given economy, which also indicates the households' purchase power regarding the housing demand. It is collected from the Board of Governors of the Federal Reserve System (US) covering the period of 1951Q3-2017Q2. In terms of credit to the housing supply side (CS), there is a lack of data that explicitly represent the credit lending to each industry, including the real estate industry. Alternatively, we use the private residential fixed investment ($PRFI$) as a proxy. Instead of focusing on how many loans are issued by MFIs to the residential real estate market, as defined in the US National Income and Product Accounts (NIPA) handbook, $PRFI$ describes the money spending by private sectors (e.g. private firms, households, and non-profit institutions serving households) for the construction and development of residential properties, such as an improvement of existing houses, a creation of new houses, and a replacement of worn out or obsolete houses, in the form of fixed investments. Thus, $PRFI$ enables us to gauge the amount of money provided by private sectors for the provision of housing supply (CS). It is available from 1946Q4 to 2017Q2, and is provided by the US Bureau of Economic Analysis.

In addition to the disaggregate bank credit, this chapter further includes a series of variables, viz. residential land market value (RLV), long interest rate (LIR), residential housing stock (HUC), inflation (DEF), and economic policy uncertainty (EPU), combined to form macroeconomic fundamentals on housing demand and supply sides, respectively. In terms of RLV, following Davis and Heathcote (2007), we approximate it using the aggregate market value of residential land, which is measured based on the S&P/Case-Shiller U.S. National Home Price Index. RLV is able to describe the housing supply/construction expenditure through a land perspective, and data are provided by the Lincoln Institute of Land Policy (1975Q1 to 2016Q1).[9] In terms of long-run interest

[8]For simplicity, non-MFIs refer to private sectors in our chapter. Moreover, according to United Nations (2008), OFCs are financial corporations other than depository corporations. They include non-MMF (Money market funds) investment funds, other financial intermediaries except insurance corporations and pension funds, financial auxiliaries, captive financial institutions and money lenders, insurance corporations, and pension funds.

[9]Data are available through http://datatoolkits.lincolninst.edu/subcenters/land-values/

rate (LIR), we approximate it using a 10-year treasury constant maturity rate. LIR measures the cost level of both housing buyers and developers in financing the house purchase and construction, respectively. The higher the LIR, the greater the borrowing costs are on both housing demand and supply sides. Then, housing prices will subsequently increase/decrease depending upon whether dominating shocks are from supply/demand sides. Its data are collected from the Board of Governors of the Federal Reserve System (US) and range from 1953Q1 to 2017Q4.

In terms of inflation (DEF), we employ the GDP deflator to describe the US price level of all domestic-produced final goods and services in a given time period. It explicitly demonstrates the inflationary and deflationary periods in the entire US economy, while its changes are directly linked to the dynamics of asset prices, such as housing prices. The data are collected from the US Bureau of Economic Analysis, and are from 1946Q4 to 2017Q3. In terms of residential housing stock (HUC), we use a series named the completion of new privately-owned housing units to approximate. This measures total amounts of completed residential properties that are currently available in the US real estate market. Available housing stocks (HUC) represent amounts of housing units that are required by the housing buyers, while they also demonstrate the amounts that are able to be provided by the housing suppliers. Thus, HUC can reflect and affect both housing demand and supply dynamics, respectively, and then impact housing prices. Its data are available from the US Bureau of Census and the US Department of Housing and Urban Development, and range from 1967Q4 to 2017Q4.

In terms of economic policy uncertainty (EPU), it is an important indicator in depicting a level of uncertainty in an economy. As explained in Baker et al. (2016), this index is constructed to measure the uncertainty through three aspects, viz. newspaper coverage of policy and economic related uncertainty, the number of federal tax code provisions set to expire in forthcoming years, and the disagreement among economic forecasters. It is well known that the persistence of uncertainty can impact housing prices through both channels of housing demand and supply. To ensure a long time-series, we use the US historical news-based policy index as a proxy for uncertainty, and it ranges from 1900Q1 to 2017Q4.[10] Moreover, one key variable in the chapter is residential housing prices. It should be able to well report movements of home prices in a specific region over a given period of time. Following related literature, in the case of the national level of the US, there exist three different ways of measures for the price, i.e. median price index, hedonic price index, and repeat sales index, respectively.

In terms of the median price index, it reports the median price for sales of single-family homes. According to whether the target properties are existing or new homes, two median price indexes are constructed, which are the National Association of Realtors

[10]Data are provided by Baker et al. (2016) and are available through www.policyuncertainty.com/index.html

(NAR) index and the Census Bureau median index, respectively. However, this measure suffers operational problems as it is counterfactual to assume that all homes are for sale at any given time period. Moreover, as houses are so special that each of them can be different from each other due to the distinction in hedonic characteristics. Thus, a failure to control for that as is found in the median price index could be questionable as observed price fluctuations could be due to changes in the composition of homes sold rather than shifts of market conditions (Noeth et al., 2011). Furthermore, as an alternative measure, hedonic price index tracks the changes in averaged price levels of all types of homes, while controlling for a bundle of hedonic attributes including both observed housing and locational characteristics. As an example, the US Census Bureaus 'Constant Quality' Housing Price Index is constructed based on this method. Although this measure possesses appealing features regarding an explicit control of hedonic factors, it is tricky to select and include appropriate housing-related characteristics in the measurement, while collecting relevant information could be also hard and time-consuming.

To deal with aforementioned issues, this chapter employs the measure of repeat sales index to represent the national level of the US housing prices. This index, which is proposed by Bailey et al. (1963) and later revised by Case and Shiller (1989), measures price changes while holding constant housing hedonic characteristics through the comparison of price levels of the same home over two or more sales. However, the repeat sales index also has some limitations. First, due to its construction mechanisms of repeat sales, it excludes to consider new homes. Second, to remain the consistency of the same home, it excludes properties that have had significant improvements or deterioration. In addition, the valid sample size can be significantly limited especially in a specific region where volumes of housing transactions are quite small over target period.

Specifically, two repeat transactions indexes are noteworthy, i.e. SP/Case-Shiller and Federal Housing Finance Agency (FHFA) housing price indexes (HPI), respectively. These two indexes track housing price movements differently regarding data coverage, inclusion of refinance appraisal values, use of geographical weights, etc (Noeth et al., 2011). This chapter finally decides to employ the former one (SP/Case-Shiller HPI) due to its unique and appealing advantages over the latter (FHFA HPI). First, the FHFA HPI is built only based on the data from conforming mortgages that are financed by Fannie Mae or Freddie Mac (Canarella et al., 2012). In contrast, the data coverage of the SP/Case-Shiller HPI tends to be much broader that it includes not only first-lien conventional and conforming mortgages but also the housing transactions financed by non-conforming mortgages. Second, the SP/Case-Shiller HPI only includes the real housing transactions and does not consider appraisal values of refinance sales. However, the FHFA HPI includes refinance appraisals, even the refinance-to-refinance cases, which could lead to the problem of appraisal smoothing bias during the calculation of the index (Edelstein and Quan, 2006; Geltner, 1989). Overall, the SP/Case-Shiller HPI can be concluded to more precisely report movements of housing prices in the US in contrast to the FHFA HPI in our case. In addition, it is also consistent with the housing price index used in the calculation of RLV. Therefore, we employ the S&P/Case-Shiller US National Home Price Index to approximate the US national residential real estate prices. Data are from S&P Dow Jones Indices LLC and range from 1975Q1 to 2017Q3. In addition, except for RLV and EPU, all aforementioned time series are retrieved from the Federal Reserve of St. Louis (FRED), US.

In addition to the above introduced variables, there exist some other variables, which also could potentially determine housing demand and supply functions, such as GDP, aggregate money, construction cost, and credit to other financial corporations (OFCs). However, we do not include them in our empirical research mainly due to the following concerns, viz. a multicollinearity problem, a usage of a better proxy, and a limitation of available data. Specifically, for example, although GDP reflects the overall income level of domestic housing buyers, it is highly correlated with GDP deflator (DEF), which is a proxy for the inflation level of the entire economy and has already been included. Moreover, the purchase power of the households in buying residences can be better depicted by outstanding mortgage debts (CD); similarly, a better approximation of credit to the supply side is private residential fixed investment (CS) against credit to OFCs. Therefore, we decide to use disaggregate credit, which can disentangle impacts of credit on housing prices through demand and supply channels, respectively, rather than aggregate credit. In addition, although we intend to include total residential construction costs, its data are nevertheless only available from 1993Q1, which is too short to form our empirical dataset. Instead, we have considered alternatives to measure the financing expenditure of the housing supply such as long interest rate (LIR) and residential land value (RLV).

4.6 Data Transformation and Preliminary Observations

4.6.1 Seasonal adjustment

It is well known that there exist short-term disturbances, namely seasonal effects that are systematically calendar-related to certain time periods within a year, which can obscure and volatilize the dynamics of macroeconomic variables in the long-run (UK Office for National Statistics, 2007). Thus, before proceeding with the empirical analysis, we transform target raw time series by first removing potential seasonal effects. By assuming that each series is composed of different components, i.e. seasonal component, trend-cycle component and irregular component, in an additive format, we employ the X-13ARIMA-SEATS statistical package developed by the US Census Bureau to seasonally adjust all target variables.

Figure C.1 in Appendix C shows moving patterns of the seasonal component of variables such as CD, RHP, RLV, LIR, and EPU, and it also explicitly illustrates the short-run periodic fluctuations in those variables with a serrated shape. Indeed, removal of seasonal effects unfolds the true dynamics of each variable in the long-run. In addition, there is no need to conduct the adjustment for other target variables, such as CS, HUC and DEF, as their original series have already been adjusted.

4.6.2 Business cycles removal

In addition to the seasonal effects, following Lucas (1981), repeated fluctuations also exist in the mid/long-run movements of aggregate economic variables, and are usually longer than a year. Such repeated dynamics within variables' growth patterns are defined as *business cycles* (Hodrick and Prescott, 1997). Specifically, business cycles describe periodic behaviours of a given variable that first start to increase/decrease from a reference time point until a peak point/trough point, and then decreases/increases until the end of a downturn/upturn. Thus, further removing business cycles from each original series is of paramount importance to unfold its long-run movements. After removing periodic disturbances in both the short-run (seasonal effects) and the mid-/long-run (business cycles) from our target raw series, a reliable and robust empirical study can then be carried out.

Broadly, there exist two filtering methods to remove business cycles, i.e. Hodrick-Prescott (H-P) filter and Hamilton's filter. It is well-know that the H-P filter proposed by Hodrick and Prescott (1997) is popular for business cycle removal by decomposing a given series into trend and cyclical components, respectively. Given its imposed assumption that a trend component varies smoothly over time, an economic variable can be formulated in an additive conceptual model as

$$y_t = g_t + c_t \tag{4.34}$$

where t = 1, ..., T. y_t is composed of a trend term (g_t) and a cyclical term (c_t). Thus, in light of (4.34), H-P filter aims to minimize the following objective function

$$\min_{g_t} \left\{ \sum_{t=1}^{T} \Big(y_t - g_t\Big)^2 + \lambda \sum_{t=1}^{T} \Big[\Big(g_t - g_{t-1}\Big) - \Big(g_{t-1} - g_{t-2}\Big) \Big]^2 \right\} \tag{4.35}$$

where $\sum_{t=1}^{T} \Big(y_t - g_t\Big)^2$ denotes the sum of squares of c_t. $\sum_{t=1}^{T} \Big[\Big(g_t - g_{t-1}\Big) - \Big(g_{t-1} - g_{t-2}\Big) \Big]^2$ denotes the sum of squares of the second difference of g_t, which is used to model the smoothness of the variation of g_t. The larger the value of parameter λ, the smoother the growth of g_t. In particular, the value of parameter λ is suggested to be 1600 given a quarterly dataset in our empirical research. In spite of a popularity of the

H-P filter, its accuracy and rationale are still in dispute. The main criticism lies in its assumption of a white noise cyclical component, which is too strict and far from reality. More so, its decomposed cyclical term tends to demonstrate a strong autocorrelation property, which is a feature imposed by the H-P method instead of that possessed by the true data generating process (DGP).

Moreover, there exists an alternative method proposed by Hamilton (2017), which is able to avoid the weaknesses of the H-P filter. According to Hamilton's filter, given a non-stationary series (y_t), its cyclical component at time $t+h$, viz. c_{t+h}, can be defined as the difference between the real value of y at time $t+h$ and its expected value at time t conditional on the available information set prior to time t. c_{t+h} is formulated in (4.36). Thus, this method enables us to capture business cycles which encompass the shocks whose effects last over time h, while they are still transient and tend to disappear in the long-run.

$$c_{t+h} = y_{t+h} - g_t \tag{4.36}$$

where $h = 1, \ldots, T-t$. $g_t = E(y_{t+h} \mid y_t, y_{t-1}, \ldots, y_{t-p+1})$, and is defined as the trend component of y_{t+h}. In light of (4.36), y_{t+h} can be expressed as

$$y_{t+h} = \beta_0 + \sum_{i=0}^{p} \beta_{j+1} y_{t-i} + u_{t+h} \tag{4.37}$$

where the residuals in (4.37) represent the cyclical component, viz. u_{t+h}; and the difference between y_{t+h} and u_{t+h} can be defined as the trend component. As suggested by Hamilton (2017), numbers of lags (p) are selected to be four to both ensure the stationarity of u_{t+h} and maximize available observations of specific series; a two-year standard setting is employed to capture business cycles indicating that h equals to $2, 8$ and 24, for annual, quarterly, and monthly data, respectively. Thus, the cyclical term describes shocks that last within two years, while are still 'transient'. Overall, in contrast to the H-P filter, which imposes a strict assumption to obtain a smooth-varying trend term, the Hamilton's filter ensures the stationarity of the cyclical component for any given non-stationary series and better duplicates the real data generating process (DGP). Therefore we apply Hamilton's filter for business cycle removal in our empirical research.

Moreover, comparative preliminary observations of cyclical and trend components of each target series using both filtering methods are also plotted respectively in Figures C.2 to C.7 in Appendix C. In each figure, movements of business cycles are shown in the left-hand side of panels, while both trend components and non-decomposed variables are depicted in the right-hand side of panels. Each variable is demeaned to eliminate common characteristics and make observations from each cumulative series comparable over time. Specifically, variables in levels are first used in Figures C.2 to

C.4, where both cyclical and trend components of each target series decomposed by H-P and Hamilton's filters can be observed, although movements of each component particularly at an early period appear to be similar between both filters. Thus, to better illustrate and compare the results of business cycle removal by using these two filters, we further transform each target series in a logarithmic format and multiply transformed variables by 100. Plots using corresponding transformed variables are depicted in Figures C.5 to C.7. Moreover, this transformation is also able to clearly demonstrate the growth of each variable, viz. a unit increase of a log-transformed variable is equivalent to a 1% unit increase of the variable in levels. In addition, regarding Hamilton's filter, a suggested two-year setting is applied to identify business cycles.

Indeed, we observe that H-P filtered trend series demonstrate a more smoothly moving pattern compared with the ones filtered by the Hamilton's method. On the other hand, movements of business cycles obtained by the Hamilton's filter tend to be more volatile, while it appears to be a more sophisticated and precise way to replicate true DGP than the H-P filter, which artificially imposes a 'guarantee' of a smooth-varying growth path (Hamilton, 2017). In addition, it can also explain why de-cycled series filtered by the H-P method would express exceptional integration orders, which are hard to explain both empirically and theoretically. Overall, all of these motivate us to employ Hamilton's filter to remove business cycles from our target variables preceding with the further fractional cointegration VAR estimation.

To further observe notable disturbances of business cycles and to illustrate the excellent performance of Hamilton's filter, we carry out a comparison of autocorrelation function (ACF) plots between decomposed (de-cycled) and non-decomposed (non-de-cycled) series. Specifically, in Appendix C, Figures C.8 and C.9 report comparative ACF plots of selected variables including logged credit to the housing demand, credit to the housing supply, land value and logged land value. All these variables are differenced once to remove potential non-stationary elements, following a conventional unit root assumption, in order to better observe effects of business cycles.[11] De-cycled and non-de-cycled series are presented in the right- and left-hand side panels, respectively. Interestingly, instead of behaving as a general stationary series, ACF movements of non-de-cycled variables behave like a sine or cosine function. They first witness a gradual decay until zero and keep sinking negatively until a trough; then they turn to move back towards zero once again. Such periodic dynamics occur repeatedly although the amplitudes reduce gradually over time and are expected to eventually diminish towards zero in the long run. In contrast, the ACF movements of de-cycled series move like a stationary process without aforementioned periodic fluctuations. Thus, the above comparisons further confirm that the Hamilton's filter can well minimise periodic disturbances induced by business cycles.

[11] We only plot the ACF for the variables that show the strongest periodic moving patterns.

In light of existing studies related to the housing-macroeconomic cycles, durations of boom-bust cycles of housing prices and macroeconomic variables are normally longer than a two-year standard setting. Specifically, the duration of debt cycles is suggested to be five years (Hamilton, 2017). Cesa-Bianchi (2013) chooses five-year as the length of rolling window for the calculation of cross-country average correlations of real housing prices and real GDP in different sub-country groups (e.g. advanced economies and emerging market economies.). Moreover, Igan and Loungani (2012) measure the length of housing cycles as well as durations of downturn and upturn of housing prices for different countries. They find that durations of housing cycles for the US are different in different time periods, e.g. 5.25 years (Peak: 1973Q4; Trough: 1975Q3), 10.75 years (Peak: 1979Q1; Trough: 1982Q4), and 17 years (Peak: 1989Q4; Trough: 1995Q3). In addition, given empirical observations in European cross-country real estate markets, both Duan et al. (2018a) and Duan et al. (2018b) suggest that cycles of housing prices and macroeconomic fundamentals on housing demand and supply sides tend to last for 10 years.

Overall, according to relevant literature and data availability in our case, we generally select 10-year as the cycle duration for variable with a relatively long time series. On the other hand, credit cycles for CD have been identified as five years following Hamilton (2017). Cycles of other housing-related variables, e.g. RHP, HUC, and RLV, are set to have a five-year duration due to their constrained data. Once periodic disturbances from both seasonal and cyclical components have been removed from raw data series, the real long-run dynamics of target variables can then be unfolded to guarantee a precise empirical analysis. In addition, regarding the following empirical study, whether a variable is added in levels or a logarithmic format depends upon which one can better demonstrate the variable's long-memory property. Employed dataset has been trimmed to be strongly balanced and runs from 1980Q1 to 2016Q1 for the FCVAR estimation. In the next step, we start the empirical section by first testing the existence of a fractional integration in each target series.

4.7 Results

4.7.1 Univariate analyses

Before proceeding with the FCVAR estimation, a series of tests needs to be conducted to demonstrate whether there exists a long-memory property in our target series. To do that, we apply three univariate analyses discussed as follows.

(1) Visual evidence of a long memory

As implied by (4.8), a fractionally integrated series behaves with a long-memory property indicating that its impulse response coefficients decay hyperbolically over time in contrast to a geometric decay of a short-memory stationary series for example, a stationary AR(1) process. Following Jones et al. (2014), the long memory can be checked by plotting the autocorrelation function (ACF) and the spectral density. In specific, if a specific series has a long-memory, its autocorrelation values should decay hyperbolically until zero in the long-run, in contrast to a geometric decay. In addition, evidence of a long-memory can be also captured by examining the zero frequency of its spectral density figure, where a fractionally integrated process will have mass densities near the zero frequency which are proportional to f^{-2d}. Parameter f stands for the frequency value.

Figures C.10 to C.13 in Appendix C depict movements of both ACF and spectrum of each series. In terms of ACF drawn until 100 lags, its values of each variable decay slowly towards zero by taking a long time period. Such ACF moving patterns with long-memory implications are consistent with existing applications (See for instance, Jones et al., 2014; Kumar and Okimoto, 2007; Tkacz, 2001, among others). In particular, although the ACF value of residential housing stocks depicted in Figure C.11 dwindles towards zero for a long time period, it appears to fluctuate periodically while such patterns are less significant against its analogies with similar moving patterns presented in the left panels of Figures C.8 and C.9. In addition, this comparison speaks in favour of the strong performance of the Hamilton's filter discussed in Section 4.6.2 regarding the removal of cyclical disturbances. Interestingly, the positive ACF value of residential land value shown in Figure C.13 first witnesses a gradual decrease until zero for 40 lags, then it keeps decreasing beyond the zero line and moves negatively throughout rest of the periods. Moreover, as demonstrated from the spectrum figures, there exist mass values at around the zero frequency of each target variable, which provides further visual evidence in favour of a long-memory property in our dataset. In addition, we continue testing in the following subsections whether our target series are fractionally integrated or not.

(2) Stationarity and unit root tests

In theory, a fractionally integrated time series should reject the null hypotheses of both stationary test and unit root test. That is to say, if a given series is non-stationary while it does not have a unit root, it can be defined as a fractionally integrated series with a long-memory property. Thus, we carry out the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test and the Augmented Dickey-Fuller (ADF) test to examine the stationarity and the unit root of each series, respectively. Corresponding results are reported in Table 4.3.

All series reject the null hypothesis of the KPSS test, implying the existence of a non-stationary feature at the 5% significance level expect for the residential land value (RLV) with a 10% significance level. In terms of the ADF test, except for credit to the housing demand side (LCD) and inflation ($LDEF$), all the other variables significantly reject the null hypothesis, implying no unit root. Thus, variables that reject both null hypotheses indicate a fractional integration, while both LCD and $LDEF$ appear to have a unit root. In the next step, we further estimate the integration order (d) of each series through different estimate techniques.

