Essays on Financial Stability

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Abstract

This thesis investigates several aspects of economic activity that are strongly linked to the stability of the financial system. First, I examine the possible build-up of systemic risk in the shadow banking system as an unintended consequence of the implementation of macroprudential policies. Second, I analyze the short-run and long-run interactions between house prices and household debt in Australia and study relevant policy implications. Finally, I propose the use of automatic model selection, namely Least Absolute Shrinkage and Selection Operator (LASSO) with cross-validation, to improve the forecasting performance of the conventional early warning system for systemic banking crises. The findings provide insights for policymakers about several aspects of potential vulnerabilities stemming from different segments of the financial sector, and improves the early warning system so as to help policymakers better identify and monitor systemic risk in the financial system.

In Chapter 2, I investigate the impact of macroprudential policies on shadow banking activities using a panel data analysis with fixed effects containing 24 countries from 2002 to 2013. I find that the effectiveness of macroprudential policies targeting the demand for credit, namely loan-to-value and debt-to-income ratio caps, is partially undermined by regulatory arbitrage through the shadow banking system. Such a strategy is generally not found for supply-side policies with two exceptions. Sector-specific capital requirements are found to be associated with negative shadow banking growth, while loan-loss provisionings could lead to counter-productive outcomes.

In Chapter 3, I empirically investigate the short-run and long-run interactions between house prices and their drivers, with a particular focus on household debt, in a Structural Error Correction Model (SVECM) framework for Australia over the sample period 1990-2016.

The cointegration analysis suggests one equilibrium relationship exists between the real house prices and the long-run determinants: household debt, housing stock, household disposable income, and the real interest rate. Household debt and housing supply are the main drivers for the equilibrium house prices. Household disposable income and the real interest rate affect the equilibrium house prices through the credit channel. In the short run, house prices and household debt are found to be mutually reinforcing. The dynamic impacts of the structural shocks suggest that macroprudential policies, if they act in a manner similar to an exogenous tightening of credit conditions, may be preferable to monetary policy leaning against the wind, if and when policies are needed to reinforce financial stability.

In Chapter 4, I propose using LASSO with cross-validation approach to automate the variable selection process of the conventional multivariate logit econometric framework, the purpose being to improve the prediction of systemic banking crises. Using a dataset covering 23 OECD countries with quarterly data from 1970Q1 to 2018Q3, the model performance is evaluated in a recursive out-of-sample forecasting exercise, taking policymakers preference of missed crises and false alarms into account. The results suggest that the automatic variable selection process can enhance the predictive performance of the early warning system. They also highlight the importance of extracting information from variable interactions and lags that may not be easily identified and accessed by typical subjective variable pre-selection. This simple approach is easy to interpret and is transparent, which are important aspects for effective policy communication. Five variables, namely credit growth, domestic and global credit gaps, real house price growth and the real effective exchange rate, are identified as the most important key indicators of systemic banking crises.

Declaration

This thesis comprises only my original work except where due reference is made. Due acknowledgment has been made in the thesis to all other material used. The thesis is no more than 100,000 words in length, exclusive of tables, appendices and bibliographies.

Xianglong (Locky) Liu

Dedication

I dedicate this thesis to my dear parents

Liu Yongbao
and
Meng Huang

for their endless love and support

You have raised me to be the person I am today

You have always been there for me

I love you

Preface

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Chapter 1

Introduction

The enormous economic and social costs of the 2007-08 financial crisis prompted a renewed focus on financial stability, which is critical to ensuring stable macroeconomic outcomes. Prudential regulation, which aimed to address risks in the individual financial institutions, was shown by the financial crisis to be necessary, but not sufficient, to address systemic risk, which if realized may lead to a cascading and catastrophic failure of the whole financial system.

To achieve the ultimate objective of safeguarding financial stability, it is critical to understand the build-up of systemic risk in different segments of the financial system. Systemic risk stemming from the interactions among different components of the financial system needs to be recognized and mitigated by policymakers implementing appropriate measures. The effects of various policy tools need to be examined from the perspective of how they address vulnerabilities not just in the targeted segments but in the financial system as a whole. A well-designed early warning system is necessary for policymakers to monitor evolving risks and adopt preemptive policies to reduce the probability of any potential systemic event.

This thesis aims to assist policymakers by developing a better understanding about how to promote financial stability from these perspectives. My first chapter investigates the extent of systemic risk build-up in the Shadow Banking (SB) system in response to the implementation of macroprudential policies. My second chapter analyzes the short-run and long-run interactions between house prices and household debt in Australia. The third chapter proposes using Absolute Shrinkage

and Selection Operator (LASSO) together with cross-validation to automate the variable selection process of the early warning system, enabling better prediction of systemic banking crises.

A general consensus has emerged to call for policy interventions with a systemic focus, i.e., Macroprudential Policies (MAP). The aim of macroprudential policies is to mitigate excessive procyclicality and reduce systemic risk, thereby reinforcing the overall stability of the financial system. Recently, macroprudential policies have been frequently used in both emerging economies and advanced economies (see Lim et al., 2011). The effectiveness of macroprudential policies has been assessed mainly in the banking and housing sectors (e.g. Kuttner and Shim, 2016). Outside the regulatory framework, the shadow banking system is a significant source of systemic risk and an important channel for regulatory arbitrage. The questions about how macroprudential policies could affect shadow banking activities and what they imply for the financial system stability, however, have not yet been investigated empirically using panel data analysis.

In Chapter 2, I empirically investigate the impact of macroprudential policies on the shadow banking system and the implications for financial stability. This study uses a fixed effects model to analyze the dataset comprising a panel of 24 countries over 2002-2013. The effectiveness of policies primarily affecting the demand for credit, namely caps on Loan-To-Value ratio (LTV) and caps on Debt-To-Income ratio (DTI), are found to be partially undermined by increased shadow banking activities through policy circumvention and systemic risk transfer. I do not find evidence of such policy mitigation for supply-side measures in general, except Loan-Loss Provisionings (LLP). Tightening LLP are found to be associated with more active shadow banking activities, indicating regulatory arbitrage and systemic risk transfer. In contrast, credit intermediation in the shadow banking system becomes less active when sector-specific capital requirements are tightened.

This study contributes to the literature on macroprudential policy by investigating the effects of macroprudential policies on credit intermediation outside the traditional banking sector. It highlights the necessity for macroprudential authorities to recognize that the ultimate objective of macroprudential policies is to promote *overall* financial stability. The results of this study suggest that policymakers should take a broad perspective and consider how well macroprudential measures not only address the key externalities and market

failures that will lead to systemic risk build-up in the traditional banking system, but also their likely impacts on the shadow banking system.

Many countries experienced a large credit boom and increased household borrowings preceding the 2007-08 financial crisis. While household debt may support economic growth by facilitating intertemporal consumption smoothing, high household indebtedness is also a significant source of financial vulnerability. In particular, it may give rise to systemic risk stemming from the housing market, thereby increasing the probability of a financial crisis occuring (Mian and Sufi, 2011). In the context of Australia, both house prices and household debt grew rapidly relative to income after the financial liberalization of the 1980s and the subsequent decline in nominal interest rates and inflation as monetary policy switched to inflation targeting in the early 1990s. According to Goodhart and Hofmann (2007), mutual reinforcing boom-bust cycles in credit and housing markets may increase the likelihood of financial fragility.

In Chapter 3, I empirically investigate the short-run and long-run interactions among Australian house prices and their drivers, with a particular focus on household debt. With a quarterly dataset covering 1990-2016, I estimate the long-run equilibrium relationship using cointegration analysis and then analyze the short-run interactions among Australian house prices and their possible drivers, namely household debt, the housing stock, household disposable income, and the real interest rate in a Structural Vector Error Correction (SVECM) model.