Table 4.3: **The Stationarity and Unit Root Tests**

	LCD	LCS	RHP	LHUC	LIR	LDEF	RLV	EPU
KPSS Test	0.201**	0.154**	0.255***	0.165**	0.694***	0.222***	0.129*	1.260***
ADF Test	-1.313	-3.785**	-4.032***	-3.959**	-3.247*	1.798	-3.242*	-3.722**

Note: (i) * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level; (ii) the logarithmic variables begin with a prefix 'L'; (iii) numbers of lags for both tests are selected based on the information criteria (IC).

(3) Univariate d estimates

We further proceed with univariate d estimates for each target series using different estimates, viz. 'LW', '2ELW', and '2ELWdm'. Specifically, 'LW' denotes the local Whittle estimator (Kuensch, 1987; Robinson, 1995); '2ELW' denotes the two-step exact local Whittle estimator (Shimotsu, 2010; Shimotsu et al., 2005); and '2ELWdm' denotes the two-step exact local Whittle estimator with demeaning and detrending procedures. Univariate d estimates are executed using both static and dynamic types, respectively.

First of all, using the time series covering the entire available time periods of each target series, Table 4.4 reports results of the static estimates with different bandwidth values (B) from 0.4 to 0.8 with a 0.05 increment. Overall, d estimates with different bandwidths overwhelmingly speak in favour of the existence of fractional integration in all target series except for LCD and $LDEF$, while suggesting their d values broadly range from 0.5 to 1, viz. $0.5 < d < 1$. Interestingly, LCD could perform an 'exceptional' d estimates, viz. $1 < d < 2$, except when the bandwidth (B) is very small or large. It helps explain the unit root conclusion of LCD as earlier suggested by the result of its ADF test. Indeed, a unit root assumption in the ADF test tends to be irrational due to its assumption of an integer value rather than a fractional value for the integration order. Overall, in light of all of these, LCD is suggested to be fractionally integrated with $1 < d < 2$, while it should contain a unit root.

Moreover, $LDEF$ is also examined as a fractionally integrated series indicating $0.5 < d < 1$ with most moderate bandwidths (B), although its d values are nearly approaching to 1. Its d values tend to equal to or greater than 1 and less than 2 when B is very small or large. Thus, this also helps explain the unit root conclusion in $LDEF$ by the ADF test. In addition, it is also worth noting that our d estimates of LIR are consistent with the empirical findings in Tkacz (2001) and Jones et al. (2014). Specifically, as shown in Table 4.4, except for a unit root suggestion when $B = 0.40$, all its d values range from 0.5 to 1. In the case of both USA and Canada, Jones et al. (2014) empirically find that d estimates of LIR are close to 1 when B is small, viz. $B = 0.4$, while its values witness a gradual decrease with an increase of B. In particular, the estimated d of LIR with $B = 0.6$ that Jones et al. (2014) calculate using the Geweke and Porter-Hudak (GPH) estimator is 0.886, and its value is roughly equal to our d estimates with the same B by using ELW, 2ELW, and 2ELWdm, which are 0.825, 0.833, and 0.837, respectively. Overall, the static d estimates confirm the existence of a fractional integration and indicate a long-memory property in our target series.

Table 4.4: **The Univariate 'd' Estimates**

Bandwidth	B = 0.40				B = 0.45				B = 0.50			
Variable	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD
LCD	0.444	0.900	1.466	0.167	0.723	1.446	1.434	0.146	1.146	1.546	1.518	0.127
LCS	0.490	0.945	0.537	0.167	0.510	0.890	0.511	0.146	0.600	0.890	0.575	0.127
RHP	0.751	0.845	0.749	0.148	0.669	0.803	0.653	0.127	0.588	0.729	0.578	0.109
LHUC	-0.037	0.200	-0.011	0.177	0.054	0.242	0.062	0.156	0.356	0.458	0.346	0.137
LIR	1.048	1.043	1.047	0.137	0.759	0.759	0.771	0.116	0.783	0.785	0.794	0.099
LDEF	1.108	1.186	1.154	0.167	0.994	0.995	0.871	1.146	0.929	0.977	0.846	0.127
RLV	0.760	1.293	1.320	0.186	1.237	1.336	1.362	0.164	1.190	1.328	1.349	0.145
EPU	0.668	0.841	0.809	0.131	0.787	0.858	0.838	0.111	0.713	0.763	0.734	0.094
Bandwidth	B = 0.55				B = 0.60				B = 0.65			
Variable	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD
LCD	1.183	1.576	1.498	0.111	1.183	1.584	1.510	0.096	0.988	1.244	1.246	0.084
LCS	0.830	0.945	0.714	0.111	1.117	1.079	1.043	0.097	1.081	1.222	1.223	0.084
RHP	0.471	0.671	0.471	0.094	0.575	0.703	0.575	0.080	0.768	0.813	0.772	0.069
LHUC	0.444	0.544	0.464	0.120	0.590	0.647	0.624	0.106	0.532	0.592	0.568	0.093
LIR	0.821	0.823	0.829	0.084	0.825	0.833	0.837	0.071	0.750	0.758	0.762	0.061
LDEF	0.722	0.929	0.784	0.111	0.642	0.912	0.797	0.096	0.744	0.950	0.877	0.084
RLV	0.837	1.061	1.078	0.128	0.722	0.933	0.939	0.114	0.718	0.838	0.829	0.100
EPU	0.661	0.684	0.606	0.079	0.677	0.671	0.627	0.067	0.763	0.748	0.733	0.057
Bandwidth	B = 0.70				B = 0.75				B = 0.80			
Variable	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD	LW	2ELW	2ELWdm	SD
LCD	1.016	1.189	1.205	0.073	1.020	1.175	1.182	0.064	0.886	1.015	1.050	0.057
LCS	0.921	1.019	0.989	0.073	0.823	0.937	0.874	0.064	0.684	0.870	0.780	0.058
RHP	0.756	0.801	0.774	0.059	0.850	0.896	0.889	0.051	0.833	0.913	0.909	0.044
LHUC	0.507	0.580	0.558	0.082	0.623	0.698	0.697	0.072	0.745	0.859	0.859	0.063
LIR	0.664	0.676	0.680	0.052	0.689	0.712	0.715	0.044	0.745	0.791	0.792	0.037
LDEF	0.816	1.031	1.000	0.073	0.915	1.169	1.165	0.064	0.922	1.257	1.258	0.056
RLV	0.661	0.766	0.752	0.088	0.590	0.729	0.713	0.078	0.608	0.717	0.697	0.069
EPU	0.659	0.633	0.623	0.048	0.736	0.710	0.700	0.040	0.788	0.787	0.782	0.034

Note: (i) the logarithmic transformed variables begin with a prefix 'L'; (ii) 'LW' stands for the local Whittle estimator, '2ELW' stands for the two-step ELW estimator, '2ELWdm' stands for the two-step ELW estimator used for the demeaned and detrended variable; (iii) stand errors of the estimates with different bandwidths (B) are saved in columns named 'SD'. SD is calculated as $(4\psi)^{-1/2}$, $\psi = N^B$. N is the number of observations and B represents the value of estimation bandwidth.

In addition to the static d estimates, we further proceed with the dynamic univariate d estimates with a 10-year rolling-window setting. We start estimating d by using the first 10-year data of each variable, while data are then updated with a four-quarter (equivalent to one-year) increment, and d is accordingly re-estimated using an updated window until approaching to the end of the data sample. A same rolling window setting is also employed in Kumar and Okimoto (2007). Through the dynamic estimates, we aim to confirm the long-memory property of our target series, test the sensitivity of static d estimates with the changing data sample, and study how the integration order of each variable evolves over time. As earlier applied in the static estimates, the same estimators, i.e. LW, 2ELW and 2ELWdm, are also employed in the rolling-window estimates. Corresponding results of each series with different B are illustrated in Figures C.14 to C.19 in Appendix C.

Overall, in light of above overwhelming evidence from both static and dynamic d estimates, we confirm the existence of fractional integration in our target variables. In particular, some key patterns from the dynamic estimates emerge. First, the estimated d with a lower bandwidth, particularly when $B = 0.4$ and $B = 0.5$, tend to be more volatile and striking in contrast to the ones with a higher B, and this is in line with Kumar and Okimoto (2007). It implies that moderate bandwidth values, such as 0.6 and 0.7, appear to be more rational in our empirical case. Second, in terms of inflation, its persistence witnessed a gradual decline after the 1990s with many small fluctuations across the period. This finding is consistent with many existing studies (Cogley and Sargent, 2001, 2005; Kumar and Okimoto, 2007; Taylor, 2000). In addition, in terms of LCD, although its estimated d fluctuates over the unit root line ($d = 1$), its values mainly behave as greater than 1 with different rolling-window periods and bandwidths.

In the next section, we proceed with the FCVAR estimation of both housing demand and supply functions involving the calculation of fractional cointegration order of the system, the determination of model specifications, the investigation of the long-run equilibriums between housing prices and macroeconomic factors through both the functions.

4.7.2 FCVAR estimation results

Given that the dynamics of housing prices are determined by macroeconomic shocks on both housing demand and supply sides, a fundamental assumption of the chapter is that a macroeconomic determinant of housing prices can impact through the channel of either demand or supply; or both of them. For example, the shocks of economic policy uncertainty can depress both house buyers' purchase intentions and house constructors' development intentions, implying a simultaneous fall of both housing demand and supply, and then, depending upon which one is dominant, housing prices could shift negatively or positively. Thus, without a clear identification of the distinct channels of housing price determination on demand and supply sides, the real effects of our target variables, which could impact on both the sides, would not be disentangled but instead remain intertwined.

Overall, both housing demand- and supply-driven housing price determination functions are constructed, respectively, by using the FCVAR model. The estimates of both functions are presented in the following subsections. As assumed earlier in Section 4.4.2, $d = b$. It implies that the fractional order (d) of the group of our target variables is cointegrated to zero. That is to say, any long-run cointegrating relationship(s) among our target variables tends to be a short-memory stationary process. In addition, to both remove common unchanged characteristics and minimize non-stationary deterministic elements induced by 'the continued and inertial movements' over time, we further demean and detrend each target variable by using Shimotsu's (2010) method after the data transformation.

Furthermore, after the FCVAR estimations, a five-year-ahead forecasting of the future movements of both variables and obtained cointegrating relationship(s) from demand and supply functions are respectively executed to examine the validation of model estimates. Finally, by solving the simultaneous equilibrium relationships in these two functions, an overall housing determination equation involving macroeconomic factors from both the functions can be eventually derived. In addition, in light of the significance test of the cointegrating parameters (α and β) of each target variable, robustness checks by employing rational restricted FCVAR estimates further confirms our conclusions.

4.7.2.1 Determination of model specification

After selecting variables to form both demand and supply functions, the primary issue then is to determine the FCVAR model specification by choosing the optimal model parameters, such as the lag order and the number of ranks, in the FCVAR system for each function. First of all, we need to gauge the highest lag order (p) to form the short-run corrections. We follow Jones et al. (2014) and select the optimal lag order by a series of Likelihood Ratio (LR) tests through a *'general to specific'* strategy. The LR test starts from a very generous lag order, viz. $p = 8$, by assuming that potential short-run interdependence among target variables exists within eight quarters (equivalent to two years).

For each LR test, the null hypothesis is that the coefficient of the highest lag order (p) is not significant ($H_0 : \Gamma_p = 0$), in contrast to the alternative hypothesis in favour of the significance of Γ_p ($H_1 : \Gamma_p \neq 0$). If the null hypothesis is accepted, the highest lag order (p) should then be dropped and the model will be re-estimated until it can be significantly rejected. Within each LR test, we also perform a white noise test through the Ljung-Box Q-test to examine if the residuals are autocorrelated.[12] If its null hypothesis of no autocorrelation is rejected, we have to drop that specified highest lag order

[12]The number of lags in the test is chosen as 12 in the following estimations; we also tried other lag orders such as 4, 8, and 16, and the test results are qualitatively the same.

and move one step back in the determination of model specification. On top of these principles, another important question is how to confirm the highest lag order (p) that we choose is the best among all qualified candidates, which all can significantly reject the H_0 and have no autocorrelation in the residuals of their LR tests. We can answer this question and eventually determine the optimal lag order through the information criteria (IC) technique, such as the Akaike information criteria (AIC) and the Bayesian information criteria (BIC), whose values with different p are reported during each LR test. The optimal order should have a minimum value of the IC.

Once the optimal p has been decided, we move on to determine the number of ranks ($rank$) in the FCVAR system, i.e. the number of the long-run cointegrating relationships. To do this, we follow Johansen (1995) and identify $rank$ through a series of the Likelihood Ratio (LR) tests. The sequential constructed null hypotheses are $H_0 : rank = k$ for $k = 0, 1, \ldots, K$ against the same alternative hypothesis implying the *full rank*, i.e. $H_1 : rank = K$ where K is the number of variables and equals to the *full rank* in the system. Finally, the selected rank order is the one that first accepts its corresponding null hypothesis. It represents the number of long-run equilibrium relationships among target variables. Once both lag orders and ranks of the FCVAR system are determined, we can then move forward to proceed with the FCVAR model estimation.

Furthermore, as pointed out by Johansen (1995), the parameters of cointegrating relationship(s), viz. α and β, cannot be separately identified without additional restrictions of the matrix normalization for Π in (4.23). Thus, in the following estimations, we impose an identification restriction that normalizes β regarding housing prices (RHP). The second variable selected to do the β normalization is residential housing stocks (HUC) but only in the case when model ranks are greater than one. This normalization setting is meaningful for the chapter because it enables us to resolve our key research questions regarding how equilibrium housing prices are determined by and interact with macroeconomic factors from demand and supply sides, respectively.

4.7.2.2 The demand-driven determination function of housing prices

The group of demand-driven factors includes residential housing stocks ($LHUC$), inflation ($LDEF$), long interest rate (LIR), credit to the housing demand (LCD), and economic policy uncertainty (EPU). They are either exclusive demand variables, which affect housing prices only on the demand side, viz. $LDEF$ and LCD, or dual-impact variables, which can impact on both demand and supply sides, viz. $LHUC$, LIR, and EPU. The target explanatory variable of the demand function is housing prices (RHP^D), where its superscript (D) indicates that it is the specific housing prices determined by the demand function instead of the supply function. In particular, in light of the discussions in Section 4.7.1, we further differentiate both $LDEF$ and LCD to remove their potential unit root and conveniently capture all target variables' long-memory properties in the specified FCVAR system.

Table 4.5: **Lag-order Selection - FCVAR (Demand Function)**

p	K	$\hat{d}$	$LogL$	LR	P-$value$	AIC	BIC	$PmvQ$
8	6	1.404	-2138.50	63.21	0.003	4938.99	5915.03	1.00
7	6	1.508	-2170.10	40.31	0.285	4930.20	5800.08	1.00
6	6	1.401	-2190.25	71.70	0.000	4898.51	5662.24	1.00
5	6	1.294	-2226.10	50.18	0.059	4898.21	5555.78	1.00
4	6	0.624	-2251.19	87.40	0.000	4876.38*	5427.80	0.98
3	6	1.224	-2294.89	87.11	0.000	4891.78	5337.04	1.00
2	6	1.209	-2338.45	83.69	0.000	4906.89	5246.00	0.40
1	6	0.856	-2380.29	86.39	0.000	4918.58	5151.53	0.00
0	6	0.784	-2423.48	0.00	0.000	4932.96	5059.76*	0.00

Note: (i) number of observations (T) in sample is 141; (ii) order of the white noise test is 12.

Table 4.6: **Rank Tests - FCVAR (Demand Function)**

$Rank$	$\hat{d}$	$LogL$	$LRstatistic$	P-$value$
0	0.77	-2316.228	130.073	0
1	0.687	-2288.641	74.899	0.001
2	0.68	-2271.028	39.672	0.045
3	0.641	-2254.864	7.344	0.926
4	0.616	-2252.225	2.067	0.945
5	0.625	-2251.194	0.004	0.998
6	0.624	-2251.192	—-	—-

Note: (i) number of observations (T) in sample is 141; (ii) order of lags is 4.

Following procedures discussed in Section 4.7.2.1, to determine the model specification, we first perform the lag order selection with the corresponding results presented in Table 4.5. Each LR test with different highest lag orders (p) ranging from 0 to 8 demonstrates the significance of p at either the 5% or 1% significance levels except when $p = 5$ and $p = 7$. Meanwhile, for the autocorrelation check of the residuals in each LR test, it suggests no autocorrelation except when $p = 0$ and $p = 1$. In light of these results, the optimal p has eventually been chosen as 4 due to its lowest AIC value.[13] In addition, the estimated d of the FCVAR system equals to 0.624 when $p = 4$, which directly speaks in favour of a fractional co-integration order of the group of demand-driven variables.

In terms of the selection of ranks, we conduct a series of LR tests. Corresponding results with different null hypotheses are presented in Table 4.6. Specifically, the first two null hypotheses of $rank = 0$ and $rank = 1$ are respectively rejected against the alternative hypothesis of $rank = 6$, viz. the *full rank*, given that both P values are less than the 1% significance level. Then updated null hypotheses continue to be tested with higher rank numbers. Given that our main research focus is the impacts of demand factors on housing price dynamics, we would like to retain as many housing demand factors as possible in the cointegrating relationship with β normalized by housing prices (RHP). Thus, we eventually accept the following null hypothesis of $rank = 2$ with $P = 0.045$ at the 1% significance level. It implies that there exist two cointegrating relationships ($rank = 2$) in the demand function. Overall, in terms of the demand-driven FCVAR

[13] We do not follow the BIC in selecting the optimal p. This is because the residuals with the BIS's suggested p do not pass the white noise test, while its suggestion ($p = 0$) of no short-run corrections is counter-factual and hard to explain in reality.

function, lag augmentations of its short-run terms are 4 and rank numbers are equal to 2.

Thus, based on the general FCVAR specification shown in (4.23), the estimated demand-driven function is presented in (4.38) following by two stationary cointegrating relations shown in (4.39) and (4.40). With regard to (4.38), both $Y_t - \rho$ on the left hand side and α on the right hand side are expanded in matrix form with corresponding estimated values; column vector ν_t stands for $\beta' L_d(Y_t - \rho)$ in (4.23); the highest lag order of the short-run dynamics is 4. Moreover, estimated d of the demand function (4.38) is 0.680 with standard error of 0.039, implying a factional co-integration order. It is also consistent with the obtained d value in Table 4.5 when $p = 4$, which is 0.624. The P value of the Ljung-Box Q-test with 12 lags is 0.996 shown in the parenthesis below the test statistic, denoting that the residuals in (4.38) are well-behaved with no signs of autocorrelation.

Estimated Unrestricted FCVAR model:

$$\Delta^{\hat{d}} \left(\begin{bmatrix} RHP^D \\ LHUC \\ LDEF \\ LIR \\ EPU \\ LCD \end{bmatrix} - \begin{bmatrix} 3.709 \\ 0.050 \\ -0.127 \\ -11.004 \\ -20.442 \\ -31.173 \end{bmatrix} \right) = L_{\hat{d}} \begin{bmatrix} -0.142 & 2.161 \\ 0.036 & -3.117 \\ -0.143 & 0.788 \\ 0.148 & -0.192 \\ 0.074 & 1.838 \\ -0.056 & 2.335 \end{bmatrix} \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix} + \sum_{i=1}^{4} \hat{\Gamma}_i \Delta^{\hat{d}} L^i_{\hat{d}} (Y_t - \hat{\rho}) + \hat{\varepsilon}_t \tag{4.38}$$

$\hat{d} = \underset{(0.039)}{0.680}$, $Q_\varepsilon(12) = \underset{(0.996)}{358.611}$, $LogL = -2271.028$

The Demand-driven Equilibrium Relationships (long-run):

$$\begin{aligned} RHP_t^{D*} = -2.4548 - 14.238 \times LDEF_t - 2.415 \times LIR_t - 0.865 \times EPU_t \\ + 1.280 \times LCD_t + \nu_{1t} \end{aligned} \tag{4.39}$$

$$\begin{aligned} LHUC_t^{D*} = 0.0837 - 0.279 \times LDEF_t - 0.024 \times LIR_t - 0.002 \times EPU_t \\ + 0.012 \times LCD_t + \nu_{2t} \end{aligned} \tag{4.40}$$

With regard to (4.39) and (4.40), these two cointegrating relationships are built with β normalized by residential housing prices (RHP^D) and residential housing stocks ($LHUC$), respectively. Referring to Section 4.3, RHP^{D*} and $LHUC^{D*}$ respectively denote the level of housing prices (RHP^D) and residential housing stocks ($LHUC$) in the equilibrium condition achieved through the housing demand side. Regarding the demand function, the first relation shown in (4.39) demonstrates how housing demand factors drive the equilibrium housing prices given that $\nu_{1t} = 0$; the second one shown in (4.40) describes how these factors determine the equilibrium level of housing stock provisions given that $\nu_{2t} = 0$.

The cointegrating relationships derived from the demand function are consistent with theoretical expectations. As shown in (4.39), housing demand factors such as inflation ($LDEF$), long interest rate (LIR), and economic policy uncertainty (EPU) negatively affect RHP^{D*}, while the money supply to the housing demand side (LCD) exerts a positive impact on RHP^{D*}. Specifically, a 1% unit change of the growth of DEF induces a 14.238 unit decline of RHP^{D*}; the downward impact of LIR on RHP^{D*} is greater than that of EPU, which are -2.415 and -0.865 respectively; and LCD positively affects RHP^{D*} (1.280). In terms of the second relation in (4.40), similar to the first relation regarding signs of the effect, $LDEF$, LIR, and EPU negatively affect $LHUC^{D*}$, while LCD provides a positive effect (0.012). In comparison between (4.39) and (4.40), impacts of demand factors on $LHUC^{D*}$ are much smaller than their counterparts on RHP^{D*}.