There are several dimensions to the main findings. First, household debt and housing supply are found to be the significant long-run determinants of the equilibrium level of house prices. The cost of financing and household disposable income only affect the equilibrium level of house prices indirectly through the credit channel. Second, the short-run analysis finds evidence that Australian house prices and household debt are mutually reinforcing, suggesting the potential for a boom and bust cycle in the housing market, which may undermine the resilience of households as well as financial stability.

Analyzing the dynamic impacts of the structural shocks, a credit condition tightening shock is found to result in a lower household debt burden and higher housing affordability. Finally, after incorporating monetary policy into the framework, I found that a contractionary policy rate shock reduces house prices but increases household debt, which indicate that highly indebted households may

need further borrowings to smooth the shock. My results suggest that if macroprudential policies act in a similar manner as an exogenous tightening in credit conditions, they might be a preferable way to reinforce the resilience of the financial system, compared to using monetary policy to lean against the wind of asset price misalignments.

The contribution of this chapter to the literature is as follows. First, this is the first study that empirically investigates the Australian housing market focusing on the linkage between house prices and household debt using a SVECM framework. I highlight the importance of the credit channel in house price determination in Australia. Second, I explore the interactions between house prices and the macroeconomic fundamentals including household debt, while similar studies in the literature primarily focus on the impact of various shocks on house prices only. Third, in order to let the results be driven by data to the largest possible extent, this study imposes minimal restrictions to identify the model and therefore allows for contemporaneous interactions between house prices and household debt, unlike similar studies in the literature (e.g. Oikarinen, 2009; Anundsen and Jansen, 2013). Fourth, I analyze the main factors affecting recently housing market developments using a historical decomposition. Credit condition shocks and housing demand shocks are found to be the main drivers of the house price boom before and after 2000. Housing demand shocks contributed the most to increases in house prices which have occurred since 2013. Finally, I contribute to the international literature investigating the role of monetary policy in influencing the joint dynamics of house prices and household debt.

To avoid the devastating economic and social consequences of systemic banking crises, Early Warning Systems (EWS) are used by policymakers to guide the activation of regulatory policies and to guard against potential systemic events. If an early warning system is used to for these purposes, it should be able to (1) identify the most important predictors to optimize the *out-of-sample* performance, and (2) be transparent and interpretable.

In Chapter 4, I propose applying the LASSO method with cross-validation to automate the variable selection process in order to improve the performance of the conventional multivariate logit model in predicting systemic banking crises. Using a quarterly dataset covering 23 OECD countries from 1970 to 2018, I evaluate the model performance in a recursive *out-of-sample* forecasting exercise, taking policymakers' preference of missed crises and false alarms into account.

The results demonstrate that the predictive performance of the multivariate logit model can be significantly improved via automatic variable selection by the LASSO method coupled with cross-validation. This approach identifies the most important predictors for the systemic banking crises to be domestic credit growth, the domestic and global credit to GDP gaps, real house price growth, and the real effective exchange rate. The proposed model can utilize information from the lags and interaction terms that are not typically included in the conventional multivariate logit model to improve the forecasting performance. In contrast with some other more complicated machine-learning methods, it also maintains the transparency which is necessary for effective policy communication, by focusing on enhancing only the variable selection process.

This chapter contributes to the early-warning literature of systemic banking crises by highlighting the importance of a systematic variable selection process and proposing the use of LASSO with cross-validation as a feasible, transparent and interpretable method to automate this process. I show that this approach improves the out-of-sample forecasting performance relative to a benchmark model from the literature.

In summary, this thesis discusses the build-up of vulnerabilities in several sectors of the financial system and provides insights into how policymakers could promote financial stability with appropriate measures. It also proposes an improved early warning model to help policymakers better identify and monitor emerging systemic risk in the financial system.

Chapter 2

Looking outside the banking sector: The impact of macroprudential policies on shadow banking activities

2.1 Introduction

After the 2007-08 financial crisis, the issue of financial stability has received greater policy focus since it is now recognized as being critical to ensuring stable macroeconomic outcomes (Blanchard et al. 2010). Traditional policy tools, such as monetary policy and microprudential-based regulation, are necessary, but insufficient by themselves, to ensure overall financial stability. A general consensus has emerged on the need to incorporate macroprudential policies into the current regulatory and prudential framework to address systemic risk and safeguard the financial system (Blanchard et al. 2010). To evaluate the actual effectiveness of macroprudential policies, it is essential to justify their ability to mitigate the key

externalities and market failures that lead to the build-up of systemic risk (Brunnermeier et al. 2009; De Nicoló et al. 2012; Claessens 2015).

Many empirical studies find evidence that macroprudential policies, especially those designed to restrict the demand for credit, such as the loan-to-value caps and the debt-to-income caps, are effective in curbing credit growth and the housing market development (e.g., Claessens et al. 2013; Cerutti et al. 2017; Kuttner and Shim 2016). Such studies mainly assess the effectiveness of macroprudential policies by focusing on the banking and housing sectors. What happens outside the banking sector after the policy adoption, however, has been rarely investigated. Concerns have grown regarding the impact of potential regulation arbitrage to macroprudential policies, specifically, whether the effectiveness of macroprudential policies could be undermined by financial institutions outside the prudential framework (Goodhart, 2008; Claessens et al., 2013; Cizel et al., 2019).

This chapter aims to take a perspective outside the regulatory framework and study the impact of macroprudential policies outside the regular banking system, which is known as the Shadow Banking system.

The shadow banking system is defined broadly as "the system of credit intermediation that involves entities and activities, fully or partially, outside the regulated banking system" (FSB 2012). Shadow banking system constitutes an important part of the finance industry by providing alternative funding sources other than traditional banks and supplying more liquidity to the financial system. However, being unregulated and vulnerable, it is also a significant source of systemic risk. The shadow banking system is highly pro-cyclical, fragile and strongly interconnected with the banking system. It could undermine the effectiveness of financial regulation by channeling credit risk transfer and regulatory arbitrage (FSB 2011). Negative externalities could arise from the highly fragile and opaque shadow banking sector and counteract the positive impact of policies that aims to promote financial stability. However, the specific impact of macroprudential policies on the shadow banking system, to the best of our knowledge, has not yet been empirically investigated.

The motivation of my research is to fill this gap. The aim here is to empirically investigate the impact of macroprudential policies on shadow banking activities and the implications for financial stability. This analysis will help us to understand the following questions. First, how would shadow banking activities respond to

the implementation of macroprudential policies? Is there any systemic risk transfer through regulatory arbitrage? Second, what kinds of macroprudential policies are more likely to be circumvented, those targeting the demand-side or the supply-side of credit? Third and last, would it mean increased systemic risk outside the prudential framework and thus potentially threaten financial stability? The empirical analysis is based on a panel model with fixed effects using quarterly data of 24 countries for the period covering 2002 to 2013.

I find the effects of demand-side MAPs, namely caps on loan-to-value ratio and caps on debt-to-income ratio, are mitigated by policy circumvention and systemic risk transferring to the shadow banking system. If the adoption of these policies only focuses on systemic risk in the banking sector and overlooks such risk transfers, the policy effectiveness to address financial vulnerability will be overestimated. There is no evidence of such policy mitigation for supply-side measures in general, except loan-loss provisionings. Tightening LLP leads to credit expansion in the shadow banking system, indicating the existence of risk transfer and policy circumvention. In contrast, sector-specific capital requirements, which are based on risk-weighted assets, may help suppress shadow banking activities since the implementation leads to poorer credit growth in the shadow banking system.