In theory, on the housing demand side, the stationary equilibrium relation (4.39) explains to what extent demand-driven factors determine the equilibrium housing prices, and the results are consistent with our theoretical expectations in light of the market equilibrium theory. Specifically, in an overheated economy with high inflation, interest rate tends to experience an upward pressure, implying an increasing cost of borrowing money. This depresses housing demand leading to a fall in housing prices. Similarly, a direct increase of interest rate leads to a fall of housing prices by depressing the housing demand. In addition, the existence of high uncertainty in the economy potentially unnerves investors and subdues their intentions of consumption/investment; therefore housing prices tend to dwindle given that housing demand witnesses a downturn. More importantly, understanding the impact of money/credit supply in the long-run is one of our main focuses. Credit provided to the housing buyers, which is measured by using mortgage debt outstanding for the residential properties, can exert a positive impact on determining housing prices. The more money that housing buyers own, the greater their purchasing capabilities/powers should be.

Moreover, the second equilibrium equation demonstrates the long-run relation between available housing stocks and other demand-driven factors. As theoretically expected, their nexuses can be interpreted in detail through the housing demand channel. First, the appreciation of inflation depresses the housing demand by increasing the interest rate, while the intention of housing supply also dwindles, all of which indicate a decrease of both house buyers' required housing stocks and house suppliers' provision intentions. Eventually, available amounts of housing stock completion in the real estate market tend to decrease. A similar effect mechanism is also applied to other demand factors on housing stocks. The escalation of long interest rate will similarly depress housing demand and then decrease available housing stock. Moreover, an exposure of the economy to a high-level of uncertainty stagnates housing demand by depressing house buyers' purchase intentions, therefore the number of housing stocks in circulation will decrease. Besides, a tightened constraint of credit supply will also restrict housing stocks by dipping the housing demand.

To evaluate the reliability of the above reported FCVAR estimation results and corresponding theoretical explanations, this chapter further conducts forecasting evaluation exercises to assess the predictive accuracy of the employed FCVAR model, while its predictive improvement over the traditional vector error correction model with strict assumption of integer integration order, i.e. CVAR model, is also examined accordingly. Following (4.33), the model forecasting performance is measured through the calculation of RMSFE. Based on the forecasting algorithms as discussed in Subsection 4.4.4, we conduct nine out-of-sample forecasting with h-step/$\frac{h}{4}$-year ahead where $h = 1, 5, 10, 15, 20, 25, 30, 35, 40$ for the price determination function on the housing demand side estimated by using the FCVAR and CVAR models, respectively.

Table 4.7: **RMSFE calculations (Demand Function)**

Model	Forecast horizon (h)								
	1 step	5 step	10 step	15 step	20 step	25 step	30 step	35 step	40 step
(a) The magnitudes of RMSFE values									
FCVAR	0.0069	0.0059	0.0148	0.0256	0.0302	0.0617	0.0466	0.0321	0.0184
CVAR	0.0046	0.0067	0.0284	0.0630	0.2075	0.1743	0.0633	0.2514	0.1449
(b) Percentage change in RMSFE values									
FCVAR versus CVAR	50.2906	-12.2085	-47.7410	-59.3619	-85.4452	-64.5979	-26.3334	-87.2188	-87.3032

Note: (i) forecasting performance of the overall demand-driven model system is measured by the RMSFE values. (ii) Section (a) reports the values of RMSFE for the multivariate model system of the FCVAR and CVAR. (iii) Section (b) reports the comparisons of RMSFE values between the FCVAR and CVAR; negative reported values favour the FCVAR model.

The magnitudes of RMSFE values for each h-step ahead until 40-step/10-year for both the two models are reported in Section (a) in Table 4.7. Specifically, it is clear that the FCVAR model outperforms the CVAR model throughout all nine forecasting evaluations with smaller RMSFE values except at the one-step ahead forecast horizon where the RMSFE values for both models are quite similar and the one from the CVAR is slightly greatly than that from the FCVAR. The forecasting accuracy of the FCVAR model is increasingly much higher than that of the CVAR model with the increase of forecast horizons.

Furthermore, the improvement degree of forecasting accuracy of the FCVAR model over the CVAR model can be measured by reporting the percentage change in RMSFE values of the FCVAR model relative to the CVAR model following

$$100 \times \left\{ \frac{RMSFE_{FCVAR}}{RMSFE_{CVAR}} - 1 \right\} \tag{4.41}$$

where its reported negative results favour the superiority of the FCVAR model while positive results favour the superiority of the CVAR model in terms of the model predictive performance. Relevant results are accordingly reported in Section (b) in Table 4.7 and show that the RMSFE of the FCVAR model can be as much lower as 87% than that of the CVAR model. Overall, the results in Section (a) are broadly consistent with that in Section (b), and both demonstrate that the FCVAR model behaves smaller FMSFE values than that of the CVAR model except at the one-step ahead forecast horizon where FMSFE values of both models are similar. We can finally conclude that the forecasting performance of the FCVAR model is checked to be more accurate than that of the CVAR model in the case of the demand-driven housing price determination function.

In the next, we carry out a five-year-ahead forecasting exercise for the incorporated series and its estimated equilibrium relationships. Their predictions can be clearly observed in Figure C.20 in Appendix C. To summarize, the in-sample dynamics of each series fluctuate frequently over the zero line, while the out-of-sample forecast broadly predicts a consistent movement where each series gradually converges to the zero line. In particular, variables such as RHP, LCD and EPU witnessed a more striking movement from 2008 onwards probably due to the outbreak of the global financial crisis. They particularly experienced a significant decrease after 2010; their downward momentums are then expected to be curbed from 2016 while they start to recover gradually towards the zero point. In terms of the cointegrating relationships, the one normalized by RHP has a more volatile movement than the one normalized by $LHUC$, while both are also expected to converge towards zero in the forecast.

4.7.2.3 The supply-driven determination function of housing prices

The group of supply-driven factors includes variables such as residential housing stocks ($LHUC$), economic policy uncertainty (EPU), long interest rate (LIR), residential land value (RLV), and credit to the housing supply (LCS). They are either exclusive supply variables, which affect housing prices only on the supply side, viz. RLV and LCS, or dual-impact variables, which affect housing prices on both demand and supply sides, viz. $LHUC$, LIR, and EPU. The target explanatory variable is housing prices (RHP^S), where its superscript (S) indicates that it is determined by the supply function instead of the demand function. In addition, we decide to not include inflation ($LDEF$); otherwise there would be a multicollinearity problem in the supply-driven function as $LDEF$ is highly correlated with LCS.[14]

Similar to Section 4.7.2.2, we start the FCVAR estimation by first determining the model specification. In terms of the optimal highest lag order (p), it should be selected based on a series of tests including LR test, corresponding white noise test, and information criteria. As indicated in Table 4.8, we prefer the optimal $p = 5$ due to its minimum AIC value, while it also passes both the LR test and corresponding white noise test. In addition, the fractional order d with $p = 5$ equals to 0.876, implying the long-memory

[14] $LDEF$ is approximated by the GDP deflater, which is calculated based on the nominal GDP, while parts of GDP form the private residential fixed investment, which proxies LCS. Therefore, both tend to be highly correlated.

Table 4.8: **Lag-order Selection - FCVAR (Housing Supply)**

p	K	$\hat{d}$	$LogL$	LR	$P\text{-}value$	AIC	BIC	$PmvQ$
8	6	1.577	-2162.43	52.12	0.040	4986.86	5965.24	1.00
7	6	1.070	-2188.49	88.47	0.000	4966.98	5838.95	1.00
6	6	1.340	-2232.73	50.71	0.053	4983.45	5749.01	1.00
5	6	0.876	-2258.08	91.94	0.000	4962.16*	5621.31	1.00
4	6	1.129	-2304.05	98.29	0.000	4982.10	5534.84	0.96
3	6	0.927	-2353.19	37.52	0.399	5008.38	5454.71	0.59
2	6	0.010	-2371.95	125.13	0.000	4973.90	5313.82	0.00
1	6	0.066	-2434.52	220.35	0.000	5027.04	5260.55*	0.00
0	6	0.860	-2544.69	0.000	0.000	5175.39	5302.49	0.00

Note: (i) number of observations (T) in sample is 142; (ii) order for the white noise test is 12.

Table 4.9: **Rank Tests - FCVAR (Housing Supply)**

$Rank$	$\hat{d}$	$LogL$	$LRstatistic$	$P\text{-}value$
0	0.873	-2305.240	94.318	0.040
1	0.872	-2287.005	57.849	0.263
2	0.907	-2274.238	32.313	0.676
3	0.827	-2263.226	10.290	0.962
4	0.874	-2259.783	3.404	0.984
5	0.877	-2258.085	0.007	1.000
6	0.876	-2258.081	—	—

Note: (i) number of observations (T) in sample is 142; (ii) order of lags is 5.

property in the group of supply-driven factors. In terms of the rank number, as shown in Table 4.9, the first null hypothesis of $rank = 0$ is rejected while the second one of $rank = 1$ is accepted against the same alternative hypothesis of $rank = 6$, viz. the *full rank*. Thus, it implies one cointegrating relationship among supply-driven factors. To sum up, regarding the FCVAR system of the supply function, its short-run correction terms are up to order 5, while its rank is equal to 1. In light of this, we then proceed with the FCVAR estimation and produce the results shown as follows.

Estimated Unrestricted FCVAR model:

$$\Delta^{\hat{d}}\left(\begin{bmatrix} RHP^S \\ LHUC \\ EPU \\ LIR \\ RLV \\ LCS \end{bmatrix} - \begin{bmatrix} 6.234 \\ -1.509 \\ -14.985 \\ -9.547 \\ 3.446 \\ -19.121 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.020 \\ -0.259 \\ 0.509 \\ 0.811 \\ 0.271 \\ -0.719 \end{bmatrix} \nu_t + \sum_{i=1}^{5} \hat{\Gamma}_i \Delta^{\hat{d}} L^i_{\hat{d}}(Y_t - \hat{\rho}) + \hat{\varepsilon}_t \tag{4.42}$$

$\hat{d} = \underset{(0.025)}{0.872}$, $Q_\varepsilon(12) = \underset{(0.999)}{347.802}$, $LogL = -2287.005$

The Supply-driven Equilibrium Relationship (long-run):

$$RHP_t^{S*} = -0.5229 - 0.827 \times LHUC_t + 0.065 \times EPU_t + 0.143 \times LIR_t + 1.312 \times RLV_t - 0.174 \times LCS_t + \nu_t \tag{4.43}$$

With regard to the estimated FCVAR supply function presented in (4.42), both estimated drift term (ρ) and short-term adjustment speed parameter (α) have been shown on the left and right hand sides, respectively. The parameter, ν_t, viz. $\beta' L_d(Y_t - \rho)$, is expanded in (4.43), which demonstrates the long-run cointegrating relationship between housing prices (RHP^S) and supply-driven variables given that $\nu_t = 0$, and it is normalized by RHP^S. Key parameters of the FCVAR estimation are presented below (4.42). The fractional integration order (d) of the system is 0.872. The statistic of the Ljung-Box Q-test is 347.802 with P value=0.999, implying a strong indication of no autocorrelation in the residuals. Moreover, the long-run cointegrating relationship between housing prices and supply-driven factors is shown in (4.43).

Referring to Section 4.3, RHP^{S*} denotes the level of housing prices in the equilibrium condition that is achieved on the housing supply side. Specifically, residential housing stocks ($LHUC$) and credit to the housing supply (LCS) negatively affect housing prices (RHP^{S*}), while economic policy uncertainty (EPU), long interest rates (LIR), and residential land value (RLV) positively affect RHP^{S*}. A 1% unit change of HUC and CS can induce a 0.827 unit and a 0.174 unit change of RHP^{S*} in the opposite direction, respectively; the positive effects of EPU, LIR, and RLV on RHP^{S*} are 0.065, 0.143, and 1.312, respectively.

In terms of theoretical explanations, through the housing supply channel, our estimated long-run equilibrium relationship between housing prices and supply-driven factors shown in (4.43) is consistent with the theoretical expectations. Specifically, the excess provision of housing stocks implies the excess housing supply in circulation; this will directly discourage housing builders' intention of further housing supply, while housing prices then tend to slump. Moreover, the exposure of high-level economic policy uncertainty will depress not only the housing demand but also the housing supply, which further affects housing prices. An increasing uncertainty level indicates a heightening uncertainty of the investment return for the real estate construction; it will depress the housing supply and subsequently increase housing prices. In particular, regarding the dual effects of uncertainty on affecting housing prices in our empirical estimation, its positive effect through the supply channel is much less than its negative impact through the demand channel. This suggests that the overall effects of uncertainty, which aggregate its effects from both demand and supply channels, tend to be negative on housing prices.

Similarly, long interest rates also exert dual effects in affecting housing prices on both demand and supply sides. Regarded as a proxy for levels of borrowing costs/expenditures for the housing construction/development, the larger the costs are, the much greater the constraints will be on housing supply; then housing prices will rise correspondingly. Thus, in light of its stronger negative effect on the demand side versus its relatively less negative effect on the supply side, the aggregate effect of long interest rates on housing prices tends to be negative. Indeed, our elaborations of specific factors with dual impacts, such as uncertainty and interest rates, offer a precise way to disentangle their real effects on housing prices. In terms of residential land (market) value, its increase enlarges the housing production costs and then dwindles the housing supply, therefore housing prices will then witness a rise. In addition, an increase in available money/credit provided to housing suppliers, which is represented by the levels of residential investment for the housing construction, can stimulate a rise in housing suppliers' intention in developing housing units. Therefore, the housing supply will increase while housing prices tend to decline.

In the next, to demonstrate the reliability of above-reported FCVAR estimations and the model validation, similar to the forecasting performance evaluation process conducted in previous section regarding the demand-driven function, in the case of housing price determination function on the supply side, we follow (4.33) to calculate RMSFE values of the FCVAR model. Then its calculated RMSFE values are compared with that of the CVAR model. Through this, the forecasting accuracy of the FCVAR model can be well examined.

Corresponding results in Section (a) in Table 4.10 report that the RMSFE values of the FCVAR model are checked to be greater than that of the CVAR model except at 25-step and 30-step ahead forecast horizons where the two models possess similar RMSFE values. Moreover, as depicted in Section (b) in Table 4.10 and calculated based on (4.41), the improvement degree of forecasting accuracy of the FCVAR model can be as much as 99% compared with the CVAR model, while the results obtained from both Sections (a) and (b) are consistent. Overall, in the case of housing supply-driven function, we can conclude that the FCVAR model outperform the traditional model of vector error corrections with the assumption of integer integration order, i.e. CVAR model.

Table 4.10: **RMSFE calculations (Supply Function)**

Model	Forecast horizon (h)								
	1 step	5 step	10 step	15 step	20 step	25 step	30 step	35 step	40 step
(a) The magnitudes of RMSFE values									
FCVAR	0.0073	0.0084	0.0261	0.0532	0.0269	0.0900	0.0421	0.0273	0.0129
CVAR	0.0091	0.0227	0.0667	0.0579	0.0300	0.0457	0.0346	0.1552	1.5336
(b) Percentage change in RMSFE values									
FCVAR versus CVAR	-19.9531	-63.1356	-60.9260	-8.0968	-10.1478	96.7783	21.5241	-82.3900	-99.1620

Note: (i) forecasting performance of the overall supply-driven model system is measured by the RMSFE values. (ii) Section (a) reports the values of RMSFE for the multivariate model system of the FCVAR and CVAR. (iii) Section (b) reports the comparisons of RMSFE values between the FCVAR and CVAR; negative reported values favour the FCVAR model.

Finally, by using the FCVAR model, we carry out forecasting exercises to predict the future 5-year movements of the incorporated variables and the obtained cointegrating relationship in the housing supply-driven function. The corresponding results are acorrdingly plotted in Figure C.21 in Appendix C. Overall, the in-sample movements of variables in the supply function tend to be similar to the ones in the demand function that fluctuate frequently across the zero line. The outbreak of financial crisis markedly affects their dynamics, which induced a plunge after 2010. Their movements tend to gradually become stable during the out-of-sample forecast, while the forecast of dual-effect factors, such as $LHUC$, EPU and LIR, behave consistently in both demand and supply functions as observed in Figures C.20 and C.21, respectively. With regard to the cointegrating relationship, it witnessed a striking fluctuation after the financial crisis, and is expected to taper off and converge to zero during the forecast.

4.7.2.4 The overall determination function of equilibrium housing prices

Eventually, we have learnt that there exist factors that exclusively affect housing prices through demand or supply sides, and dual-effect factors that can impact on both sides. The equilibrium housing prices tend to be determined as a trade-off between impacts from distinct housing demand and supply effect channels. According to Sections 4.7.2.2 and 4.7.2.3, we have already gauged the extent of impacts that factors from both demand and supply channels separately exert in contributing to the equilibrium housing price determination. Indeed, as theoretically elaborated, the equilibrium housing prices can achieve when both demand and supply functions reach a level of market clearing. In that condition, demand and supply curves intersect, viz. demand and supply are equal in the real estate market: that is, $RHP^{*} = RHP^{D*} = RHP^{S*}$.

Thus, we further investigate what impacts macroeconomic fundamentals eventually exert on the equilibrium housing prices after considering the two distinct effect channels. This question can be answered by solving two simultaneous equilibrium relations between housing prices and demand/supply factors as shown in (4.39) and (4.43), while an overall determination function is then derived and presented in (4.44). In particular, aggregate impacts of specific variables with dual effects are measured by combining their distinct effects from housing demand and supply sides.

The Combined Equilibrium Relationship:

$$\begin{aligned} RHP_t^{*} = -1.48885 - 7.119 \times LDEF_t + 0.640 \times LCD_t - 0.4135 \times LHUC_t - 0.087 \times LCS_t \\ +0.656 \times RLV_t - 0.400 \times EPU_t - 1.136 \times LIR_t + \nu_t^{*} \end{aligned} \tag{4.44}$$

where $\nu_t^{*} = (\nu_{1t} + \nu_t)/2 = 0$ in equilibrium. The exclusive demand-driven factors, viz. inflation ($LDEF$) and credit to the housing demand (LCD), exert negative and positive effects, respectively; the exclusive supply-driven factors, viz. credit to the housing supply (LCS) and residential land value (RLV), depict negative and positive effects, respectively.

With regard to factors with a dual-impact, such as economic policy uncertainty (EPU) and long interest rates (LIR), their real impacts on housing prices are all negative at -0.400 and -1.136, respectively. This is because both of their much stronger negative effects from the housing demand channel offset their relatively less positive impacts from the housing supply channel. After combining impacts from both channels, they both eventually exert negative effects which are smaller than the ones exerted from the demand channel in absolute value. In addition, due to the normalization requirement of the cointegrating relationship, the specific dual-effect factor, residential housing stocks ($LHUC$), does not enter the demand-driven equilibrium. Thus, its negative impact depicted in (4.44) is from the supply channel, which is -0.4135.

What policy insights are implied in light of the above findings? Since the aggregate estimates of macroeconomic effects would result in confusing and biased conclusions, policy-makers could gain a clearer comprehension about their real impacts on determining housing price dynamics through a precise recognition of the distinct effect-transmission channels on housing demand and supply sides, respectively. In particular, by doing this, policy-makers are able to minimize the micro-level information loss by recognizing the possible dual roles of specific macroeconomic variables that can alter demand and supply curves simultaneously. Moreover, the long-memory featured shocks that intrinsically exist in the macroeconomy-housing market interaction also cannot be neglected. A failure to identify their presence could give rise to an inaccurate understanding of the equilibrium co-movement between housing prices and macroeconomic fundamentals.

4.7.3 Robustness exercises: Sensitivity of unrestricted FCVAR results to restrictions

To examine the robustness of both unrestricted demand- and supply-driven FCVAR estimations presented in Subsections 4.7.2.2 and 4.7.2.3, respectively, we re-estimate both unrestricted functions with reasonable imposed restrictions that consider the significance of their cointegrating parameters, viz. β and α. To do that, we first conduct a series of hypothesis tests based on (4.24) and (4.25) by using the Likelihood Ratio (LR) test. In theory, if a given null hypothesis for β is rejected, the tested variable(s) can enter and form the long-run cointegrating relationship(s). If a given null hypothesis for α is rejected, the tested variable(s) can contribute to the adjustments/error corrections towards the equilibrium; if not, then it is long-run weakly exogenous. The null hypothesis of each test in demand and supply functions can be seen in Tables 4.11 and 4.13, respectively. Corresponding test results are depicted in Tables 4.12 and 4.14, respectively.

Specifically, results of the hypothesis testing are summarized as follows. First, the significant rejections of H_D^d and H_S^d indicates the validity of fractional integration setting in modelling both the demand- and supply-driven functions. In terms of the demand-driven function, β of EPU is restricted to be zero in favour of the result of H_{D5}^{β} in Table 4.12. In terms of the supply-driven function, α of RLV is restricted to be zero in favour of the result of H_{S5}^{α} in Table 4.14. In addition, it is worth noting that while the P value for the hypothesis test H_{D1}^{α} that RHP is weakly exogenous is 0.192, we do not impose this restriction in the demand function. This is because RHP is the key variable of this chapter, therefore both its short-run corrections and long-run equilibrium behaviours cannot be ignored in both the housing demand and supply functions, respectively. Similarly, we also do not impose the restriction described in H_{S3}^{β} that support for $LHUC$ does not enter the cointegrating relationship in the supply function. Overall, the estimation results and obtained cointegrating relationships of restricted demand- and supply-driven functions are demonstrated in (4.45)-(4.49), respectively.