Demand-side policies could effectively address vulnerability in the banking sector and in the housing market by suppressing mortgage-related bank credit growth, as many analyses have shown (e.g., Kuttner and Shim 2016; Crowe et al. 2013; Akinci and Olmstead-Rumsey 2017). This study concludes that the associated regulatory arbitrage would lead to a systemic risk shifting to unregulated and fragile shadow banking sector from the traditional banking sector. If the design, implementation and evaluation of macroprudential policies only focus on the traditional banks, we will only have an incomplete picture of the policy outcome and overlook the externalities generated by shadow banks. The possible policy distortions and circumventions may, in the worst case, lead to a perverse impact in the financial system. Therefore, without understanding to what extent macroprudential policy could address externalities in both regulated banks and unregulated shadow banks, it is hard to evaluate how promising macroprudential policies are at safeguarding the financial system. I address this limitation of the existing research in this paper.

This study contributes to literature on macroprudential policy by highlighting the regulation circumvention and systemic risk transfer by shadow banking activities

when macroprudential policies are implemented. It is important to recognize the ultimate goal of macroprudential policies is to promote overall financial stability. My results suggest that macroprudential authorities should take a broad perspective and consider how well the policy tools could address the key externalities and market failures that will lead to systemic risk build-up in both traditional banking and shadow banking system.

I adopt the broad noncore liability approach by Harutyunyan et al. (2015) to measure the size of the shadow banking system. This broad noncore liability measure captures the unstable sources of funding of both banks and non-bank financial institutions, as well as the intra-shadow-banking-system positions. Compared to the entity-based measures that only focus on non-bank financial institutions, this measure: firstly, takes shadow banking activities of both banks and non-banks into account; and secondly, reflects the overall exposure of shadow banking activities to the financial system.

To examine the implications for financial stability, it is not enough to only study the policy impact on the growth rate of shadow banking activities. More active shadow banking credit intermediation does not necessarily lead to higher systemic risk to the overall financial system. To shed light on how such regulatory arbitrage may the reinforce the build-up of systemic risk outside the regulatory framework, I also investigate how macroprudential policies may change the composition of funding sources. Apart from the *absolute* growth rate of shadow banking activities, I also look at the impact of policy implementation on the *relative* growth of shadow banking activities, which is defined as the growth of the ratio of the shadow banking credit to the traditional banking credit. By capturing how fast the shadow banking sector is outgrowing the traditional banking sector, the *relative* shadow banking growth reflects the relative pro-cyclicality of the shadow banking system, as well as changes in the liquidity position of the financial system. Responding to a policy tightening action, a higher *relative* shadow banking growth would reflect that the funding sources had changed from the regulated traditional banking system to the unregulated shadow banking system to circumvent the policy. Such systemic risk transfer to the unregulated sector, if overlooked by the regulators, may undermine the stability of the financial system.

To quantify the stance of macroprudential policies, I use a count approach following Cerutti et al. (2016) and Kuttner and Shim (2016). By cumulating the tightening-net-of-easing policy actions, I construct an aggregate measure of general

macroprudential policy stance, the MAP index, as well as two categories of policies: the demand-side policy index and the supply-side policy index.

Since macroprudential policies could be used to tame the expansion of shadow banking credit, to address the issue of endogeneity, I study the lagged impact of the macroprudential measures to allow time for policies to be effective. The approach of lagging explanatory variables is quite common in similar macroprudential policy studies, for instance Kuttner and Shim (2016), Cerutti et al. (2017), and Akinci and Olmstead-Rumsey (2017). To further address this issue, I conduct the Wooldridge strict exogeneity test with fixed effects developed by Wooldridge (2010). The test results do not reject the null hypothesis of strict exogeneity and suggest there are no endogeneity issues.

The chapter is structured as follows. Section 2 reviews the literature. Section 3 describes the data used in the analysis, explains the noncore liability approach to measure shadow banking activities, and constructs the macroprudential policy indices. Section 4 presents the benchmark model for analysis. Section 5 provides the estimation results of the benchmark model on the impact of macroprudential policies on shadow banking. Section 6 presents a range of robustness checks. Section 7 concludes with a summary of the main themes covered here.

2.2 Literature review

This section on the research is related to a growing body of literature on financial stability, particularly about shadow banking and macroprudential policies.

Discussion about the potential threat of the shadow banking system to financial stability increased after the 2007-08 financial crisis. The shadow banking system is highly pro-cyclical and fragile as it creates seemingly-safe liquid claims, which reinforce credit boom in upturn, but become illiquid in downturns and could lead to fire sales (Geanakoplos 2010; Shleifer and Vishny 2010; Boot and Ratnovski 2016). Shadow banks are strongly interconnected with traditional banking. FSB (2012) identified several channels that regular banks can be directly involved in shadow banking activities, such as being a part of the shadow banking chain or supporting and investing in shadow banking product. The contagion of risk spreads through

these direct channels, as well as through indirect channels, such as fire-sales resulting in falls in asset prices across the financial system (Tucker 2012).

Concerns have been expressed about shadow banks acting to circumvent policy and engage in regulatory arbitrage. Tightening prudential regulations would provide incentives to shift activities towards the less-regulated part in the financial system (Goodhart 2008). Valckx et al. (2014) also finds that regulatory arbitrage plays a role in shadow banking growth. Aiyar et al. (2014) use bank-level data in UK and find tightening bank-specific minimum capital requirements could reduce the lending of regulated banks. They also find more active lending activities by the unregulated banks such as resident foreign branches in response to tightened regulations.

Several cross-country studies explored the effectiveness of macroprudential policies on financial stability. Many empirical analyses find that some frequently used macroprudential tools, such as LTV caps and DTI caps, reserve requirements and dynamic provisioning rules could effectively reduce bank credit and leverage growth, especially in emerging market economies (e.g. Lim et al. 2011; Cerutti et al. 2017).

A range of empirical studies particularly investigate the effectiveness of macroprudential policies on stabilising housing market. Using data going back to the 1980s, Kuttner and Shim (2016) investigate the effectiveness of a range of non-interest rate policy tools including macroprudential policies on housing market. They find the DTI caps and housing-related taxes have significant negative effects on housing credit. Crowe et al. (2013) investigate the impact of policies like the LTV caps on the real estate cycle and find some evidence suggesting maximum LTV could help curb a boom, while measures aiming at strengthening the banking system, such as dynamic provisionings, could help cope with the bust but not the boom. Akinci and Olmstead-Rumsey (2017) analyze the effect of macroprudential policies on general credit conditions as well as housing credit and house prices. They find bank credit growth can be restrained by both housing and non-housing measures, but only housing-related macroprudential policies, particularly LTV and DTI caps, can constrain credit growth and price appreciations in housing markets.

Furthermore, another strand of empirical studies focuses on examining the impact of macroprudential tools using bank-level data. Claessens et al. (2013) find demand-side policies are effective in reducing bank assets growth, especially during

upswing, and are more effective in advanced countries. Zhang and Zoli (2016) focus on Asia and find LTV caps could effectively curb bank credit supply and house price growth.

In line with many studies supporting the effectiveness of LTV and DTI caps in reducing systemic risk in the banking system, Claessens (2015) argues that these policies can be effective in addressing banking vulnerabilities for two reasons. First, demand-side measures mainly aim at the real-estate markets, which are primary sources of systemic risk in the financial system. Second, they directly address the demand for credit and therefore have less concerns of actual implementation and circumvention as real estate markets are generally well monitored and regulated. Crowe et al. (2013) argue that the narrow focus of the LTV and DTI caps could reduce the costs of actual policy adoption, but may also make it easier to circumvent and encourage regulatory arbitrage and risk transfer. Subsequently, the implementation from a political economy standpoint becomes complicated.