Overall, the results of both restricted demand- and supply-driven functions are highly consistent with their unrestricted counterparts, respectively, with regard to both the signs and magnitudes. That is to say, regarding both the housing demand and supply functions, restricted and unrestricted FCVAR estimations give rise to qualitatively the same conclusions. Particularly, in terms of the restricted estimations, the specific variable with a dual role, e.g. LIR, demonstrates a negative impact on RHP through the demand channel in contrast to its far smaller positive effect through the supply channel. Speaking in favour of the unrestricted estimations, it implies that the aggregate effect of LIR on RHP should be negative. Thus, the robustness of our unrestricted FCVAR estimates can be explicitly and conveniently checked.

4.8 Conclusions

This chapter sheds new light on the investigation of the real role of macroeconomic fundamentals in determining equilibrium housing prices through a clear identification of two distinct channels. These channels describe macroeconomic effects on housing price movements through both demand and supply sides of the housing market, respectively. Both the long memory property of stochastic shocks within a macroeconomy-housing market interaction and the gradual price adjustment towards a market clearing are elaborated. Moreover, short-run corrections and long-run equilibrium relationships between housing prices and demand- or supply-driven factors are precisely gauged. In addition, the significance of the cointegrating parameters on both the sides is explicitly examined. Model validation is also tested through a five-year-ahead forecast of future movements of the target variables and the cointegrating relationship(s).

To summarize, our estimates are consistent with theoretical expectations. The chapter not only measures the impacts of factors that exclusively affect housing prices through a demand or supply channel, but also provides a novel strategy in interpreting what real impacts the dual-effect factors exert from both demand and supply sides. Particularly, in light of an overall equilibrium housing price determination, we argue that the negative impacts of variables such as economic policy uncertainty and long interest rates reported in the extant literature, are aggregate impacts. However, the real impacts of these factors, which can exert a dual-effect on determining housing prices, cannot be disentangled without a clear identification of the distinct macroeconomic effect channels. Finally, we find that aggregate negative effects of these factors tend to be an offset between the stronger negative effects from the demand side and relatively smaller positive effects from the supply side. In addition, the estimations of restricted FCVAR models further support our conclusions.

Table 4.11: **Hypothesis Tests of the Demand Function**

H_D^d	The fractional order, d, equals to one.	H_{D1}^α	RHP is weakly exogenous.
H_{D1}^β	HPI and HUC do not enter the cointegrating relationships.	H_{D2}^α	LHUC is weakly exogenous.
H_{D2}^β	All demand-driven variables except HUC do not enter the cointegrating relationships.	H_{D3}^α	LDEF is weakly exogenous.
H_{D3}^β	LDEF does not enter the cointegrating relationships.	H_{D4}^α	LIR is weakly exogenous.
H_{D4}^β	LIR does not enter the cointegrating relationships.	H_{D5}^α	EPU is weakly exogenous.
H_{D5}^β	EPU does not enter the cointegrating relationships.	H_{D6}^α	LCD is weakly exogenous.
H_{D6}^β	LCD does not enter the cointegrating relationships.		

Table 4.12: **Hypothesis Test Results of the Demand Function**

	H_D^d	H_{D1}^β	H_{D2}^β	H_{D3}^β	H_{D4}^β	H_{D5}^β	H_{D6}^β
df	1	4	8	2	2	2	2
LR Statistic	35.228	38.878	19.136	8.136	38.037	3.751	107.991
P-Value	0.000***	0.000***	0.014**	0.017**	0.000***	0.153	0.000***
	H_{D1}^α	H_{D2}^α	H_{D3}^α	H_{D4}^α	H_{D5}^α	H_{D6}^α	
df	2	2	2	2	2	2	
LR Statistic	6.098	108.636	16.580	228.568	278.629	192.560	
P-Value	0.192	0.000***	0.002***	0.000***	0.000***	0.000***	

Note: (i) *: significant at the 10% level, **: significant at the 5% level, ***: significant at 1% level; (ii) df denotes the degree of freedom; (iii) LR is the abbreviation for the Likelihood Ratio test.

Estimated Restricted Demand-driven FCVAR model:

$$\Delta^{\hat{d}}\left(\begin{bmatrix} RHP^D \\ LHUC \\ LDEF \\ LIR \\ EPU \\ LCD \end{bmatrix} - \begin{bmatrix} 2.948 \\ 0.135 \\ -0.307 \\ -9.655 \\ -21.971 \\ -30.672 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.032 & 2.056 \\ 0.053 & -2.868 \\ -0.049 & 1.103 \\ 0.039 & -0.615 \\ 0.002 & 0.860 \\ -0.018 & 2.054 \end{bmatrix} \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix} + \sum_{i=1}^{4} \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^i (X_t - \hat{\rho}) + \hat{\varepsilon}_t \tag{4.45}$$

$\hat{d} = \underset{(0.037)}{0.693}$, $Q_\varepsilon(12) = \underset{(0.998)}{351.949}$, $LogL = -2272.903$

The Demand-driven Equilibrium Relationships (long-run):

$$RHP_t^{D*} = -3.130 - 61.142 \times LDEF_t - 8.219 \times LIR_t + 3.001 \times LCD_t + \nu_{1t} \tag{4.46}$$

$$LHUC_t^{D*} = 0.069 - 1.074 \times LDEF_t - 0.122 \times LIR_t + 0.047 \times LCD_t + \nu_{2t} \tag{4.47}$$

Table 4.13: **Hypothesis Tests of the Supply Function**

H_S^d	The fractional order, d, equals to one.	H_{S1}^{α}	RHP is weakly exogenous.
H_{S1}^{β}	RHP does not enter the cointegrating relationship.	H_{S2}^{α}	LHUC is weakly exogenous.
H_{S2}^{β}	All supply-driven variables do not enter the cointegrating relationship.	H_{S3}^{α}	EPU is weakly exogenous.
H_{S3}^{β}	LHUC does not enter the cointegrating relationship.	H_{S4}^{α}	LIR is weakly exogenous.
H_{S4}^{β}	EPU does not enter the cointegrating relationship.	H_{S5}^{α}	RLV is weakly exogenous.
H_{S5}^{β}	LIR does not enter the cointegrating relationship.	H_{S6}^{α}	LCS is weakly exogenous.
H_{S6}^{β}	RLV does not enter the cointegrating relationship.		
H_{S7}^{β}	LCS does not enter the cointegrating relationship.		

Table 4.14: **Hypothesis Test Results of the Supply Function**

	H_S^d	H_{S1}^{β}	H_{S2}^{β}	H_{S3}^{β}	H_{S4}^{β}	H_{S5}^{β}	H_{S6}^{β}	H_{S7}^{β}
df	1	5	1	1	1	1	1	1
LR Statistic	16.757	3.053	24.124	2.418	43.997	68.836	70.016	118.443
P-Value	0.000***	0.081*	0.000***	0.120	0.000***	0.000***	0.000***	0.000***
	H_{S1}^{α}	H_{S2}^{α}	H_{S3}^{α}	H_{S4}^{α}	H_{S5}^{α}	H_{S6}^{α}		
df	1	1	1	1	1	1		
LR Statistic	18.736	6.961	37.494	18.479	2.635	38.463		
P-Value	0.000***	0.031**	0.000***	0.000***	0.268	0.000***		

Note: (i) *: significant at the 10% level, **: significant at the 5% level, ***: significant at 1% level; (ii) df denotes the degree of freedom; (iii) LR is the abbreviation for the Likelihood Ratio test;

Estimated Restricted Supply-driven FCVAR model:

$$\Delta^{\hat{d}}\left(\begin{bmatrix} RHP^S \\ LHUC \\ EPU \\ LIR \\ RLV \\ LCS \end{bmatrix} - \begin{bmatrix} 6.273 \\ -1.558 \\ -15.197 \\ -9.981 \\ 3.584 \\ -18.961 \end{bmatrix}\right) = L_{\hat{d}} \begin{bmatrix} -0.204 \\ -0.288 \\ 0.506 \\ 0.811 \\ 0.000 \\ -0.672 \end{bmatrix} \nu_t + \sum_{i=1}^{5} \hat{\Gamma}_i \Delta^{\hat{d}} L_{\hat{d}}^i (X_t - \hat{\rho}) + \hat{\varepsilon}_t \quad (4.48)$$

$\hat{d} = \underset{(0.025)}{0.868}$, $Q_\varepsilon(12) = \underset{(0.998)}{350.796}$, $LogL = -2288.045$

The Supply-driven Equilibrium Relationship (long-run):

$$RHP_t^{S*} = -0.631 - 0.816 \times LHUC_t + 0.060 \times EPU_t + 0.156 \times LIR_t + 1.282 \times RLV_t \\ -0.184 \times LCS_t + \nu_t \quad (4.49)$$

Chapter 5

Conclusions

5.1 Overview

This final chapter summarises the main results of the dissertation and outlines policy implications for each of the three main chapters. This is provided in Section 5.2. Section 5.3 emphasises their overall research contributions. Section 5.4 presents an overview of research outputs from the thesis. Section 5.5 and Section 5.6 present limitations of the study and identify possible directions of future research.

5.2 Concluding Remarks and Policy Implications

This thesis sheds new light on the dynamic interaction between housing prices and macroeconomic fundamentals via three significant instruments, viz. the role of 'space', the 'credit disaggregation', and the 'long-memory shocks', and from these, several insightful findings have been produced.

In Chapter 2, we have identified the mediating role of 'space' in investigating the impacts of macroeconomic policy interventions on housing price dynamics in spatially-interdependent international housing markets. A spatial housing production function has been built to theoretically model the impacts of macroeconomic co-movements on housing price determinations by identifying the cross-country spatial interdependence of macroeconomic variables and housing prices. Moreover, we have employed a dynamic spatio-temporal analytical framework to examine our theoretical explanations, while the dynamic spatial Durbin model (SDM) has been chosen due to its superiority over other model specifications. Discussions regarding the selection of the Maximum Likelihood (ML) estimation technique and a comparative analysis between the ML and other methods have been also elaborated on in this chapter. In addition, the endogeneity issues raised in the estimation can be ameliorated by the SDM model specification, which considers both spatial endogenous and exogenous interactions.

Overall, using a panel dataset of European countries over the period 1985-2015, we have found that while macroeconomic policy variables can affect cross-country housing price movements, disregarding the existence of spatial spill-over effects in conventional non-spatial methodologies can give rise to the significant over-estimation of these variables. Therefore, the housing market will also be incorrectly regarded as under-reaction. Our empirical results are robust to various robustness checks using different estimation techniques, replacing variables, data sensitivity check to the structural break, and broadening the sample coverage as well as the model performance test by using different post-estimation routines.

The findings of this chapter hold important policy implications to understand the real impacts of macroeconomic interventions on regulating housing prices in a cross-location context with a clear identification of the role of 'space'. Failure to account for the existence of spatial spillover effects would result in a serious over-estimation of the macroeconomic policy impacts on directing the housing price fluctuations across spatially-adjacent real estate markets. Consequently, this over-estimation by traditional non-spatial models would induce policymakers unknowingly over-emphasize the role of macroeconomic variables in the real estate market, while mistakenly concluding the macroeconomic policy ineffectiveness and real estate market under-reaction. Indeed, excessive macroeconomic regulation and control would ultimately give rise to the over-heating of housing markets, as well as the broader economy, by extension. Overall, in a setting of cross-region within a single country or a setting of cross-country sharing a common economic market, for instance, members in the European Union, precise identification of the mediating role of 'spatial spillover effects' in determining macroeconomic impacts on cross-location housing price movements should be of interest and focus for policymakers.

Motivated by both existing conflicting empirical results and sparse theoretical discussions regarding the interactive relationship between credit and housing prices, in Chapter 3, we have followed a Keynesian thought of bank credit disaggregation and segregated total credit into *credit to the real economy* and *credit to the asset markets*. A conceptual framework has been constructed to explain the interactive relationships between different disaggregate credit and housing prices through housing demand and supply credit-circulation channels, respectively, in a macroeconomic context. To test our theoretical explanations, we have employed a panel vector autoregressive (PVAR) model; meanwhile, its generalised method of moments (GMM) estimators have been demonstrated to effectively minimise the endogeneity issues. Through the applications of several identification strategies related to the PVAR model using a quarterly panel dataset covering nine industrialised countries over the period 1990Q1-2014Q1, theoretically expected results have emerged especially after a consideration of business cycles.

Overall, we have found a mutually positive reinforcing relationship between *credit to the real economy* and housing prices, while a more complex dynamics between *credit to the asset markets* and housing prices have also been obtained. Specifically, *credit to the asset markets* demonstrates an insignificant and negative impact on housing prices in the short-run, and it becomes significant and positive in the long-run. In addition, echoed in the post-Keynesian quantity theory of credit, only *credit to the real economy* contributes to the economic growth (nominal GDP), while *credit to the asset markets* only exerts insignificant effects. A series of robustness checks has been conducted in this chapter, viz. accounting for economic policy uncertainty and controlling for the global financial crisis, to corroborate our benchmark estimates. In addition, we have further uncovered the important role of economic policy uncertainty in strengthening dynamics between different disaggregate credit and housing prices. Adverse information such as uncertainty and the global financial crisis has been demonstrated to negatively affect housing prices and nominal GDP.

These results give rise to insightful policy suggestions that optimal credit allocation should depend upon a clear identification of distinct credit-circulation channels rather than using credit in the aggregate form. Since aggregate credit is only a representation of the 'averaged out' effects of its components, replying on credit in the aggregate format in the policy-making would mask the true and individual interactions between housing prices and different credit components flowing to the housing demand and supply functions, respectively. Consequently, it could eventually weaken the robustness of the monetary policy regarding the sensible money supply to the real estate markets, as well as the sensible supply to the real economy and the financial markets, respectively. Indeed, clear identification of the distinct credit-circulation channels through the demand and supply functions of a housing market could offer a naturally-reasonable way to investigate how bank credit lending to housing buyers and developers can distinctly direct housing price movements. Meanwhile, the applied mechanism of credit disaggregation to the real economy and the financial markets can also provide a precise comprehension of the role of credit in economic growth and asset price appreciation, respectively. Overall, results of this chapter suggest that policymakers should favour close monitoring of credit allocation to the housing demand and supply circulations, as well as the extent of pump-priming resource allocation to the real economy, in order to dampen risks of 'overheating the real estate markets and the broader economy'.

In Chapter 4, we have followed the thought of credit disaggregation employed in Chapter 3, and further introduced the high-dimensional shock interaction mechanism where a stochastic shock inherently converges slowly to a long-run equilibrium than being conventionally assumed and modelled. We have allowed the system to have a long-memory and then separately studied the macroeconomy-housing market comovements by clearly identifying effect-transmission channels via both housing demand and supply functions. This chapter not only quantifies impacts of demand- or supply-exclusive variables, but also provides a way to separately gauge dual effects of the specific variables whose dynamics shift both demand and supply curves simultaneously. Both the slowly-converged shocks and the gradual pricing adjustment towards the market clearing have been explicitly considered in a long-memory cointegration research structure. In light of these, we have constructed a theoretical framework to explain the long-run equilibrium housing price determinations by macroeconomic fundamentals through both the functions, respectively, and the short-run disequilibrium error corrections.

Proceeding with the empirical analysis, a rigorous data-transformation process has been conducted to eliminate potential periodic disturbances, while the long-memory shocks of target variables have also been identified. Moreover, with a quarterly dataset of the US over the period 1975Q1 to 2016Q1, we have empirically employed the fractionally cointegrated vector autoregressive (FCVAR) model to execute our theoretical construct. The FCVAR model validation has also been evaluated through a five-year forecasting exercise for target series and obtained cointegrating relationship(s). Eventually, an overall equilibrium housing price determination function has been derived by solving the separately-estimated simultaneous housing demand and supply functions. In light of the significance of cointegrating parameters in our unrestricted FCVAR estimates, we have further examined the robustness of our conclusions by conducting rational restricted FCVAR estimates of both the functions.

Overall, the unique three-pronged strategy this chapter has employed, viz. the identification of distinct effect-transmission channels of the macroeconomy-housing market interaction, the long-memory shocks in the interaction, and the gradual pricing adjustment in the housing market, sheds new light on the way macroeconomic policy adjustments impact asset price movements. The strategy employed in this chapter helps us characterise disequilibrium and its transitive effects more thoroughly than is currently studied in the literature. The conclusions of this chapter give rise to insightful policy considerations that digging into the micro-level information and correctly quantifying the magnitude of 'memory' in the interactive system can equip policymakers with better insights and greater predictive power of the evolving system.

Specifically, since conventional research strategy mostly uses an aggregated function to analyse the equilibrium determination of housing prices, policymakers replying on this strategy would unknowingly disregard the potentially-existing distinct and dual roles of macroeconomic fundamentals on impacting housing prices through the housing demand and supply sides, respectively. Instead, only the averaged estimates of the macroeconomic impacts are reported from such an aggregated price determination function. Thus, regarding any a given macroeconomic variable with dual-roles, the use of that conventional research strategy could only produce an 'averaged out' estimate, which tends to be a combination of its overwhelming impacts from the demand side and its relatively smaller impacts from the supply sides in the case of this chapter. In other words, the impacts from the demand side for such a factor with dual-roles are seriously over-emphasized compared with that from the supply side. Hence, policymakers could gain a more precise comprehension of the true macroeconomic impacts on determining equilibrium housing prices through a clear identification of the distinct effect-transmission channels from the demand and supply sides of a housing market. Furthermore, rather than imposing a unit root assumption by using conventional approaches, the naturally-existing long-memory featured shocks in the macroeconomy-housing market interactive system cannot be disregarded. Thus, accurate identification of effect transmission channels and measurement of memory features in the interactive system should be of interest for policymakers to truly investigate the equilibrium comovements between housing prices and macroeconomic variables.

5.3 Contributions

This thesis has several appealing contributions to the investigation of the dynamic interaction between housing prices and macroeconomic fundamentals. Distinct contributions of each specific chapter are presented as follows.

Chapter 2 has theoretically identified the role of space in the international spatially-interdependent housing markets and developed an empirically testable analytical framework to model the spatial spillover effects on moderating the impacts of macroeconomic policy interventions on cross-country housing price movements. Through a comparative empirical analysis, we have found a significant and consistent over-estimation of macroeconomic variables in conventional non-spatial methodologies, in contrast to a smaller and more accurate estimation measured by the dynamic spatial Durbin model.

Chapter 3 has studied the importance of credit disaggregation strategy, through which aggregate credit is segregated into *credit to the real economy* and *credit to the asset markets* based on the distinct housing demand and supply credit-circulation channels. Through this, the bi-directional interactions between different disaggregated credit and housing prices are disentangled in a macroeconomic context. In addition, we have also found the important role of economic policy uncertainty in deepening the interactions. The obtained empirical results are consistent with our theoretical expectations especially after treating the business cycles.

Chapter 4 has identified various distinct effect-transmission channels in the macroeconomy-housing market interaction on both housing demand and supply sides. This novel strategy can not only measure effects of demand- or supply-exclusive factors, but also the ones that have dual roles in determining housing prices on both sides. The equilibrium housing price determinations on both sides have been separately modelled in a long-memory cointegration framework, through which both the slowly-converged shocks in the interaction and the gradual pricing adjustment towards the market equilibrium have been conveniently considered.

5.4 Research Outputs

An overview of current research outputs of the thesis is presented as follows.

Two publications:

- Duan, K., Mishra, T., Parhi, M., Wolfe, S., 2018. "How Effective Are Policy Interventions in a Spatially-embedded International Real Estate Market?", *The Journal of Real Estate Finance and Economics*. Forthcoming. [Chapter 2].

- Duan, K., Mishra, T., Parhi, M., 2018. ”Space Matters: Understanding The Real Effects of Macroeconomic Variations in Cross-country Housing Price Movements”, *Economics Letters* 163, 130-135. [Chapter 2].

Two academic papers available on-line in the SSRN eLibrary:

- Duan, K., Mishra, T., Parhi, M., Wolfe, S., 2018. ”To Segregate or to Aggregate?: Uncovering the Real Effects of Credit in Housing Price Dynamics”. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3236678. [Chapter 3].
- Duan, K., Mishra, T., Parhi, M., 2018. ”Value the ’Memory’!: Identifying Macroeconomic Variations in Housing Price Determination”. Available at SSRN: http://dx.doi.org/10.2139/ssrn.3236674. [Chapter 4].

Six conference presentations:

- Duan, K., Mishra, T., Parhi, M., Wolfe, S., ”To Segregate or To Aggregate: Uncovering the Real Effects of Credit in Housing Price Dynamics”, Refereed Session, The 25th Annual Meeting of The European Real Estate Society (The ERES 2018), June 2018, Reading.
- Duan, K., Mishra, T., Parhi, M., Wolfe, S., ”To Segregate or To Aggregate: Uncovering the Real Effects of Credit in Housing Price Dynamics”, 2018 Doctoral Research Conference on Transforming Research and Practice Through Cross-disciplinary Insights in Business, Law and Art, April 2018, Winchester.
- Duan, K., Mishra, T., Parhi, M., Wolfe, S., ”Disaggregated Bank Credit and Housing Price Movements: Disentangling The Real Effects”, The 58th Annual Meeting of The Italian Economic Association (The SIE 2017), October 2017, Cosenza.
- Duan, K., Mishra, T., Parhi, M., Wolfe, S., ”Macroeconomic Variations and Spatial Frictions in Housing Price Behaviours in Europe”, Portsmouth-Fordham Conference on Banking and Finance, September 2016, Portsmouth.
- Duan, K., Mishra, T., Parhi, M., ”Macroeconomic Variations and Spatial Frictions in Housing Price Behaviours in Europe”, PhD Conference in Monetary and Financial Economics, Supported by The Royal Economic Society, June 2016, Bristol.
- Duan, K., Mishra, T., Parhi, M., ”So Close Yet So Distant: The Dynamics of Space in Housing Price Behaviours in Europe”, Southampton Business School PhD Conference, March 2016, Southampton.

5.5 Research Limitations

While this thesis presents strong results and insightful policy implications in interpreting the dynamics nexus between housing prices and the macroeconomy, some limitations and shortcomings are acknowledged as follows.

In Chapter 2, the dataset for the empirical estimates covers 16 European countries mainly located in Western and Northern Europe. However, countries that locate in Central and Eastern Europe are currently excluded due to the constrained data availability particularly for a long time period. Moreover, the application of the dynamic spatial Durbin model (SDM) imposes an underlying assumption of the single causal direction of effects from the independent variables (macroeconomic variables) to the dependent variable (housing prices). This assumption may lose the information that both types of variable could have a bi-directional interaction. However, Chapter 2 does not consider this due to the following reasons. First, although sparse, there indeed exist applications on studying the interdependence among variables under a spatial framework, such as the Spatial Vector Autoregressive (SpVAR) model (See Chen and Conley, 2001; Neusser, 2008, for instance) and the Spatial Autoregressive (SAR) model (See Duan et al., 2018a, for instance). However, they can only consider the spatio-temporal dependence of a single variable among different geographic/economic agents, which are inappropriate to answer our research question, viz. modelling the multi-directional interactions among different variables across different spatial locations over time. Second, as the research focus in Chapter 2 is the effects of macroeconomic interventions on housing price dynamics, therefore studying the determination of macroeconomic variables as a function of housing prices has already gone beyond its scope. In addition, the research routine of this chapter is also echoed in existing housing-related research (See Arestis and Gonzalez-Martinez, 2016, for instance).

In Chapter 3, the US is not included in the current empirical dataset due to its limited data availability for *credit to the asset markets*, where its proxy (credit to other financial corporations) only available from 2001Q4 in the case of the US. Thus, it is too short to be compatible with the other countries in the dataset with a longer time series starting from 1990Q1. Moreover, Chapter 3 does not model the equilibrium relationship among target variables due to the difficulty in adding the error correction term in its employed panel vector autoregressive (PVAR) model. However, this chapter indeed both theoretically and empirically elaborates on the dynamic interaction, although its studies do not involve the market equilibrium situation. As a continuation, Chapter 4 aims to improve on this by exploring the equilibrium relationship between housing prices and macroeconomic fundamentals in a long memory cointegration framework.

In Chapter 4, the amount of credit lending to the housing suppliers is not included due to the limited data availability, while it is an important variable to depict the levels of credit provisions to the housing supply. However, we rather proxy it by using the private residential fixed investment to measure how much money is invested in total home constructions and development. Moreover, Chapter 4 assumes that the fractional cointegration order in the system is equal to the integration order of target variables, while these two orders could be different numbers in reality. It is because that this chapter aims to measure the stationarity in equilibrium relationship(s) among target variables. Thus, the difference between cointegration and integration orders is assumed to equal to zero.

5.6 Future Research Directions

A number of possible directions for future research of this thesis are identified as promising.

First, in Chapter 2, instead of using static geographical distance, the construct of spatial weights matrix can be further improved by measuring the dynamic economic distance between every pair-wise countries, where elements can also vary over time, although this would require new calculation algorithms and variables, such as the identification of a temporal dynamic weights matrix by using the cross-country bilateral trade flow (Lee and Yu, 2016).

Second, in Chapter 3, rather than only measuring the averaged estimates over included countries, future research could focus on quantifying the individual patterns of and the cross-country transmission effects on the interactive relationship among target variables in each country within a panel VAR model setting, which tends to be meaningful than the averaged-out explanations. It could probably be achieved by using a Bayesian Panel VAR model (See Canova and Ciccarelli, 2013; Koop and Korobilis, 2016, for instance) or a global VAR model (See Dees et al., 2007, for instance). Moreover, current dataset could also be extended to make the research findings applicable to more countries.

Third, in Chapter 4, current research only studies the condition in which orders of the cointegration and integration are the same. Future research could relax this assumption by allowing for different values of these two orders, while the impulse response function technique should also be further developed in the FCVAR model specification. Moreover, a long-memory cointegration analysis extended in the panel dataset could be another future direction in the spirit of Robinson (1995).

In addition, future research could also focus more on the micro-level information to identify and model heterogeneous patterns of the housing transaction determinations in sub-samples with different classified quantiles using specified response variables in a spatial research framework. This could be modelled by using the Bayesian Spatial Quantile Regression (Reich et al., 2011).

Appendix A

Supplement to Chapter 2

The Representation in matrix form

We know from equation (2.5) that our aggregate productivity, $A_i(t)$, is given by

$$A_i(t) = \Gamma(t)(mh_i(t))^{\delta} \prod_{j \neq i}^{N} A_j(t)^{\beta D_{ij}}$$

By re-expressing this equation in logarithmic form, we get

$$\ln A_i(t) = \ln \Gamma(t) + \delta \ln(mh_i(t)) + \ln(\prod_{j \neq i}^{N} A_j(t)^{\beta D_{ij}})$$

We re-write the third term on the right hand side of the above formula, then

$$\ln A_i(t) = \ln \Gamma(t) + \delta \ln(mh_i(t)) + \beta \sum_{j \neq i}^{N} (D_{ij} \ln A_j(t))$$

To simplify notation, we omit t from the above and expand the equation in matrix form

$$\underset{(N\times 1)}{\begin{pmatrix} \ln A_1 \\ \ln A_2 \\ \ln A_3 \\ \dots \\ \ln A_N \end{pmatrix}} = \underset{(N\times 1)}{\begin{pmatrix} \ln \Gamma \\ \ln \Gamma \\ \ln \Gamma \\ \dots \\ \ln \Gamma \end{pmatrix}} + \delta \underset{(N\times 1)}{\begin{pmatrix} \ln(mh_1) \\ \ln(mh_2) \\ \ln(mh_3) \\ \dots \\ \ln(mh_N) \end{pmatrix}} + \beta \underset{(N\times 1)}{\begin{pmatrix} \begin{bmatrix} D_{12} & D_{13} & D_{14} \dots D_{1N} \end{bmatrix} \times \begin{bmatrix} \ln A_2 & \ln A_3 & \ln A_4 \dots \ln A_N \end{bmatrix}' \\ \begin{bmatrix} D_{21} & D_{23} & D_{24} \dots D_{2N} \end{bmatrix} \times \begin{bmatrix} \ln A_1 & \ln A_3 & \ln A_4 \dots \ln A_N \end{bmatrix}' \\ \begin{bmatrix} D_{31} & D_{32} & D_{34} \dots D_{3N} \end{bmatrix} \times \begin{bmatrix} \ln A_1 & \ln A_2 & \ln A_4 \dots \ln A_N \end{bmatrix}' \\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \\ \begin{bmatrix} D_{N1} & D_{N2} & D_{N3} \dots D_{NN-1} \end{bmatrix} \times \begin{bmatrix} \ln A_1 & \ln A_2 & \ln A_3 \dots \ln A_{N-1} \end{bmatrix}' \end{pmatrix}}$$

From the above matrix equation, we further expand the third term on the right hand side

$$\underset{(N\times 1)}{\begin{pmatrix} \ln A_1 \\ \ln A_2 \\ \ln A_3 \\ \dots \\ \ln A_N \end{pmatrix}} = \underset{(N\times 1)}{\begin{pmatrix} \ln \Gamma \\ \ln \Gamma \\ \ln \Gamma \\ \dots \\ \ln \Gamma \end{pmatrix}} + \delta \underset{(N\times 1)}{\begin{pmatrix} \ln(mh_1) \\ \ln(mh_2) \\ \ln(mh_3) \\ \dots \\ \ln(mh_N) \end{pmatrix}} + \beta \underset{(N\times 1)}{\begin{pmatrix} D_{12} \times \ln A_2 + D_{13} \times \ln A_3 + D_{14} \times \ln A_4 + \dots D_{1N} \times \ln A_N \\ D_{21} \times \ln A_1 + D_{23} \times \ln A_3 + D_{24} \times \ln A_4 + \dots D_{2N} \times \ln A_N \\ D_{31} \times \ln A_1 + D_{32} \times \ln A_2 + D_{34} \times \ln A_4 + \dots D_{3N} \times \ln A_N \\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \\ D_{N1} \times \ln A_1 + D_{N2} \times \ln A_2 + D_{N3} \times \ln A_3 + \dots D_{NN-1} \times \ln A_{N-1} \end{pmatrix}}$$

In compact form, the above representation can be written as:

$$A = \Gamma + \delta mh + \beta DA$$

Here, A is the $(N \times 1)$ vector of $\ln A_i$. Γ is the $(N \times 1)$ constant vector. mh is the $(N \times 1)$ vector of $\ln(mh_i)$. D is the $(N \times N)$ Markov-matrix of D_{ij}.

The Moran's *I*

Moran's I is a popular measure of spatial autocorrelation and is given by:

$$\text{Moran's } I = \frac{[\sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})]N}{S^2 \sum_{i=1}^{N}\sum_{j=1}^{N} W_{ij}}$$

Where $S^2 = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \overline{Y})^2$; $\overline{Y} = \frac{1}{N}\sum_{I=1}^{N} Y_i$. In this case, Y_i is the house prices in country i; N represents 16 target OECD countries. W_{ij} indicates the elements of row-standardized inverse-distance spatial weight matrix W corresponding to the country pair (i, j). The expected value of I, $E(I)$, is calculated by $E(I) = \frac{-1}{N-1}$ based on the null hypothesis of no spatial autocorrelation. If $I > E(I)$, the overall distribution of Y can be characterized by positive spatial autocorrelation, indicating that spatially adjacent countries tend to have similar house prices. If $I < E(I)$, it implies negative spatial autocorrelation and presents large dispersion of house prices between spatially neighbouring countries (Pisati, 2001). Moreover, the power of spatial autocorrelation depends on the value of Z, which can be calculated as $Z = \frac{I-E(I)}{SD(I)}$. $SD(I)$ denotes the standard deviation of I. The larger is the absolute value of Z, the stronger is the power of spatial autocorrelation.

Table A.1: **Moran's *I* Statistics for House Prices (1985-2015)**

Variables	Z	p-value*	Variables	Z	p-value*
1985	1.215	0.112	2000	−0.296	0.383
1986	1.444	0.074*	2001	−0.727	0.234
1987	1.144	0.126	2002	−0.942	0.173
1988	0.906	0.182	2003	−1.511	0.065*
1989	0.904	0.183	2004	−1.856	0.032**
1990	1.095	0.137	2006	−0.991	0.161
1991	1.105	0.135	2007	−0.100	0.460
1992	0.968	0.167	2008	−0.229	0.409
1993	0.812	0.208	2009	1.161	0.123
1994	0.751	0.226	2010	1.990	0.023**
1995	0.732	0.232	2011	2.117	0.017**
1996	0.753	0.226	2012	2.036	0.021**
1997	0.780	0.218	2013	2.119	0.017**
1998	0.619	0.268	2014	2.074	0.019**
1999	0.167	0.434	2015	2.132	0.017**

Note: (i) *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; (ii) z stands for the power of spatial autocorrelation; (iii) 2005 is the reference year.

The Panel Unit Root Tests

Table A.2: **Results of Panel Unit Root Tests**

Test	hpi	cb	pdi	ur	rir	credit	tax	rri
d=0								
LLC test:								
No Panel Means	2.722	−3.735***	8.203	−1.617*	−4.983***	1.471	0.160	1.646
Panel Means	−0.596	−2.280**	−1.713**	−5.441***	0.226	−0.965	−1.179	−2.567***
Trend & Panel Means	−3.285***	−1.057	−1.908**	−6.084***	−2.399***	0.701	−0.672	−3.810***
IPS test:								
Demean	8.581	−0.255	6.036	0.494	−5.893***	3.233	0.451	2.498
PESCADF test:								
No Trend	−0.713	−1.787	−0.807	−1.172	−2.858***	−1.476	−1.366	−1.037
Trend	−0.408	−2.357	−1.037	−1.238	−3.326***	−1.815	−1.984	−0.961
d=1								
LLC test:								
No Panel Means	−7.066***	−14.805***	−4.214***	−13.703***	−16.936***	−8.400***	−13.467***	−11.421***
Panel Means	−3.968***	−8.311***	−6.117***	−9.053***	−8.759***	−3.207***	−8.655***	−7.601***
Trend & Panel Means	−2.961***	−6.257***	−5.262***	−6.989***	−6.121***	−3.245***	−7.343***	−6.276***
IPS test:								
Demean	−3.003***	−11.746***	−7.395***	−5.653***	−14.383***	−7.754***	−9.337***	−5.402***
PESCADF test:								
No Trend	−2.218**	−4.849***	−3.536***	−2.946***	−6.120***	−3.729***	−4.389***	−2.717***
Trend	−2.634*	−4.922***	−3.832***	−2.951***	−6.220***	−3.960***	−4.534***	−2.771**

Note: (i) *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; (ii) ′d=0′ denotes variables are in levels; ′d=1′ denotes variables are in the first-difference format.

Appendix B

Supplement to Chapter 3

Tables

Table B.1: **Results of Panel Unit Root Test**

	Test/Variable		$lhpi$	lcr	lcf	$lcpi$	$lngdp$	$irate$
d=0								
	IPS	Demean	1.80	0.61	-1.01	1.88	-0.09	-5.89***
		Demean & Trend	2.19	2.42	0.8	-0.41	3.29	-5.18***
	PESCADF	No Trend	-1.88	-0.45	-1.40	-2.63***	-1.2	-3.18***
		Trend	-1.94	-1.31	-2.14	-2.74*	-1.96***	-3.39***
d=1								
	IPS	Demean	-7.61***	-6.13***	-5.51***	-13.01***	-17.68***	-15.81***
		Demean & Trend	-7.01***	-5.35***	-6.63***	-13.02***	-21.05***	-15.45***
	PESCADF	No Trend	-3.22***	-2.70***	-3.18***	-5.84***	-6.59***	-12.96***
		Trend	-3.26***	-2.95**	-3.80***	-5.29***	-5.90***	-12.65***

Note: (i) *: significance at 10% level; **: significance at 5% level; ***: significance at 1% level; (ii) d=0 denotes variables are in levels; d=1 denotes variables are in first-difference format; the logarithmic variables begin with a prefix 'l'; (iii) the number of lags included in each unit root test are chosen based on information criteria (IC).

Table B.2: **Granger Causality Test: Benchmark (without Business Cycles Removal)**

Equation Variable	Excluded variable	χ^2	P-value	Equation Variable	Excluded Variable	χ^2	P-value
$dlcpi$				$dlcf$			
	$dlngdp$	0.363	0.547		$dlcpi$	2.093	0.148
	$dlhpi$	0.976	0.323		$dlngdp$	18.123	0
	$dlcf$	5.413	0.02		$dlhpi$	4.805	0.028
	$dlcr$	0.045	0.831		$dlcr$	66.244	0
	$dirate$	0.051	0.821		$dirate$	19.252	0
$dlngdp$				$dlcr$			
	$dlcpi$	13.58	0		$dlcpi$	0.126	0.722
	$dlhpi$	35.535	0		$dlngdp$	6.584	0.01
	$dlcf$	1.442	0.23		$dlhpi$	9.712	0.002
	$dlcr$	20.609	0		$dlcf$	36.649	0
	$dirate$	26.987	0		$dirate$	10.795	0.001
$dlhpi$				$dirate$			
	$dlcpi$	0.022	0.881		$dlcpi$	12.832	0
	$dlngdp$	2.375	0.123		$dlngdp$	0.286	0.593
	$dlcf$	0.179	0.672		$dlhpi$	2.016	0.156
	$dlcr$	24.464	0		$dlcf$	0.334	0.563
	$dirate$	17.178	0		$dlcr$	16.094	0

Table B.3: **Variance Decomposition: Benchmark (without Business Cycles Removal)**

Response variable	Period	Impulse Variable $dlcpi$	$dlngdp$	$dlhpi$	$dlcr$	$dlcf$	$dirate$
$dlcpi$							
	1	1	0	0	0	0	0
	5	0.9743286	0.0010372	0.006063	0.0137311	0.0031709	0.001669
	10	0.9532161	0.0030206	0.0118609	0.0181699	0.0087411	0.0049914
$dlngdp$							
	1	0.0509745	0.9490255	0	0	0	0
	5	0.1145927	0.6735948	0.0857204	0.0173003	0.03478	0.0740119
	10	0.1334329	0.6067768	0.1014608	0.0269794	0.0453593	0.0859908
$dlhpi$							
	1	0.0002672	0.0236994	0.9760334	0	0	0
	5	0.0217398	0.04144	0.7686186	0.007898	0.0373087	0.1229948
	10	0.0530881	0.0431748	0.7038702	0.0176544	0.0463722	0.1358404
$dlcf$							
	1	0.0009242	0.0041531	0.01609	0.9788328	0	0
	5	0.0319198	0.0690989	0.0730653	0.6488191	0.1322995	0.0447973
	10	0.0596461	0.0720872	0.1026292	0.5500685	0.1539267	0.0616423
$dlcr$							
	1	0.0014624	0.0113805	0.0004431	0.0143447	0.9723694	0
	5	0.002945	0.0587923	0.0460683	0.1087883	0.7778201	0.0055859
	10	0.0186563	0.0689895	0.0810867	0.1206557	0.6896216	0.0209903
$dirate$							
	1	0.0000629	0.0000303	0.0067498	0.0008236	0.0026837	0.9896497
	5	0.1203697	0.0025696	0.0145168	0.0008878	0.0487511	0.8129051
	10	0.1330255	0.0036501	0.0142468	0.0014079	0.0559244	0.7917453

Table B.4: **Granger Causality Test: Benchmark (with Business Cycles Removal)**

Equation Variable	Excluded variable	χ^2	P-value	Equation Variable	Excluded Variable	χ^2	P-value
$dlcpi$				$dlcf$			
	$dlngdp$	4.463	0.035		$dlcpi$	21.772	0
	$dlhpi$	0.118	0.731		$dlngdp$	11.567	0.001
	$dlcf$	15.31	0		$dlhpi$	32.064	0
	$dlcr$	0.047	0.829		$dlcr$	2.881	0.09
	$dirate$	0.096	0.757		$dirate$	0.048	0.827
$dlngdp$				$dlcr$			
	$dlcpi$	13.762	0		$dlcpi$	6.164	0.013
	$dlhpi$	71.302	0		$dlngdp$	7.299	0.007
	$dlcf$	2.131	0.144		$dlhpi$	22.2	0
	$dlcr$	8.906	0.003		$dlcf$	21.88	0
	$dirate$	4.571	0.033		$dirate$	39.851	0
$dlhpi$				$dirate$			
	$dlcpi$	0.099	0.753		$dlcpi$	1.622	0.203
	$dlngdp$	0.285	0.594		$dlngdp$	1.312	0.252
	$dlcf$	8.293	0.004		$dlhpi$	0.003	0.957
	$dlcr$	4.695	0.03		$dlcf$	0.225	0.635
	$dirate$	5.08	0.024		$dlcr$	8.745	0.003

Table B.5: **Variance Decomposition: Benchmark (with Business Cycles Removal)**

Response variable	Period	Impulse Variable					
		$dlcpi$	$dlngdp$	$dlhpi$	$dlcr$	$dlcf$	$dirate$
$dlcpi$							
	1	1	0	0	0	0	0
	5	0.9598573	0.0101814	0.0097697	0.0194264	0.000627	0.0001383
	10	0.9501433	0.0107761	0.0171799	0.0202462	0.0010483	0.0006061
$dlngdp$							
	1	0.0242344	0.9757656	0	0	0	0
	5	0.0561641	0.8096887	0.1041035	0.0152682	0.0119591	0.0028162
	10	0.057052	0.7841015	0.1243401	0.0167412	0.012872	0.0048933
$dlhpi$							
	1	0.0000112	0.010872	0.9891168	0	0	0
	5	0.0024938	0.0122982	0.9479483	0.0132171	0.0090757	0.0149669
	10	0.0054818	0.0134139	0.9329804	0.01543	0.0115415	0.0211524
$dlcf$							
	1	0.0002143	0.0000117	0.0094732	0.9903008	0	0
	5	0.0800899	0.0309448	0.1148106	0.7633607	0.0089461	0.0018479
	10	0.0809918	0.0314048	0.1393026	0.733406	0.0102853	0.0046096
$dlcr$							
	1	0.0009256	0.0142942	0.0004695	0.0121309	0.9721797	0
	5	0.0442898	0.0429885	0.0791975	0.045879	0.7337943	0.0538508
	10	0.0476636	0.0428302	0.1035385	0.0464922	0.7016733	0.0578021
$dirate$							
	1	0.0106065	0.0003032	0.0002805	0.0015665	0.0169743	0.9702691
	5	0.0208946	0.0004559	0.0004101	0.0015704	0.0386643	0.9380046
	10	0.0220674	0.0005986	0.0011898	0.0017471	0.039234	0.9351631

Table B.6: **Granger Causality Test: Robustness Check (Adding Uncertainty Index)**