One closely related study that addresses potential risk transfers in response to macroprudential policies is Cizel et al. (2019), who find some evidence on the cross-sector "substitution effect" of macroprudential policies using country-level data. They conclude that credit flows from bank-based intermediation to non-bank intermediation following the adoption of macroprudential policies. In their study, the nonbank credit encompasses loans and debt securities held by all the other sectors of the economy except banks, regardless of whether the financing sources are stable or not. While they demonstrate the need to extend the scope of macroprudential policies beyond the banking sector, their results do not allow for assessing the direction of risk transfer from such policy leakages. Risk may shift to institutions that are less leveraged and less subject to maturity mismatch such as pension funds. Taking one step further, this research finds systemic risk building up outside of the traditional banking sector in response to macroprudential policy implementation. The risk shifting to the fragile shadow banking sector may threaten financial stability.

2.3 Data

The empirical analysis involves three categories of data: (1) measure of shadow banking in each country, (2) macroprudential policy (MAP) index, and (3) variables controlling for other factors that may influence shadow banking activities. I describe each in turn.

2.3.1 Measure of shadow banking activities

"Shadow banking" is a term which refers to a wide range of activities conducted by a variety of entities across countries. Consequently, there is no precise and all-compassing definition of shadow banking in the literature. Attempts to quantify its extent can be either *entity-based* or *activity-based*. Most empirical studies to date have used entity-based approaches, for example Bakk-Simon et al. (2011) and Valckx et al. (2014). Currently, there are two popular entity-based measures for empirical analysis, namely the Flow of Funds measure and the Financial Stability Board (FSB) measure. The primary difference between these is that the FSB measure includes non-money-market-fund investment funds and has a broader entity set but the Flow of Funds measure takes account of balance sheet breakdowns. These measures, despite having differing coverage over financial entities and availability across countries, both capture only entity-based shadow banking activities by non-bank financial institutions. Consequently, these measures fail to capture the shadow banking activities that are directly or indirectly conducted by banks.

I adopt a measure of shadow banking that has both entity and activity characteristics, namely the size of broad non-core liabilities. Developed by Harutyunyan et al. (2015), this approach quantifies the extent of shadow banking size using noncore liabilities from both banks and non-bank financial institution. Shin and Shin (2011) were the first to develop the conceptual difference between core and non-core liabilities in the banking sector. In their work, the core liability represents credit intermediation by the traditional banking sector, where bank deposits mainly come from households and non-financial corporations, and the noncore liability represents all the other funding sources of banks. Harutyunyan et al. (2015) propose using the noncore liability approach to measure the size of shadow banking activities by expanding non-core liabilities to encompass all

non-core liabilities of both bank and non-bank financial institutions in the financial system.

Specifically, this approach defines the issuers of shadow-banking-system-like liabilities as (1) banks[1], (2) Money Market Funds (MMFs), and (3) all nonbank financial institutions (i.e. Special Purpose Vehicles (SPVs) and finance companies) except non-MMF Investment Funds (IFs), Insurance Corporations and Pension Funds (ICPFs), and financial auxiliaries. Then the non-equity funding sources used by these issuers are divided into core and noncore liabilities. Core liabilities can be viewed as the traditional funding of banks, consisting of regular deposits from ultimate domestic creditors.[2] Banks are the only core liabilities issuers. The noncore liabilities are all the other non-equity funding sources of these issuers.

I adopt the broad measure of noncore liabilities by Harutyunyan et al. (2015) to capture the total exposure of shadow banking sector to the financial system. In their paper, the narrow and broad measure of noncore liabilities differ in their counterparts. The narrow measure captures the net exposure of the shadow banking sector to other sectors. It includes the ultimate domestic creditors, non-residents, ICPFs and IFs. The broad measure includes what is covered by the narrow measure, as well as the intra-shadow-banking-sector position in addition.

Compared to other measures of shadow banking, the broad noncore liability approach is better suited to draw implications of shadow banking on financial stability and systemic risk for several reasons.

First, it includes the shadow banking activities conducted by banks. Banks have been a significant participant in the shadow banking system (Shiller 2013). The other two measures, however, omit this. For example, if a bank was to securitize a portion of its balance sheet by establishing SPVs, such shadow banking activity could be captured by the entity-based approaches. However, if the bank conducts the securitisation by issuing covered bonds, which therefore remains on the bank's

[1]Refers to all deposit takers except the central bank, including commercial banks, saving banks and credit unions

[2]Based on Shin and Shin (2011), the notion of ultimate domestic creditors refers to the domestic fund providers and include: (1) IFs, ICPFs, and financial auxiliaries, (2) nonfinancial corporations, (3) households, and (4) state and local government.

balance sheet, the above entity-based measures will not capture such activities, whereas the non-core liability approach will.

Second, it includes the intra-shadow-banking-system positions. It tracks the total exposure of overall shadow banking activities to the financial system, and provides insights into the interconnectedness within the shadow banking system.

Furthermore, the implications of noncore liabilities, of banks and of the financial system, for financial fragility have been supported by the literature. Hahm et al. (2013) investigate the role of noncore liabilities of the banking sector in signalling financial vulnerability in emerging and developing economies. They find that noncore bank liabilities can serve as a good indicator of the vulnerability to both currency and credit crises. Claessens et al. (2013) use banks' noncore-to-core liabilities to represent the liquidity position of banks. Harutyunyan et al. (2015) find strong evidence of pro-cyclicality in the US, EU and Japan using the noncore-to-core liability ratio in the context of the financial system.

The broad noncore liability approach has some shortcomings. First, it does not offer balance sheet breakdowns. Second, it covers fewer emerging markets. Third and finally, it is subject to data granularity. In other words, the level of detail may be different for each country, in particular when taking liabilities of banks and MMFs.

The extent of shadow banking in our model is quantified as the (broad) non-core liabilities from Harutyunyan et al. (2015). In this paper, I consider two alternative forms of shadow banking growth: the *absolute* growth and the *relative* growth. The shadow banking growth (SB growth) is defined as the growth rate of broad noncore liabilities. The relative shadow banking growth (relative SB growth) is defined as the growth rate of the noncore-to-core liability ratio, indicating how fast the shadow banking sector is outgrowing the traditional banking sector.

Table 2.1 below presents the descriptive statistics of noncore liability growth rate, the noncore-to-core ratio in its level and growth respectively.

Table 2.1: Descriptive statistics of the noncore liability

Variables	Mean	Median	Standard deviation
Noncore liability growth (%)	1.482	1.043	6.102
Noncore-to-core ratio	1.948	1.307	2.140
Noncore-to-core ratio growth (%)	-0.006	-0.254	6.189

2.3.2 Macroprudential policy index

Macroprudential policy can be implemented using a diverse range of instruments (for an overview see Lim et al. (2011)). The macroprudential policy action in the sample is based on the policy database created by Cerutti et al. (2016) and Kuttner and Shim (2016). My sample includes 8 commonly used macroprudential policy instruments, namely LTV caps, DTI caps, loan-loss provisionings, sector-specific capital requirements, general capital requirements, reserve requirements, concentration limits, and interbank exposure limits. The description of the macroprudential policies is presented in Table 2.2. These policies can be classified as those targeting the demand-side of credit and those targeting the supply side of credit.[3] Demand-side policies, including the LTV caps and the DTI caps, target the borrowers of credit. Supply-side policies include the rest and target the suppliers of credit, which consist of banks and non-bank financial institutions.

Table 2.2: Description of macroprudential policy instruments

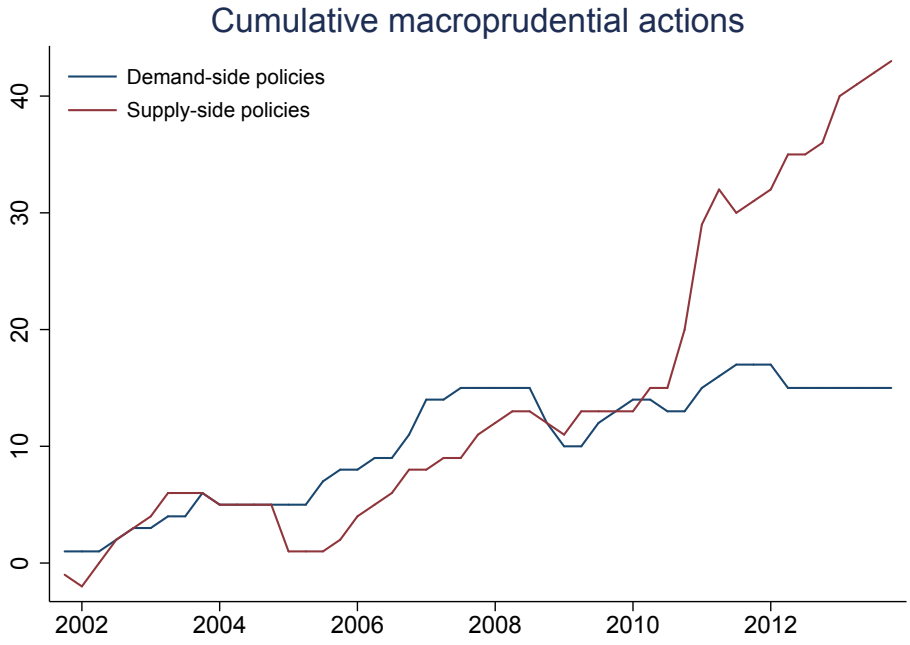
MAP	Description
Demand-side policies	
LTV caps	Restrictions on the maximum size of mortgage loans relative to the property value
DTI caps	Restrictions on the debt service payment to a fixed share of household income
Supply-side policies	
Loan-loss provisionings	Requirements for banks to set aside a larger portion of their profits as a cushion against expected defaults during upturn, thus tighten loan supply
General Capital requirement	The general capital requirements index is based on regulatory changes introduced in Basel I, II, II.5 and III.
Sector-specific Capital buffer	Capital buffer index captures regulatory changes in the size of the buffer against unexpected losses. The typical form of this kind of prudential instruments is to adjust the risk weights of specific bank exposures.
Reserve requirements	Changes in the reserve requirements in both domestic and foreign currency. The minimum amount of reserves that must be held by a commercial bank.
Concentration limits	Limits on the fraction of assets held by a limited number of borrowers
Interbank exposure limits	Limits on the fraction of liabilities held by the banking sector or by individual banks

I follow the approach of Cerutti et al. (2016) and Kuttner and Shim (2016), and create indices of macroprudential policy instruments. First, I construct the indices

[3]There are many ways in which to classify macroprudential tools. The demand-side and supply-side classification is stated by Claessens (2015) and is commonly used in the literature.

of individual policies by cumulating the number of tightening net of easing of each policy instrument since 2001Q4. To capture the overall macroprudential stance of a country, I sum across all instruments and construct the aggregate macroprudential policy index. Similarly, by summing across individual indices targeting the demand and the supply side of credit, I construct the demand-side policy index and the supply-side policy index. Figure 2.1 presents the cumulative use of demand-side and supply-side instruments across countries over time.

Figure 2.1: Macroprudential policies: cumulative actions across countries



The sample comprises 24 countries, predominantly from the OECD.[4] The frequency is quarterly, covering the years 2002 to 2013. The historical usage of macroprudential policy instruments is presented in Table 2.3. Notably, reserve requirements loosening is much more frequent than tightening in my sample. This is mainly because reserve requirements are frequently used by central banks for monetary policy purpose. For example, the European Central Bank used reserve requirements as monetary policy measures and lowering the minimum reserve ratio from 2% to 1% to reduce the banking systems need for liquidity in the Euro area on 18 January 2012. For all the other policy instruments, tightening is far more

[4]The exceptions are Malta, Thailand and South Africa.

frequent than loosening. The demand-side instruments, LTV caps and DTI caps, are both frequently tightened. In the supply-side, sector-specific capital requirements and general capital requirements, are both frequently used as well.

Admittedly, such a cumulative index, despite being common in the literature, is an imperfect measure of the stance of macroprudential policies. Intrinsically it is a simple count on the number of policy changes, treating all tightening and loosening actions the same regardless of any difference in magnitude. In reality, the magnitude of a policy action is likely to be of importance. For example, if a country lowers its cap on the LTV ratio from 80% to 60%, the macroprudential policy index would capture this regulatory tightening and add 1 to its value, but it could not capture the magnitude change of the 20% percentage points. To some extent, this would bias my cross-country analysis results. Fortunately, the implication of my results is not likely to be undermined by this issue. For example, Asian countries, especially South Korea, tend to use frequent but small adjustments in LTV caps. Such small tightening action is not expected to wield a large impact on shadow banking activities. Therefore, if any significant effect of such policy changes is found on shadow banking activities, that would indicate such estimation results are robust. It worth noting that the cumulative index does not take any policy changes before the beginning of the sample into account.

Ideally, we would want to use a measure that can capture the different impact of each single policy instrument. However, there has not been any other commonly acknowledged better measure of macroprudential policies across countries in the literature to date.[5]

[5]Some alternatives, such as that in Vandenbussche et al. (2015), appear to involve some personal judgment in their construction.

Table 2.3: Macroprudential policy tightenings(+) and easings(-) in each country

	LTV caps		DTI caps		Loan-loss provisionings		Reserve requirements		Sector-specific capital requirements		General capital requirements		Concentration limits		Interbank exposure limits	
	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-
Austria	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
Belgium	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
Estonia	0	0	0	0	0	0	3	3	1	2	1	0	0	0	0	0
Finland	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0
France	0	0	0	0	0	0	0	1	0	0	1	0	3	0	0	0
Germany	0	0	0	0	0	0	0	1	0	0	1	0	0	0	2	0
Greece	0	0	1	0	0	1	0	1	0	0	1	0	0	0	0	0
Ireland	0	0	0	0	0	0	0	1	2	0	1	0	0	0	0	0
Italy	0	0	0	0	0	0	0	1	0	0	1	0	1	0	1	0
Japan	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
South Korea	8	3	7	3	3	0	1	0	1	0	2	0	0	0	0	0
Luxembourg	0	1	0	0	0	0	0	1	1	0	1	0	0	0	0	0
Malta	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0
Mexico	0	0	0	0	1	0	0	0	0	0	2	0	1	0	1	0
Netherlands	2	0	1	0	0	0	0	1	0	0	1	0	1	0	0	0
Portugal	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0
Slovak Republic	0	0	0	0	0	0	0	3	0	0	1	0	0	0	0	0
Slovenia	0	0	0	0	0	0	1	1	1	0	1	0	0	0	0	0
South Africa	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
Spain	0	1	1	1	0	1	0	1	1	0	2	0	0	0	0	0
Thailand	1	1	0	0	0	0	1	2	4	0	1	0	0	0	0	0
Turkey	3	0	0	0	2	1	6	4	3	0	1	0	1	0	0	0
UK	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0
US	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
Total	14	6	10	4	6	3	12	27	14	2	29	0	8	0	5	0

2.4 Empirical analysis framework

In this section, I outline the benchmark model used to quantify the impact of macroprudential policies on shadow banking activities.

The model specification builts on the work of Valckx et al. (2014) to model shadow banking growth. The general econometric specification of my model as written below:

$$\begin{aligned}\Delta \ln Y_{i,t} = \mu_i + \eta_t + \alpha MAP_{i,t-1} + \sum_{k=1}^{K_\beta} \beta_k \Delta \ln GDP_{i,t-k} \\ + \sum_{k=1}^{K_\gamma} \gamma_k TermSpread_{i,t-k} + \sum_{k=1}^{K_\omega} \omega_k ShortRate_{i,t-k} \\ + \sum_{k=1}^{K_\rho} \rho_k Crisis_{i,t-k} + \theta Openness_{i,t-4} + \epsilon_{i,t}\end{aligned} \tag{2.1}$$

In the first set of regressions, the dependent variable $\Delta \ln Y_{i,t}$ represents the quarterly growth rate of shadow banking activities, as measured by broad non-core liability approach, for country i at time t. In the second set of regressions, $Y_{i,t}$ represents the noncore-to-core liability ratio and the dependent variable is the relative shadow banking growth.