Equation Variable	Excluded Variable	χ^2	P-value	Equation Variable	Excluded Variable	χ^2	P-value
$dlcpi$				$dlcr$			
	$dlngdp$	0.599	0.439		$dlcpi$	20.33	0
	$dlhpi$	0.857	0.354		$dlngdp$	6.788	0.009
	$dlcf$	16.16	0		$dlhpi$	76.449	0
	$dlcr$	0.589	0.443		$dlcf$	49.024	0
	$dirate$	0.009	0.923		$dirate$	48.965	0
	$dluncer$	2.161	0.142		$dluncer$	0.367	0.545
$dlngdp$				$dirate$			
	$dlcpi$	13.062	0		$dlcpi$	16.759	0
	$dlhpi$	127.108	0		$dlngdp$	0.819	0.366
	$dlcf$	2.592	0.107		$dlhpi$	0.001	0.972
	$dlcr$	20.675	0		$dlcf$	0.778	0.378
	$dirate$	34.408	0		$dlcr$	14.392	0
	$dluncer$	10.96	0.001		$dluncer$	0.075	0.784
$dlhpi$				$dluncer$			
	$dlcpi$	3.085	0.079		$dlcpi$	32.746	0
	$dlngdp$	3.699	0.054		$dlngdp$	1.149	0.284
	$dlcf$	13.504	0		$dlhpi$	0.025	0.875
	$dlcr$	15.423	0		$dlcf$	7.553	0.006
	$dirate$	18.653	0		$dlcr$	0.058	0.81
	$dluncer$	15.239	0		$dirate$	36.703	0
$dlcf$							
	$dlcpi$	26.191	0				
	$dlngdp$	24.378	0				
	$dlhpi$	65.479	0				
	$dlcr$	1.607	0.205				
	$dirate$	27.009	0				
	$dluncer$	0.95	0.33				

Table B.7: **Variance Decomposition: Robustness Check (Adding Uncertainty Index)**

Response Variable	Period	Impulse Variable						
		dlcpi	*dlngdp*	*dlhpi*	*dlcf*	*dlcr*	*dirate*	*dluncert*
dlcpi								
	1	1	0	0	0	0	0	0
	5	0.9560758	0.002902	0.0165695	0.019441	0.0020279	0.0014222	0.0015618
	10	0.9346388	0.0031695	0.0316836	0.0210741	0.0030401	0.0047164	0.0016776
dlngdp								
	1	0.0250216	0.9749784	0	0	0	0	0
	5	0.0374201	0.7760877	0.1345173	0.0163258	0.0155082	0.0149851	0.0051557
	10	0.0370082	0.7286173	0.1683566	0.0196224	0.0171884	0.0238771	0.0053301
dlhpi								
	1	0.0002794	0.0043074	0.9954132	0	0	0	0
	5	0.0016906	0.0035933	0.897779	0.0245408	0.0142571	0.0501632	0.007976
	10	0.0059309	0.0044329	0.8603022	0.0314365	0.01919	0.0707472	0.0079605
dlcf								
	1	0.0004121	0.0000261	0.0154038	0.984158	0	0	0
	5	0.0810206	0.0294081	0.1657326	0.6665775	0.0140992	0.0414573	0.0017046
	10	0.0778691	0.0274356	0.2171714	0.6027821	0.0175387	0.0549332	0.0022698
dlcr								
	1	0.0049093	0.0121512	0.0015418	0.0371642	0.9442334	0	0
	5	0.058764	0.0262902	0.145818	0.0871668	0.6243856	0.0562552	0.0013202
	10	0.0584658	0.0246391	0.1998034	0.0861402	0.5600911	0.0689388	0.0019217
dirate								
	1	0.00603	0.0006533	0.0000853	0.0005467	0.0143441	0.9783406	0
	5	0.0474692	0.0014642	0.0043289	0.0083876	0.0356637	0.9026313	0.0000551
	10	0.0500499	0.0017955	0.0139264	0.0102875	0.0361589	0.8876536	0.0001283
dluncer								
	1	0.0054095	0.0009902	0.023313	0.0000945	0.0002564	0.0004401	0.9694963
	5	0.0340519	0.0016341	0.0217192	0.0064077	0.00088	0.0272138	0.9080933
	10	0.0341126	0.00164	0.0218654	0.006447	0.0009212	0.0274047	0.9076091

Table B.8: **Granger Causality Test: Robustness Check (Considering Global Financial Crisis)**

Equation Variable	Excluded Variable	χ^2	P-value	Equation Variable	Excluded Variable	χ^2	P-value
$dlcpi$				$dlcr$			
	$dlngdp$	0.755	0.385		$dlcpi$	56.974	0
	$dlhpi$	0.03	0.863		$dlngdp$	2.055	0.152
	$dlcf$	14.318	0		$dlhpi$	53.44	0
	$dlcr$	1.344	0.246		$dlcf$	57.802	0
	$dirate$	1.323	0.25		$dirate$	75.061	0
	fc	30.678	0		fc	84.491	0
$dlngdp$				$dirate$			
	$dlcpi$	99.622	0		$dlcpi$	2.074	0.15
	$dlhpi$	136.046	0		$dlngdp$	0.466	0.495
	$dlcf$	0.721	0.396		$dlhpi$	3.978	0.046
	$dlcr$	31.093	0		$dlcf$	2.116	0.146
	$dirate$	11.847	0.001		$dlcr$	10.934	0.001
	fc	25.557	0		fc	1.88	0.17
$dlhpi$				fc			
	$dlcpi$	9.796	0.002		$dlcpi$	7.262	0.007
	$dlngdp$	0.09	0.764		$dlngdp$	2.349	0.125
	$dlcf$	14.613	0		$dlhpi$	0.385	0.535
	$dlcr$	13.574	0		$dlcf$	0.805	0.37
	$dirate$	19.465	0		$dlcr$	13.894	0
	fc	2.706	0.1		$dirate$	0.579	0.447
$dlcf$							
	$dlcpi$	61.872	0				
	$dlngdp$	16.757	0				
	$dlhpi$	45.85	0				
	$dlcr$	2.785	0.095				
	$dirate$	0.453	0.501				
	fc	0.217	0.641				

Table B.9: **Variance Decomposition: Robustness Check (Considering Global Financial Crisis)**

Response variable	Period	Impulse Variable						
		$dlcpi$	$dlngdp$	$dlhpi$	$dlcf$	$dlcr$	$dirate$	fc
$dlcpi$								
	1	1	0	0	0	0	0	0
	5	0.959923	0.0024588	0.0056725	0.0124566	0.0028602	0.0038656	0.0127634
	10	0.9335612	0.0027496	0.012807	0.0135018	0.0034881	0.0077373	0.0261552
$dlngdp$								
	1	0.0357958	0.9642042	0	0	0	0	0
	5	0.1353684	0.7288818	0.0887763	0.0120238	0.0220599	0.0086797	0.0042101
	10	0.1366093	0.6908532	0.109251	0.0136085	0.0233654	0.0188729	0.0074396
$dlhpi$								
	1	0.0000454	0.005091	0.9948636	0	0	0	0
	5	0.0021358	0.0093211	0.9049482	0.0131799	0.016335	0.0538463	0.0002336
	10	0.0053196	0.0101195	0.8662846	0.0146047	0.0218209	0.0815594	0.0002912
$dlcf$								
	1	0.0021465	0.0003742	0.0079878	0.9894916	0	0	0
	5	0.147551	0.022424	0.1029696	0.7053292	0.0112221	0.0100797	0.0004245
	10	0.1508462	0.0221982	0.1294935	0.6569995	0.0143915	0.0246437	0.0014273
$dlcr$								
	1	0.0090739	0.0177477	0.0012418	0.0210326	0.950904	0	0
	5	0.1341881	0.023505	0.0916573	0.0492287	0.5992087	0.0745194	0.0276928
	10	0.1399128	0.0230555	0.1219584	0.0470712	0.5398182	0.0929204	0.0352636
$dirate$								
	1	0.0093802	0.0003205	0.0001767	0.0014821	0.016909	0.9717315	0
	5	0.0216506	0.0006811	0.0103747	0.0018807	0.0392733	0.9253096	0.00083
	10	0.0257156	0.0011104	0.0191221	0.0023154	0.041095	0.9085019	0.0021396
fc								
	1	0.0001851	0.0003047	0.0000643	0.000144	0.0011993	0.0001124	0.9979903
	5	0.005194	0.0014452	0.0005079	0.000153	0.0071037	0.0003139	0.9852822
	10	0.010541	0.0020805	0.0027868	0.0002664	0.0097611	0.0017378	0.9728263

Table B.10: **Summary of the Key Literature 1**

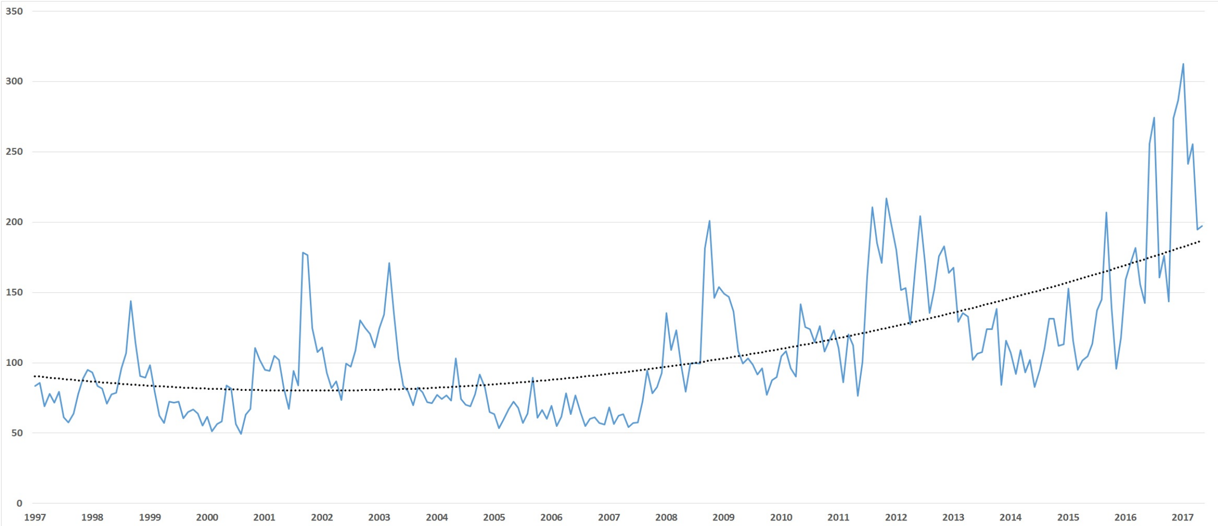
Authors	Data	Key Variables	Main findings
Werner (1997)	Japan (1981Q1-1991Q1)	GDP, credit to the real economy and credit to the asset markets	Split credit into credit to the real economy and credit to the asset markets. Only credit to the real economy is significant for economic growth.
Senhadji and Collyns (2002)	Eight Eastern Asian countries (1990M1-2001M1)	Real housing prices, real credit to private sector, and real GDP per person	Credit and GDP positively affect housing prices. Financial crisis weakens the effect of credit on housing prices.
Hofmann (2003)	20 industrialized countries (1985Q1-2001Q4)	Real housing prices, real aggregate bank credit, and real GDP	Unidirectional effect of housing prices on credit in the short-term, while bidirectional in the long-term.
Gerlach and Peng (2005))	Hong Kong (1980Q4-2001Q4)	Real housing prices, GDP, and Real aggregate credit	Unidirectional effect of housing prices on credit. Housing prices are driven by the economic fundamentals.
Almeida et al. (2006))	26 countries (1970-1999)	Housing prices, GDP, Loan-to-value ratio	Housing prices are more sensitive to GDP in countries with greater LTV ratios.
Fitzpatrick and McQuinn (2007)	Ireland (1980Q1-2002Q4)	Housing prices, mortgage credit, and other fundamental variables	Bidirectional effect of housing prices on credit in the long-run, while unidirectional in the short run. Housing prices are driven by the fundamental variables.
Goodhart and Hofmann (2008)	17 industrialized countries (1970Q1-2006Q4)	Housing prices, broad money, bank credit to the private sector, real GDP	Multi-directional interactions between the money supply, credit to the private sector, housing prices, and GDP.
Mian and Sufi (2009)	US (1991-2007)	Mortgage credit, housing prices	Mortgage credit is driven by the credit supply, while the growth of housing prices is explained by credit expansions.
Duca et al. (2011)	US (1981Q1-2007Q2)	Loan-to-value (LTV) ratio, price-to-rent, mortgage rate, and taxation on property	Both exogenous mortgage supply and LTV ratio positively affect the price to rent ratio. House price cycles stem from the credit supply cycles.
Abdallah and Lastrapes (2013)	43 US States (1976Q2-2008Q4)	Real personal disposable income, Real housing prices, real consumption per capita	Consumption in the state with greater opportunities to home equity as collateral is more sensitive to a housing demand shock than the state with few opportunities.

Table B.11: **Summary of the Key Literature 2**

Authors	Data	Key Variables	Main findings
Arslan et al. (2015)	US (1992Q2-2013Q2)	Housing prices and foreclosures	The feedback mechanism between the dip in housing prices and the increase in foreclosure rates enlarges the influence of defined macroeconomic shocks.
Favara and Imbs (2015)	US (1994-2005)	Housing prices, branching deregulation, mortgage loans, and loan to income ratio	Credit supply increases housing prices in regions with inelastic housing supply, while it increases housing stock in regions with elastic housing supply.
Justiniano et al. (2015)	US (1990-2006)	Credit constraints, collateral requirements, house prices, GDP, and mortgage rate	Unlike credit demand, an increase in credit supply drives the boom in housing prices.
Jordà et al. (2016)	17 advanced economies (1870-2011)	Mortgage credit, non-mortgage credit, and, GDP	The dynamics of mortgage credit are synchronized with the boom-bust behaviors of economic growth, while the growth has been argued to be the source of financial fragility.
Ling et al. (2016)	US (1992Q2-2013Q2)	Commercial housing prices market liquidity credit availability	Credit constraints to the housing demand side provide the negative effect on housing price behaviors especially in the markets which are highly levered and relatively illiquid.
Unger (2017)	11 European countries in the euro area (1999-2013)	Domestic bank credit to the non-financial private sector, external debt claims of domestic banks, current account balance	The increase of bank credit to the non-financial private sectors, along with a loss in competitiveness, are the intrinsic reasons for the build-up of the current account imbalances.

Figures

Figure B.1: **Trend in Global Economic Policy Uncertainty (GEPU)**



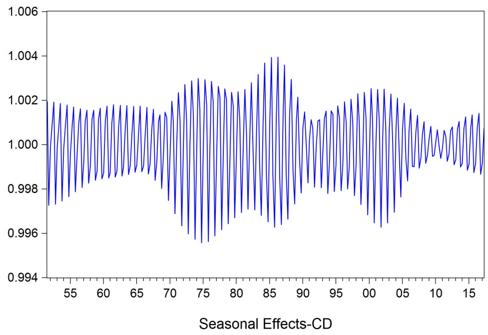
Note: (i) this figure shows the increasing dynamics of the global EPU index over the period 1997M1-2017M5; (ii) GEPU is weighted by PPP (purchasing power parity)-adjusted GDP (see details about the method in Davis, 2016); (iii) the dashed line in black is a polynomial trend line of GEPU with order two; (iv) data sources are detailed in Footnote 15 in Chapter 3.

Appendix C

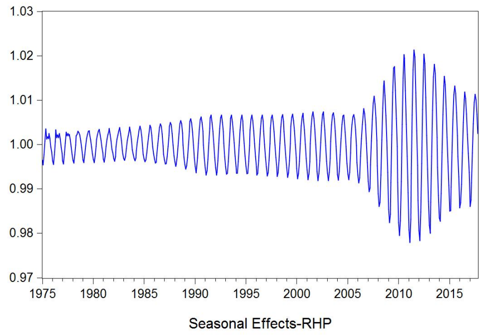
Supplement to Chapter 4

Figure C.1: **The Seasonal Effects of Variables in the US**

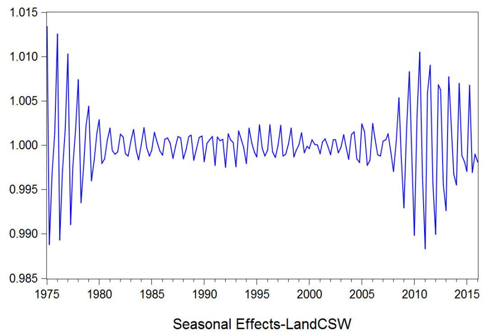
(a) Credit to the housing demand



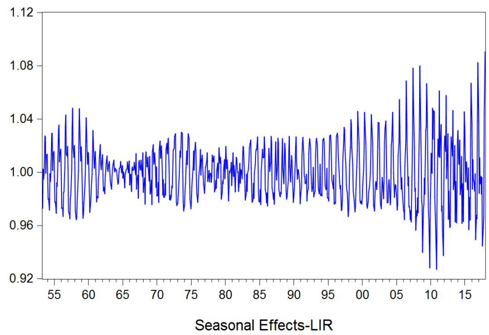
(b) Residential Housing Prices



(c) Residential land value



(d) Long-run interest rate



(e) Economic Policy Uncertainty

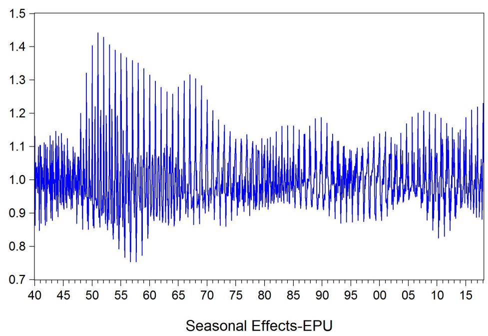
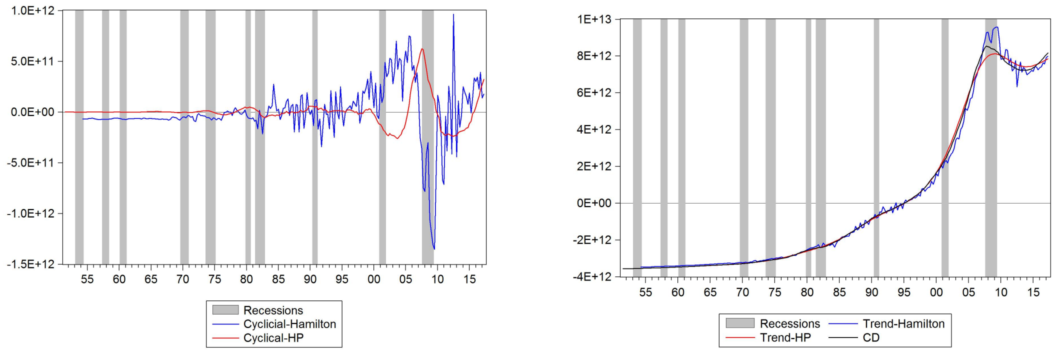
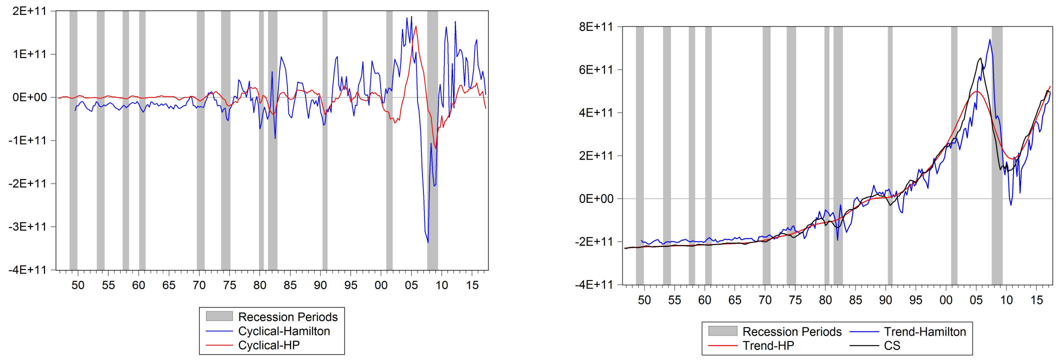


Figure C.2: **Cycles and Trends of Variables in the US (1)**

(a) Credit to the housing demand



(b) Credit to the housing supply



(c) Residential housing prices

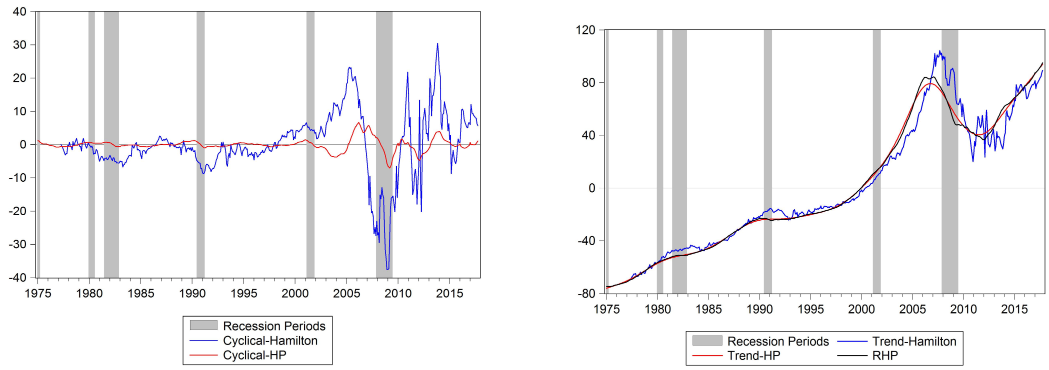
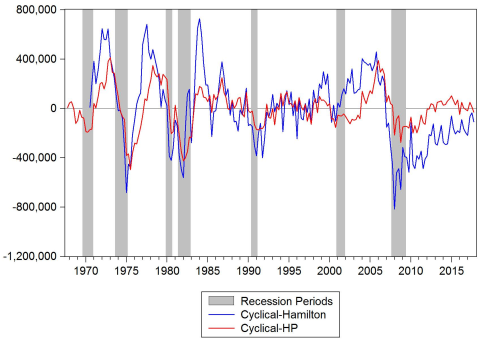
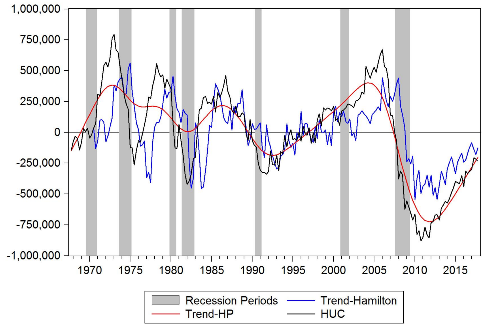