I include a fixed-effect term μ_i to capture the unobserved time-invariant country-specific characteristics, and time dummy η_t to capture time-varying impact across all countries.

The main explanatory variable of interest is the cumulative macroprudential policy index MAP. To examine the varied impacts of macroprudential policies on shadow banking activities, I split the policy tools into demand and supply-side instruments. The demand-side policy index is expected to be positively correlated with shadow banking growth, as borrowers would have incentives to seek alternative funding sources when their access to the traditional funding sources is restricted by tightened regulations. There is no clear expectation concerning the direction of impact of the supply-side policy index. Policies aiming to tighten credit supply may restrict financial institutions from supplying credit, yet may also give them incentives to actively seek regulatory arbitrage opportunities through less regulated shadow banking activities and to take on more risk. The lagged

macroprudential index is typically used in this kind of studies to allow for policy transmission, as it could take time for macroprudential policies to be effective.[6]

Three groups of other key drivers of shadow banking activities are considered to allow for other factors that may affect shadow banking growth. The details of these variables are described in Appendix Table A1.

The first group of variables are macroeconomic and financial market indicators that may influence the growth of shadow banking. Real GDP growth rate is included to capture the impact of general economic development on the demand for shadow banking credit. It is expected that higher economic growth would lead to more active shadow banking credit intermediation.

The second group of variables are intended to capture the stance of monetary policy in each country. Two variables are included, namely the short-term real interest rate and the term spread. A lower interest rate is usually associated with an expansion of credit and more active economic activities, and thus may be associated with growing shadow banking system. The term spread, calculated as the gap between the long-term bond yield and the three-month money market rate, is to capture the search-for-yield effect. As discussed by Jackson (2013), when the gap between the short-term and the long-term rate is small, it may lead to a higher demand for high-yield assets, which could be supplied by the shadow banking system. In this way, narrowing term spread is expected to contribute to higher shadow banking growth.

The last group includes the systemic banking crisis dummy and the Chinn-Ito financial openness index. The systemic banking crisis dummy, constructed by Laeven and Valencia (2013), captures both significant financial distress in the banking system as well as significant banking policy intervention response to such distress. Shadow banking activities is expected to be sizably reduced when a systemic banking crisis disrupts the economy. When a systemic banking crisis occurs, large scale loan defaults and asset price deflation would spread out to the shadow banking sector due to its strong interconnectedness with the banking sector, resulting in fire sales in the shadow banking sector and further deflation in asset prices, as shadow banking assets would quickly become illiquid during a time

[6]It is typical to study the lagged impact of macroprudential policy indices in relevant empirical studies, such as Kuttner and Shim (2016), Zhang and Zoli (2016) and Akinci and Olmstead-Rumsey (2017).

of bust. One example would be the sharp decline in the shadow banking sector after the 2007-08 financial crisis. The original database by Laeven and Valencia (2013) only covers data up to 2012. I adopt their criteria of dating the occurrence and disappearance of a systemic banking crisis and extend the systemic banking crisis variable further to 2013 to match my sample.

The Chinn-Ito financial openness index, constructed by Chinn and Ito (2008), measures a country's degree of capital account openness. I use the normalized version, with the highest degree of financial openness set at 100 and the lowest set at 0. Unlike other variables which have quarterly frequency, the Chinn-Ito index is annual and slow-moving. I lag it by one year in the benchmark model.[7] The expected relationship between financial openness and shadow banking growth is not clear. On the one hand, greater financial openness, such as relatively fewer capital control policies and regulations, could be associated with more cross-border financial transactions and hence higher shadow banking growth. On the other hand, more restrictive capital controls may provide greater incentives for regulation circumvention, which may lead to more active credit intermediation in the shadow banks.

I use a general-to-specific modelling approach to determine the appropriate lag order of variables in the model specification. Specifically, starting with four lags of each variable, I reduce the lag length incrementally until the parameter estimates have statistical significance, individually or jointly. The final benchmark model contains the second lag of real GDP growth, four lags of the term spread, the third to four lags of the systemic crisis dummy, four lags of the short-term rate and the four lag of the financial openness index.[8]

In the second set of regressions, I set the relative growth rate of shadow banking activities as the dependent variable. Apart from the MAP index, among all the other explanatory variable, only term spread is expected to have significant impact as it could provide incentives for lending activities to shift from banks to shadow banks. Other explanatory variables are not expected to enable shadow banking credit to outgrow the traditional banking credit. Nevertheless, we use the same specification for control purposes.

[7] The estimation results have no significant difference if we use 1 quarter lagged Chinn-Ito index in the benchmark model.

[8] Across all estimations using the general-to-specific modelling approach, the financial openness index and the short-term rate have no significant impact on shadow banking growth whatsoever. Nonetheless I still include them in the benchmark model for control purposes.

Reverse causality is a potential problem in studies investigating how macroprudential policies may affect credit growth. Although this study focuses on shadow banking credit growth, one cannot exclude the possibility that policymakers may deliberately tighten macroprudential policies to restrict shadow banking credit growth. Such concern is mitigated as I study the lagged impact of the macroprudential tools to allow time for policies to be effective. This identification strategy is commonly used in similar empirical studies, such as Kuttner and Shim (2016), Cerutti et al. (2017), and Akinci and Olmstead-Rumsey (2017).

In addition, I conduct the Wooldridge strict exogeneity test with fixed effects, developed by Wooldridge (2010), to the MAP index in the benchmark model. The null hypothesis of strict exogeneity is not rejected.[9] The results of the Wooldridge strict exogeneity test are presented in Table 2.4.

2.5 Results

2.5.1 Benchmark model

I start by estimating the effect of the aggregate MAP index in the fixed effects regression framework. The next step is to investigate the changes of shadow banking activities associated with the demand-side policy index and the supply-side policy index, so as to examine their implication on *absolute* shadow banking growth, that is the noncore liability growth, and *relative* shadow banking growth, that is the noncore-to-core liability growth.

Table 2.4 presents the estimation results of the benchmark model. Columns (1) and (2) show the parameter estimates of the explanatory variables on shadow banking growth, with different MAP indices. Column (1) includes the aggregate MAP index as the key explanatory variable, while in Column (2) I estimate the impact of the demand-side and the supply-side policy indices. Columns (3) and (4) present the regression results of using the relative shadow banking growth as the dependent variable. Beside each column, I report the joint test results for explanatory variables with more than one lag.

[9] I carry out this test by leading the macroprudential policy indices by 1 period in the benchmark model. The leading macroprudential indices have no statistical significance. The null hypothesis of strict exogeneity is not rejected.

Table 2.4: Regression results: benchmark model

	SB growth				relative SB growth			
Variables	(1)		(2)		(3)		(4)	
		F-test p-value		F-test p-value		F-test p-value		F-test p-value
Real GDP growth								
lag 2	0.224*		0.225*		0.101		0.102	
	(0.115)		(0.119)		(0.106)		(0.110)	
Short-term rate		0.9084		0.927		0.909		0.926
lag 1	0.268		0.271		0.412		0.415	
	(0.717)		(0.725)		(0.826)		(0.827)	
lag 2	-0.541		-0.538		-0.697		-0.695	
	(1.000)		(1.008)		(1.146)		(1.153)	
lag 3	-0.0181		0.0379		0.0852		0.131	
	(0.836)		(0.851)		(0.965)		(0.972)	
lag 4	0.281		0.226		0.217		0.172	
	(0.695)		(0.694)		(0.785)		(0.780)	
Term spread		0.0256		0.031		0.033		0.031
lag 1	-0.492		-0.505		0.0165		0.00590	
	(0.543)		(0.533)		(0.776)		(0.767)	
lag 2	-0.228		-0.213		-0.821		-0.808	
	(0.704)		(0.700)		(1.093)		(1.090)	
lag 3	0.827*		0.816*		1.129**		1.120**	
	(0.429)		(0.426)		(0.459)		(0.458)	
lag 4	-0.388		-0.407		-0.525		-0.541	
	(0.341)		(0.338)		(0.402)		(0.400)	
Systemic Crisis dummy		0.0285		0.035		0.190		0.232
lag 3	-0.449		-0.415		0.142		0.170	
	(0.928)		(0.924)		(0.913)		(0.920)	
lag 4	-1.220		-1.139		-1.111		-1.044	
	(0.816)		(0.788)		(0.884)		(0.851)	
Openness								
lag 4	-5.140		-6.185		-3.076		-3.934	
	(4.929)		(5.539)		(5.549)		(6.074)	
MAP index								
lag 1	**0.280***				0.206			
	(0.163)				(0.173)			
Demand-side MAP								
lag 1			**0.473*****				**0.364****	
			(0.156)				(0.171)	
Supply-side MAP								
lag 1			0.0116				-0.0140	
			(0.348)				(0.402)	
Observations	897		897		897		897	
R-squared	0.253		0.254		0.221		0.222	
Wooldridge strict exogeneity test		p-value		p-value		p-value		p-value
MAP index - lead 1		0.556				0.714		
Demand-side MAP - lead 1				0.923				0.930
Supply-side MAP - lead 1				0.621				0.724

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Column (1), the coefficient of the aggregate MAP index is positive and significant at the 10% level. It indicates that one tightening action on a macroprudential policy tool would lead the shadow banking growth to increase by 0.28% on average in the next quarter. This outcome suggests the existence of policy circumvention through shadow banking activities to mitigate the effect of macroprudential policies. However, the aggregate MAP index is just a cumulative count of all macroprudential policy adoptions in each country. It captures the overall macroprudential stance but also ignores the difference among macroprudential policy tools.

Nevertheless, this finding contrasts with Akinci and Olmstead-Rumsey (2017), who find that changes in the aggregate MAP index are associated with lower domestic bank credit growth. Covering a similar time horizon, my results provide evidence on

the regulatory arbitrage that may undermine the effectiveness of macroprudential policies.[10]

Among other variables that may drive shadow banking growth, lagged GDP growth is significantly positive as expected, indicating shadow banking growth is positively affected by the state of the real business cycle, possibly through the channel of credit demand. The money market rate does not explain shadow banking growth by itself, but the lags of term spread are jointly significant, while the sum of their estimated coefficients has the expected negative sign. This suggests that a narrower yield spread is associated with more active credit intermediation in the shadow banking system. In line with the discussion of Jackson (2013), my result indicates there are search-for-yield activities as investors demand high-yielding assets that could be supplied by shadow banks. The lagged systemic banking crisis indicators is jointly significant, and the sum of the estimated coefficients is negative. This suggests the shadow banking sector would be greatly affected when a systemic banking crisis occurs, which is in line with the experience during the 2007-08 financial crisis. The capital account openness indicator is not found to play a significant role in shadow banking growth, since changes in capital control policies and regulations may have a mixed impact for shadow banking activities.

The relationship between shadow banking growth and the demand-side and the supply-side MAP indices is presented in Column (2). The coefficients of other explanatory variables are similar to Column (1). It is found that a tightening action on the demand-side measures would lead to a 0.473% increase in shadow banking growth. The expected positive sign and the strong statistical significance suggest the existence of risk transfer in response to demand-side macroprudential policy adoption.

In Column (3), the overall macroprudential index has no significant impact on the relative growth rate of shadow banking activities. In contrast, Column (4) reveals that an action tightening to the demand-side policies is associated with a 0.364% increase in relative shadow banking growth on average. It indicates that attempts to limit the credit demand of borrowers by using the LTV or DTI caps could shift

[10]I also estimated an alternative model using the growth rate of core funding as the dependent variable. The variable selection follows Cerutti et al. (2017) and the specification is suggested by the general-to-specific approach. The results find a higher MAP index leads to a lower core funding growth. This is in line with typical findings of the existing empirical literature, such as Akinci and Olmstead-Rumsey (2017) and Cerutti et al. (2017).

funding sources from secured core funding to more risky noncore funding. In this way the liquidity condition of the financial system could worsen.

The findings that the demand-side MAPs are generally associated with both higher shadow banking growth and higher relative shadow banking growth are in contrast with several studies on the effectiveness of popular demand-side macroprudential policies. Many empirical studies, including both cross-country and country-specific analyses, have found evidence that supports the effectiveness of LTV caps and DTI caps to curb the growth of (mainly bank) credit and house price (Claessens et al., 2013; Zhang and Zoli, 2016; Crowe et al., 2013; Akinci and Olmstead-Rumsey, 2017; Kuttner and Shim, 2016; Cerutti et al., 2017). However, my findings suggest that the regulatory efforts to suppress the demand of credit by using macroprudential measures to target the borrowers may be compromised by shadow banking activities.

While the LTV and DTI caps could effectively restrict loans being made by the regulated traditional banking sector, borrowers may seek to circumvent the regulation by using shadow banks as an alternative source of funding. The systemic risk is then transferred to the shadow banking sector. Thus, the effectiveness of demand-side measures in addressing banking sector vulnerabilities, found in previous research, may indicate systemic risk shifting away from the traditional banking sector to the shadow banking sector. Ignoring such policy leakage and the build-up of systemic risk outside the traditional banks would lead to overestimating the effectiveness of demand-side measures.

My results also show that supply-side measures generally do not have significant impact on the absolute or relative growth rate of shadow banking activities. One possible reason could be that measures directly restricting the credit suppliers may possibly lead to strengthened regulatory pressure and more supervision, and result in less risk-transfers to the shadow banks.

Table 2.5: Correlation between individual supply-side policies

	Sector-specific capital requirements	General capital requirements	Loan-loss provisionings	Concentration limits	Interbank exposure limits	Reserve requirements
Sector-specific capital requirements	1					
General Capital requirement	0.09	1				
Loan-loss provisionings	0.28	0.02	1			
Concentration limits	0.11	0.17	0.05	1		
Interbank exposure limits	-0.09	0.15	0.01	0.23	1	
Reserve requirements	0.19	-0.22	0.22	0.08	-0.02	1

The significant positive relationship between the aggregate MAP index and shadow banking growth mainly comes from the impact of demand-side policies. The demand-side measures, the LTV caps and DTI caps, are highly correlated, as they are usually used jointly in a complementary manner.[11] For this reason, it is difficult to evaluate their individual impact on shadow banking growth. Nevertheless, as reported in Table 2.5, the low correlation between supply-side policies makes it possible to investigate the individual impact of these measures on shadow banking activities in the next section.

2.5.2 Disaggregated supply-side macroprudential policies

In the benchmark estimation, it is found that the aggregate supply-side MAP index is not associated with shadow banking growth. In this section, I investigate the impact of each individual supply-side policy, namely loan-loss provisionings, sector-specific capital requirements, general capital requirements, reserve requirements, concentration limits, and interbank exposure limits. The impact of each individual supply-side policy index is estimated at a time, while controlling for the demand-side policies and the aggregation of the other supply-side policies.