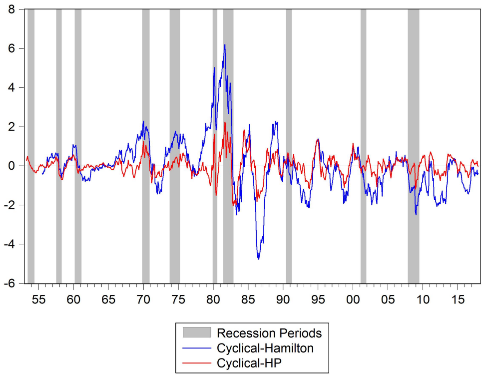
Figure C.3: **Cycles and Trends of Variables in the US (2)**

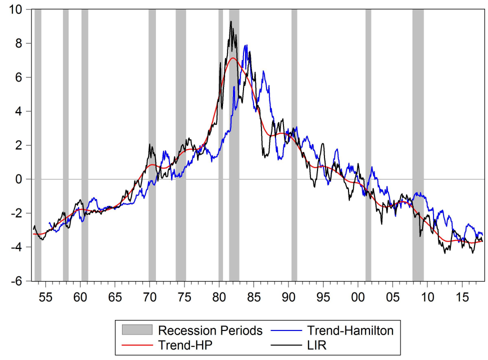
(a) Residential housing stocks



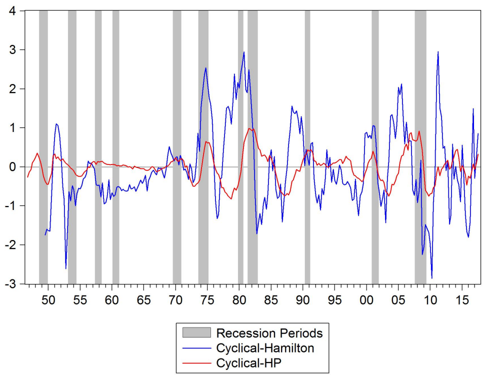


(b) Long-term interest rate





(c) Inflation



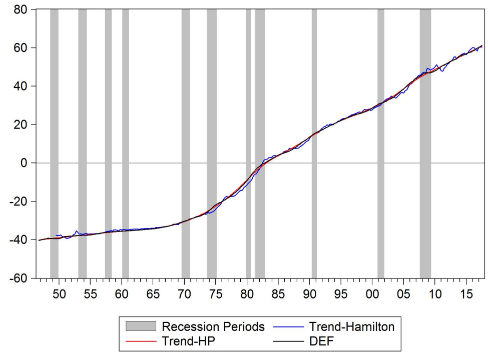
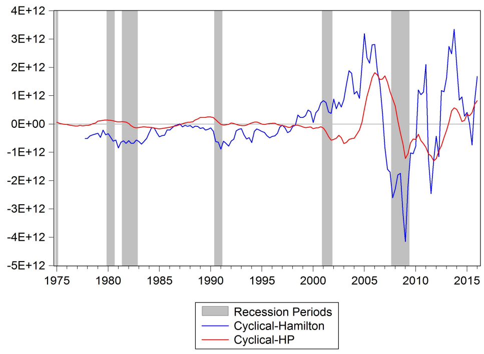
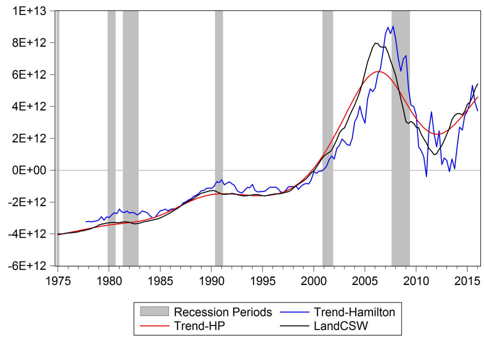


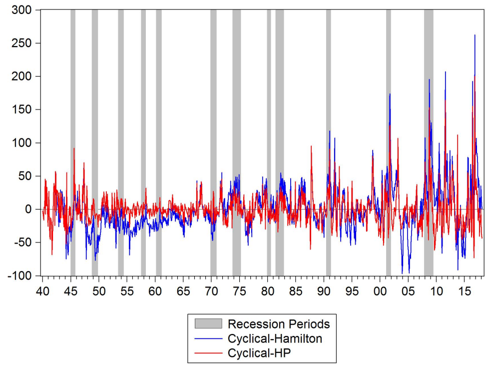
Figure C.4: **Cycles and Trends of Variables in the US (3)**

(a) Residential land value





(b) Economic policy uncertainty



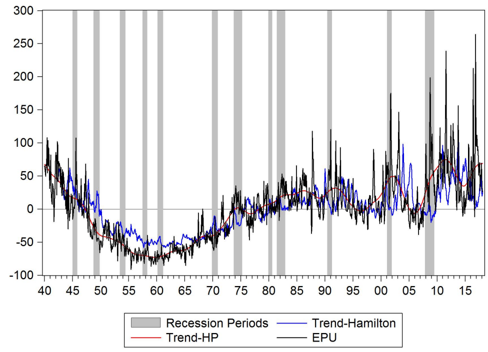
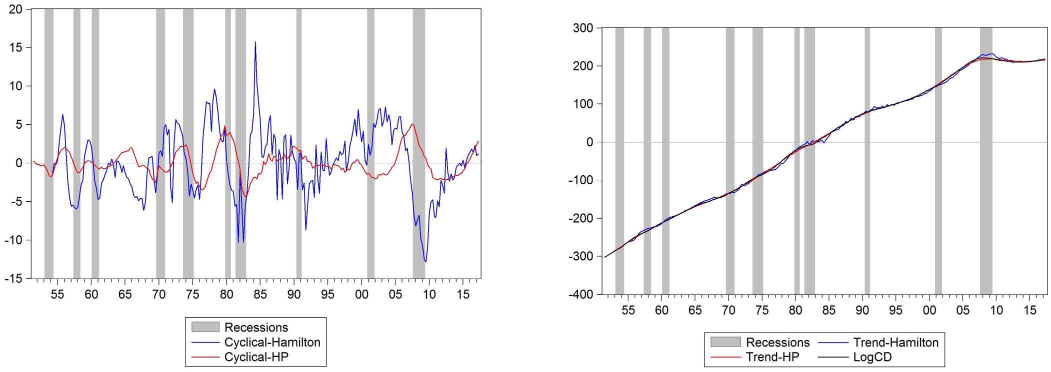
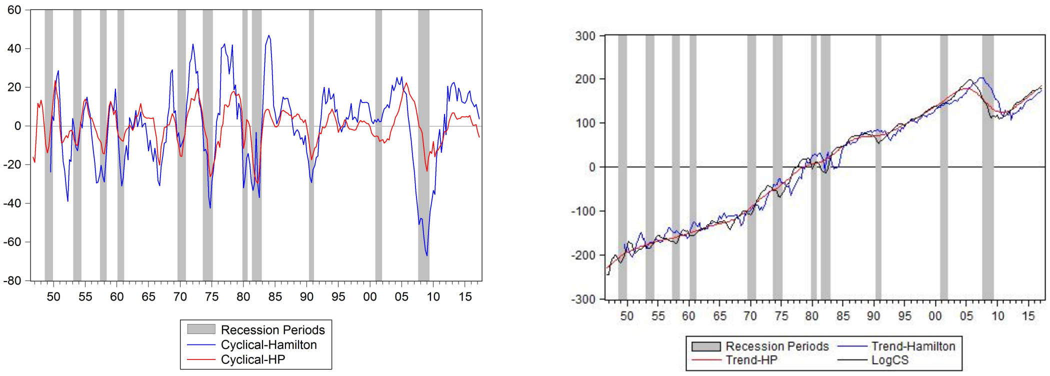


Figure C.5: **Cycles and Trends of Log-transformed Variables in the US (1)**

(a) Credit to the housing demand



(b) Credit to the housing supply



(c) Residential housing prices

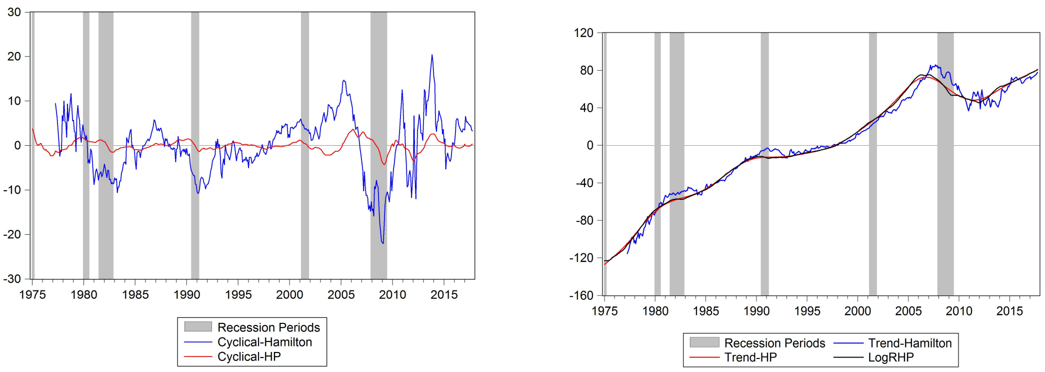
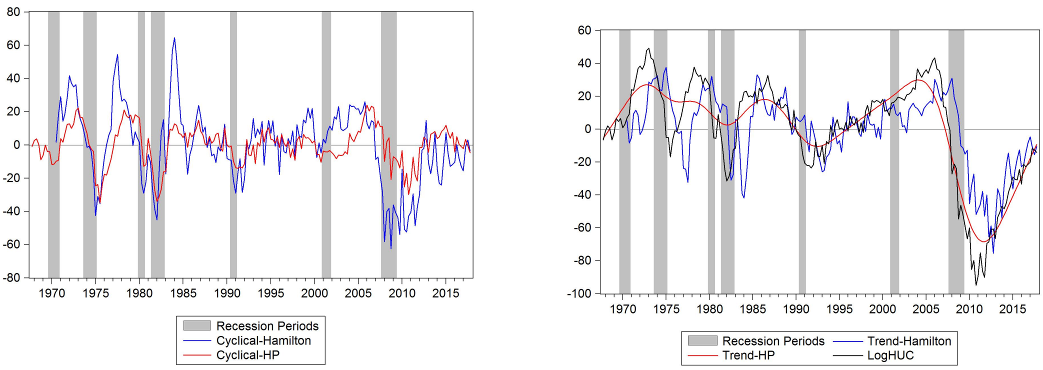
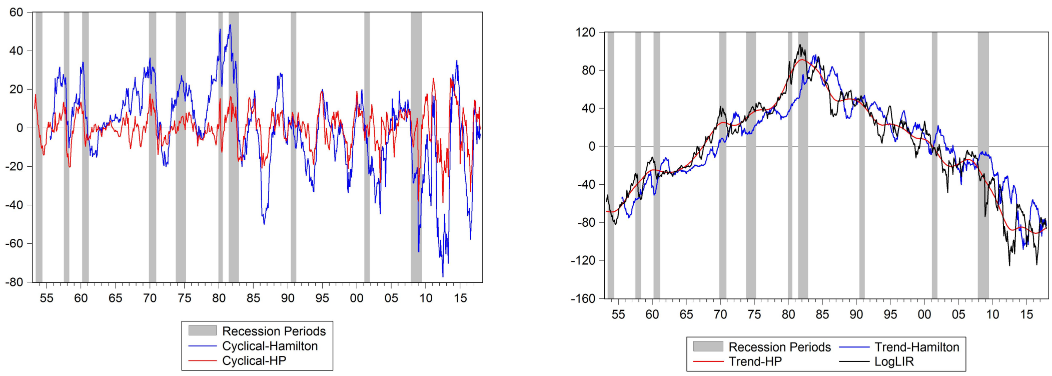


Figure C.6: **Cycles and Trends of Log-transformed Variables in the US (2)**

(a) Residential housing stocks



(b) Long-term interest rate



(c) Inflation

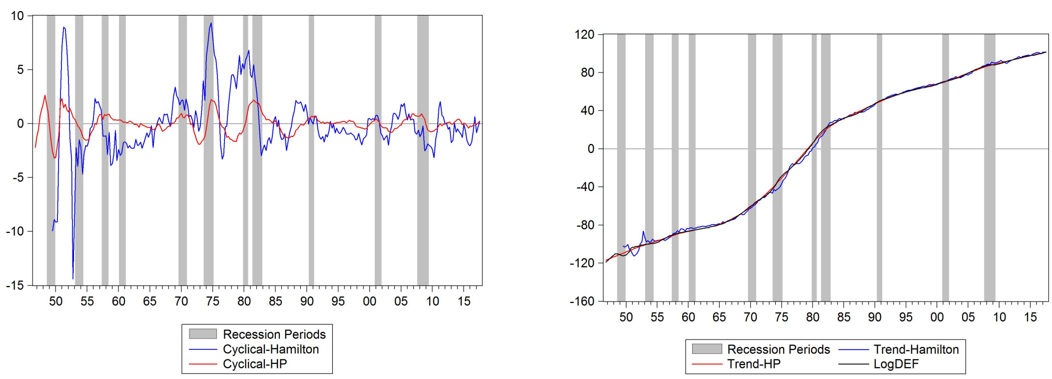
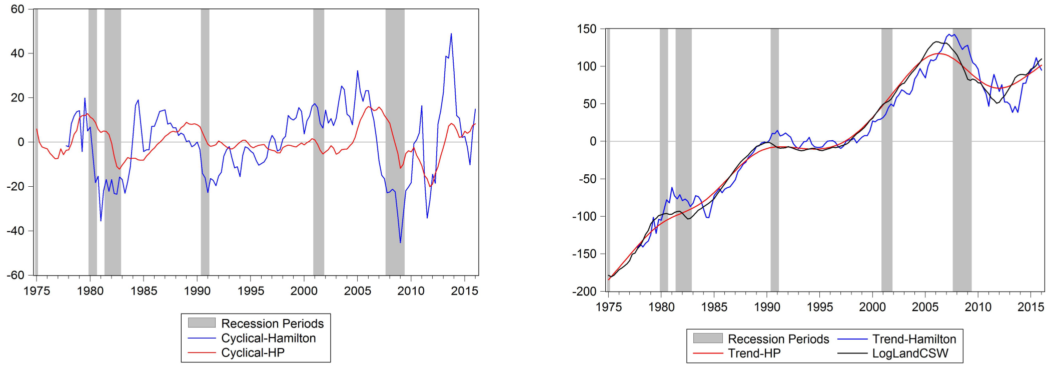


Figure C.7: **Cycles and Trends of Log-transformed Variables in the US (3)**

(a) Residential land value



(b) Economic policy uncertainty

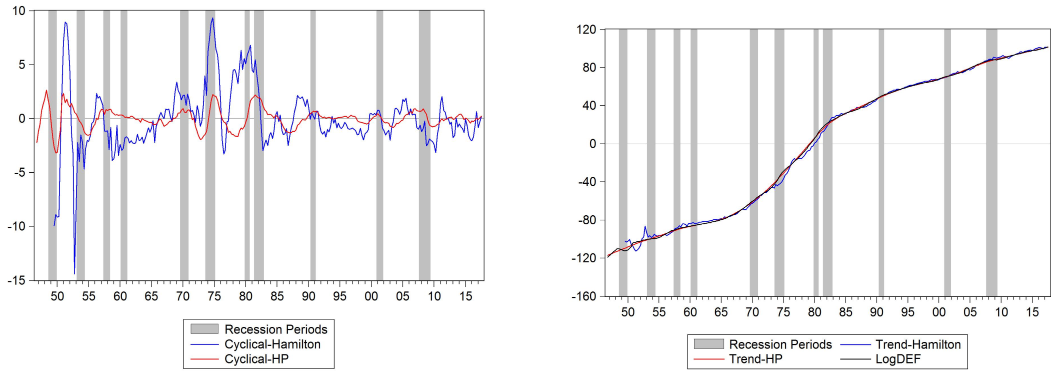
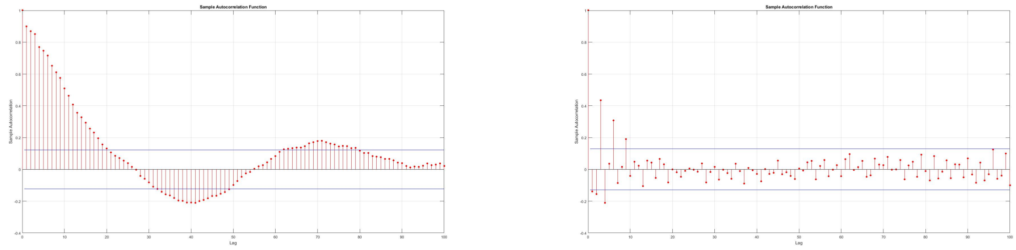


Figure C.8: **The Comparison between De-cycled and Non De-cycled Variables (1)**

(a) Credit to the housing demand



(b) Credit to the housing supply

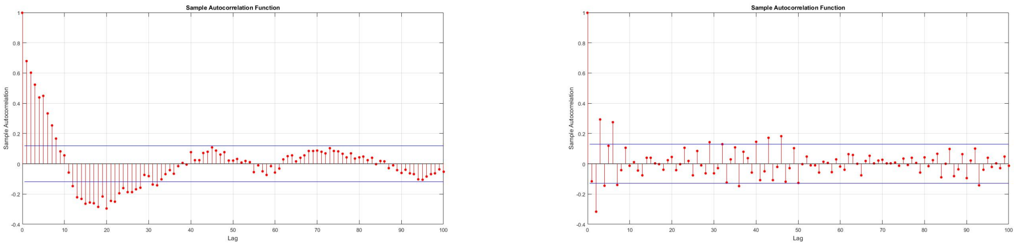
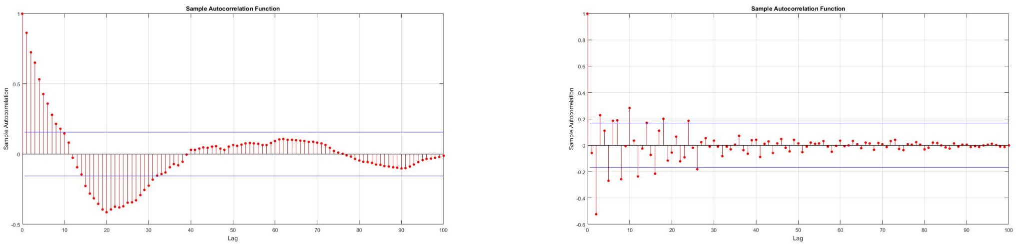


Figure C.9: **The Comparison between De-cycled and Non De-cycled Variables (2)**

(a) Residential land market value



(b) Logged residential land market value

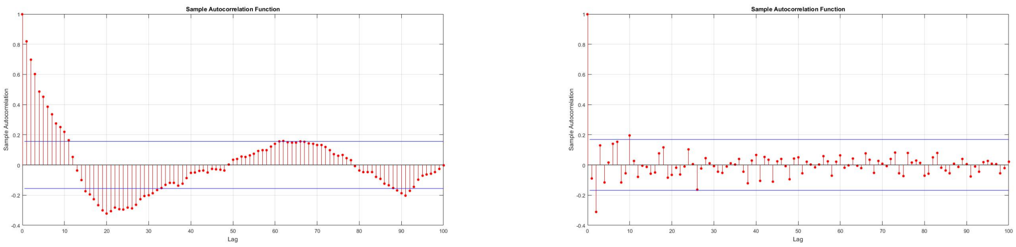
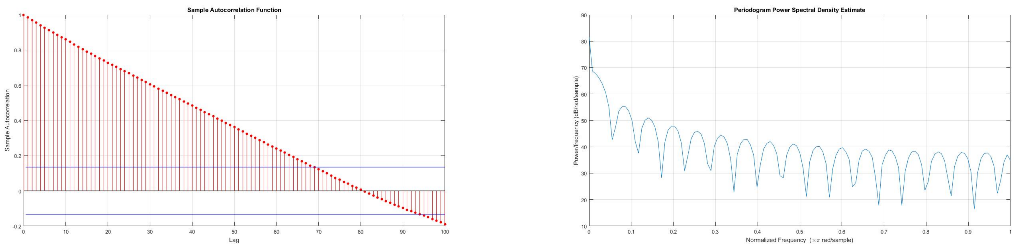


Figure C.10: **ACF and Spectral Figures (1)**

(a) Credit to the demand side



(b) Credit to the supply side

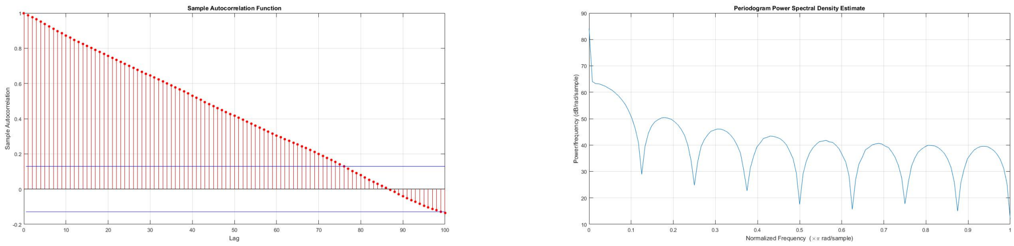
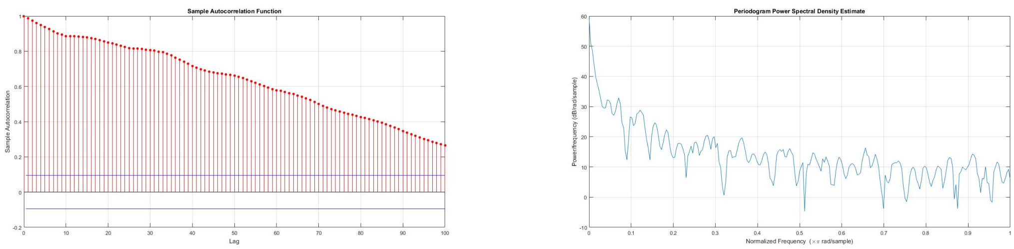


Figure C.11: **ACF and Spectral Figures (2)**

(a) Residential housing prices



(b) Residential housing stocks

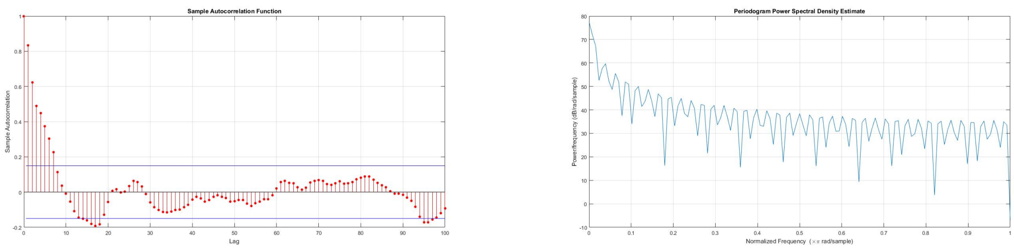
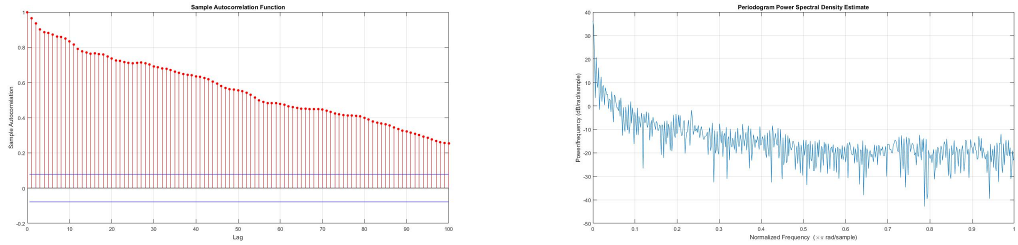


Figure C.12: **ACF and Spectral Figures (3)**

(a) Long interest rate



(b) Inflation

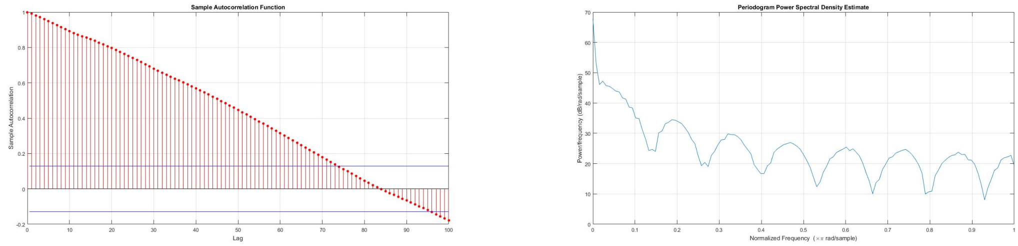
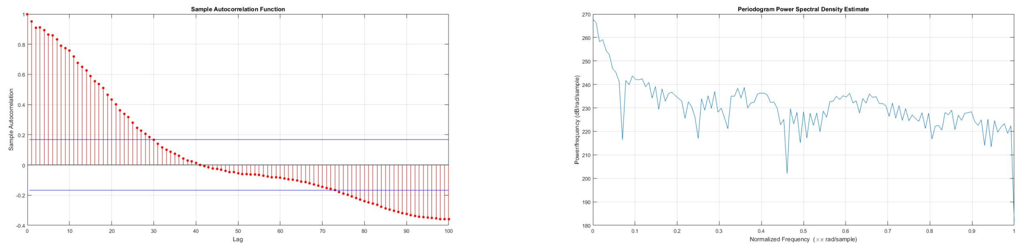


Figure C.13: **ACF and Spectral Figures (4)**

(a) Residential land value



(b) Economic policy uncertainty

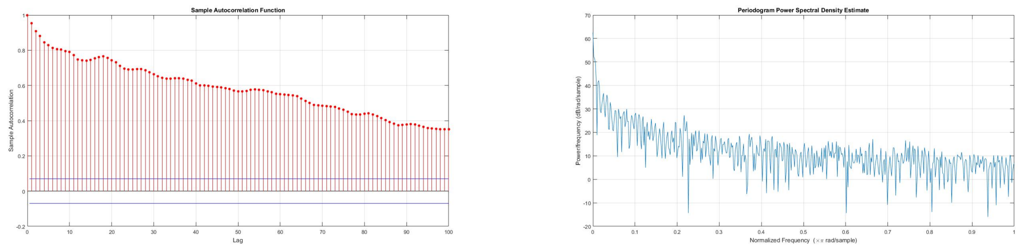
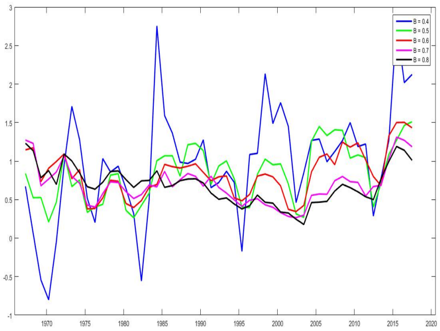
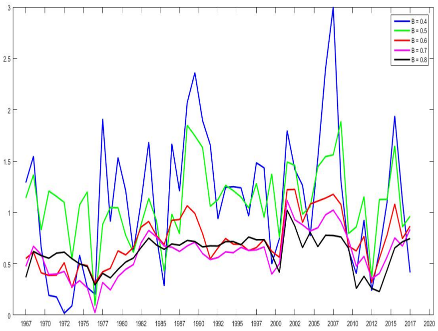


Figure C.14: **The Rolling-Window Univariate d Estimates-LW (1)**

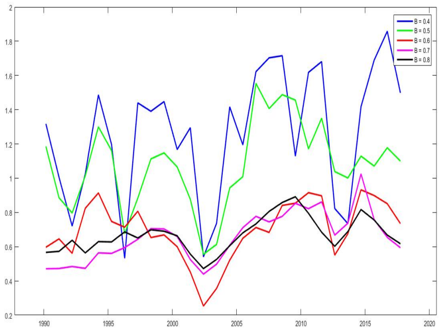
(a) Credit to the housing demand



(b) Credit to the housing supply



(c) Residential housing prices



(d) Residential housing stocks

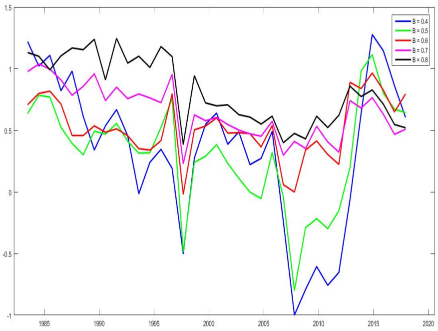
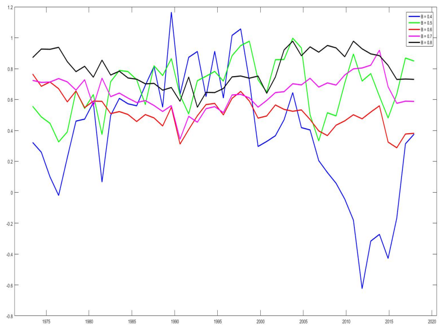
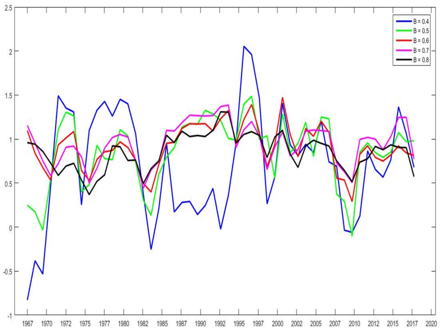


Figure C.15: **The Rolling-Window Univariate d Estimates-LW (2)**

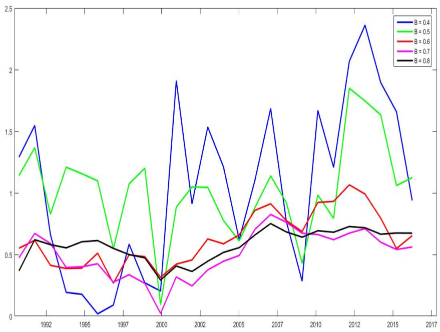
(a) Long-run interest rate



(b) Inflation



(c) Residential land value



(d) Economic policy uncertainty

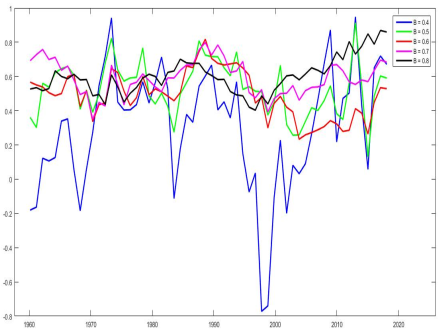
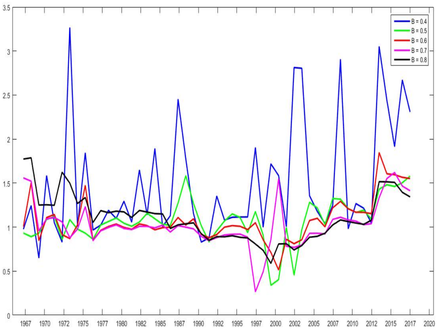
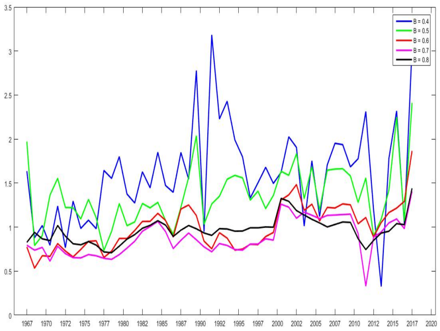


Figure C.16: **The Rolling-Window Univariate d Estimates-2ELW (1)**

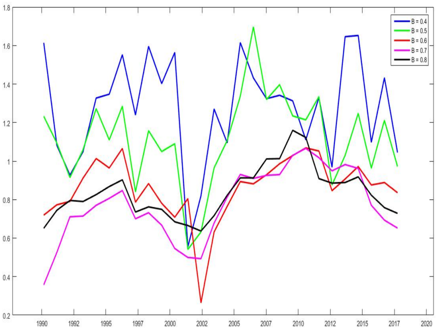
(a) Credit to the housing demand



(b) Credit to the housing supply



(c) Residential housing prices



(d) Residential housing stocks

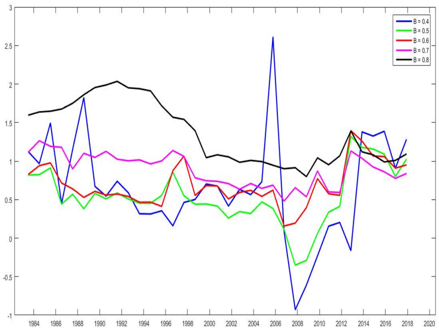
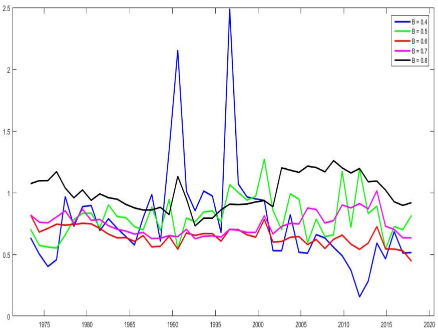
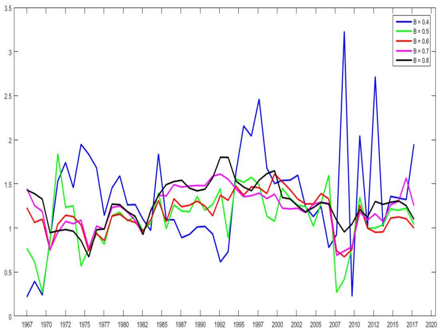


Figure C.17: **The Rolling-Window Univariate d Estimates-2ELW (2)**

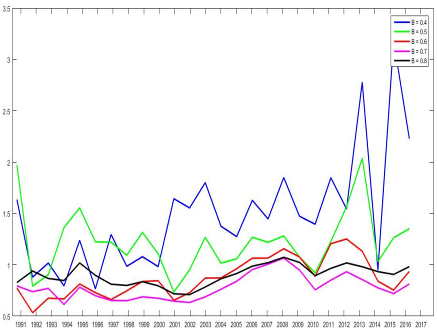
(a) Long-run interest rate



(b) Inflation



(c) Residential land value



(d) Economic policy uncertainty

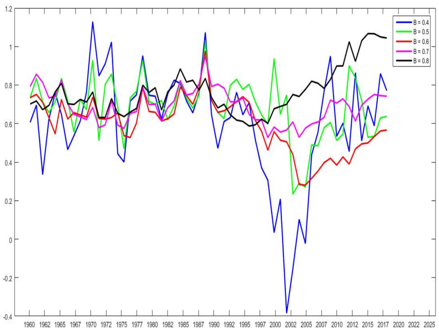
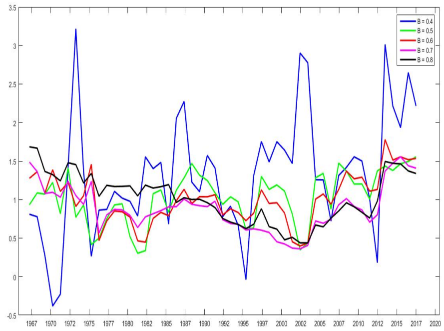
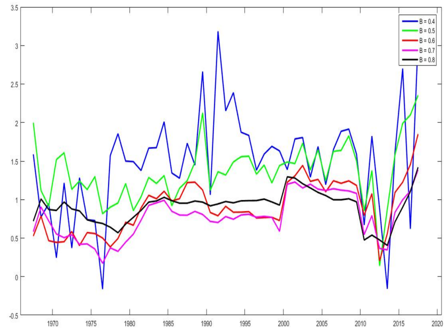


Figure C.18: **The Rolling-Window Univariate d Estimates-2ELWdm (1)**

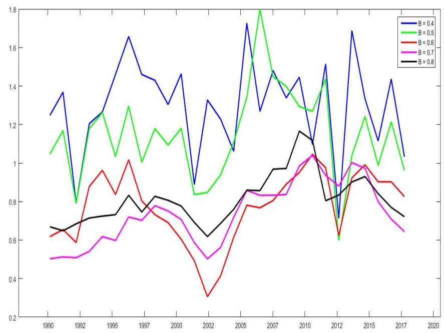
(a) Credit to the housing demand



(b) Credit to the housing supply



(c) Residential housing prices



(d) Residential housing stocks

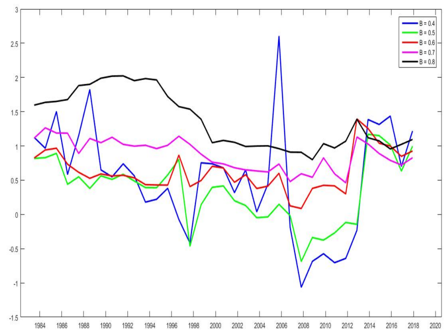
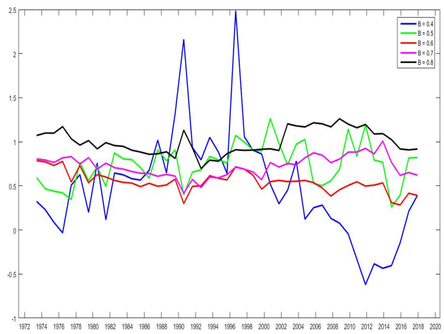
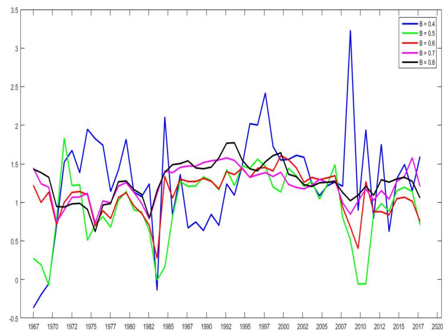


Figure C.19: **The Rolling-Window Univariate d Estimates-2ELWdm (2)**

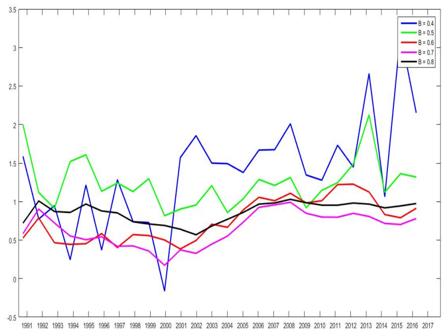
(a) Long-run interest rate



(b) Inflation



(c) Residential land value



(d) Economic policy uncertainty

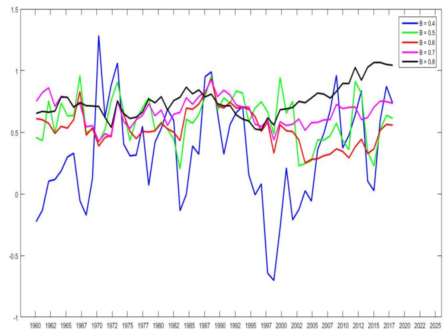


Figure C.20: **5-year Ahead Forecasts from Demand Function**

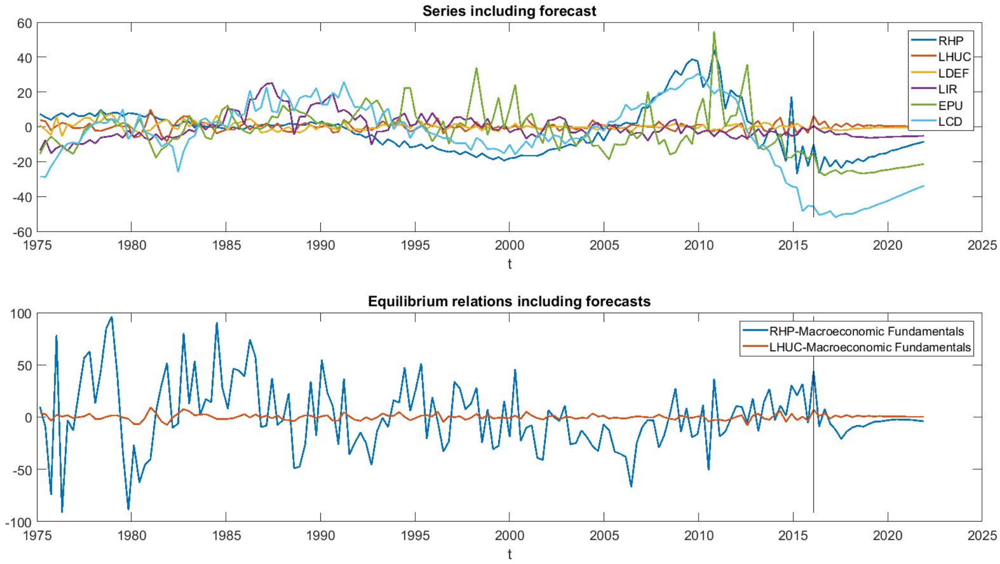
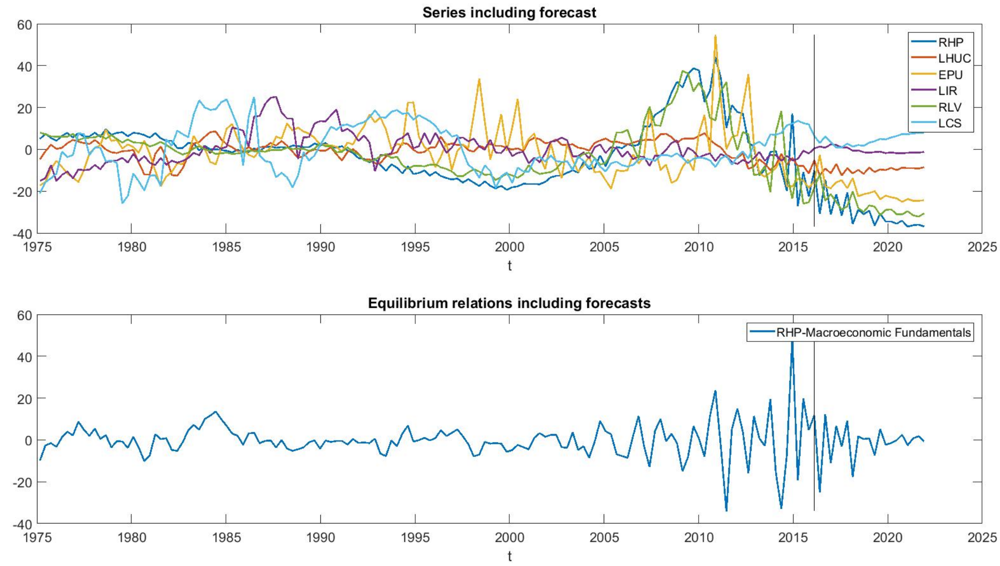


Figure C.21: **5-year Ahead Forecasts from Supply Function**



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