Table 2.6 presents the estimated effects of individual supply-side measure on the absolute and relative shadow banking growth rate, respectively. It is found that general capital requirements, reserve requirements, concentration limits, and interbank exposure limits have no impact on shadow banking activities, suggesting there no policy circumvention through the shadow banks.

The sector-specific capital requirement index has negative and significant coefficients. One tightening action is associated with a 0.898% decrease in shadow banking growth and a 0.957% decrease in relative shadow banking growth. It suggests that this policy instrument can effectively address systemic risk build-up in the shadow banks.

The index for Loan-loss provisionings, notably, has positive and significant coefficient with relatively large magnitude. One tightening action is associated with a 2.734%

[11] The correlation between the two individual policy indices is 0.79.

Table 2.6: Regression results: supply-side policies

Dependent variable: SB growth	(1)	(2)	(3)	(4)	(5)	(6)
Loan-loss provisionings	2.734***					
	(0.784)					
Sector-specific capital requirements		-0.898**				
		(0.424)				
General capital requirements			1.250			
			(0.974)			
Concentration limits				0.0726		
				(0.475)		
Interbank exposure limits					0.378	
					(0.509)	
Reserve requirements						0.422
						(0.921)
Dependent variable: Relative SB growth	(1)	(2)	(3)	(4)	(5)	(6)
Loan-loss provisionings	3.081***					
	(0.619)					
Sector-specific capital requirements		-0.957**				
		(0.367)				
General capital requirements			1.305			
			(1.102)			
Concentration limits				-0.319		
				(0.437)		
Interbank exposure limits					0.826	
					(0.546)	
Reserve requirements						0.596
						(0.952)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All the policies are one period lagged

increase in shadow banking growth and a 3.081% increase in relative shadow banking growth.

As discussed by Fonseca and Gonzalez (2008), from an ideal risk management perspective, banks would recognize the underlying risk of the financial cycle, and build up loan-loss reserves in the boom to be drawn on in the bust. As a result, loan-loss provisions should show an income-smoothing pattern. However, empirical evidence does not find loan-loss provisions being counter-cyclical (Bikker and Metzemakers, 2005; Laeven and Majnoni, 2003). Conversely, from the capital management perspective, bank managers have incentives to use loan-loss provisions to manage earnings and regulatory capital, thus reduce expected regulatory costs associated with violating capital requirements (Ahmed et al., 1999). In a study of Australian banks, Cummings and Durrani (2016) find that bank managers use their discretion in setting provisions to dampen the impact of fluctuations in credit market conditions on their lending activities. The loan-loss

provisions show both pro-cyclical and counter-cyclical characteristics.

The results of this research suggest that tightening loan-loss provisionings, by itself, is associated with shadow banking credit intermediation. It is possible that banks may conduct shadow banking activities to the tightened circumvent loan-loss provisionings. Hence the effectiveness of loan-loss provisionings as a macroprudential policy instrument to reduce systemic risk in the overall financial system requires closer examination.

Goodhart et al. (2012) propose a theoretical framework to assess a range of macroprudential policies. Under their framework, capital requirements would create strong incentives for regulatory arbitrage that push credit intermediation from the banking system to the shadow banking system, while provisionings could effectively "lean against the wind" and "tame a boom". In contrast, my results find no evidence of regulatory arbitrage by shadow banking activities associated with neither general nor sector-specific capital requirements. Loan-loss provisionings, on the other hand, are associated with strong growth in shadow banking activities, suggesting relative ineffectiveness to address regulatory arbitrage by shadow banks.

2.6 Robustness checks

I perform a series of robustness checks to test the sensitivity of the main findings.

2.6.1 Adding a regulation quality indicator

One may argue that the quality of prudential regulations may have an impact on shadow banking growth, as poorly implemented policies could not be as effective as if they were implemented thoroughly. The degree of financial system maturity, the strength of supervision, institutional quality, corruption and all sorts of factors may affect the actual implementation of macroprudential policies and lead to regulatory circumvention.

Variations in the ability of heterogeneous governments to formulate and implement sound policies and regulations is mostly captured by the fixed effects in the benchmark model. To test whether the time-varying regulation quality may affect the main findings, I add a regulation quality index to the benchmark model. This regulation quality index is constructed by Kaufmann et al. (2011), reflecting perceptions of the ability of governments to formulate and implement sound policies and regulations that permit and promote private sector development.[12] This index is not a perfect proxy for actual regulation quality as it comes with a disadvantage of only capturing people's perceptions of the general quality of regulation. Nevertheless, it still captures some aspects of a country's time-varying regulation quality.

The results are reported in Table 2.7 Columns (1) and (2). The regulation quality index is negative and statistically significant at 10% level, suggesting a expected negative correlation between regulation quality and shadow banking growth. After controlling for the regulation quality index, my conclusion on the impact of demand-side policies and supply-side policies on shadow banking continue to hold and there is little change to the magnitude of the estimated coefficients.

2.6.2 Adding additional lags of the macroprudential policy indices

In the benchmark regression, I lag the MAP indices by one period following common practice in the literature. However, it may take longer for the policies to become effectively binding. By including up to three lags of the MAP indices, the individual coefficient of the lagged demand-side MAP index becomes insignificant, but they are jointly significant at 5% (Table 2.7 Columns (3) and (4). The sum of the estimated coefficients is of a similar magnitude to the benchmark results.

[12] I standardize this annual-based regulation quality index to a range of 0 to 10. The mean is 7.29 and standard deviation is 0.96.

Table 2.7: Robustness checks

Robustness checks								
Dependent variable	SB growth	Relative SB growth	SB growth	Relative SB growth	SB growth	Relative SB growth	SB growth	Relative SB growth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES			F-test p value	F-test p value	F-test p value	F-test p value		
Demand MAP			0.023	0.0071				
lag 1.	0.543***	0.432**	-0.385	-0.527	0.477**	0.355*	0.473***	0.277***
	(0.149)	(0.167)	(0.625)	(0.769)	(0.179)	(0.191)	(0.156)	(0.0621)
lag 2.			0.361	0.471				
			(0.781)	(1.007)				
lag 3.			0.497**	1.062				
			(0.218)	(0.658)				
lag 4.				-0.665				
				(0.856)				
Supply MAP			0.906	0.9805				
lag 1.	0.061	0.0330	-0.246	-0.293	0.040	0.002	0.012	0.141
	(0.324)	(0.387)	(0.499)	(0.690)	(0.356)	(0.414)	(0.348)	(0.284)
lag 2.			0.341	0.228				
			(0.492)	(0.612)				
lag 3.			-0.067	-0.151				
			(0.475)	(0.836)				
lag 4.				0.265				
				(0.713)				
Regulation quality	-1.980*	-1.905*						
	(1.146)	(1.043)						
Euro adoption					0.000	0.000		
lag 1.					5.526***	7.111***		
					(1.450)	(1.946)		
lag 2.					2.996	0.996		
					(3.815)	(4.054)		
lag 3.					-9.053***	-8.961***		
					(1.257)	(1.327)		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.6.3 Adding a Euro adoption indicator

Four countries joined the Euro zone in my sample, namely Estonia in 2011, Malta in 2008, Slovak Republic in 2009, and Slovenia in 2007. By joining the Euro zone, these countries experienced a complete change in the currency and monetary regime, as their monetary policy and relative regulation framework became determined by the European Central Bank. One may expect the shadow banking growth rate to decrease when countries join the Euro zone, as financial institutions become subject to a more stringent regulation framework. I create a Euro adoption dummy to control for the possible impact of joining the Euro zone for these countries.[13]

As shown in Table 2.7 Columns (5) and (6), we can see that the main findings are still robust when the Euro adoption dummy is included in the regression. Up to 3 lags of the Euro adoption dummy are also jointly significant.

[13]The Euro adoption dummy takes a value of 0 before these countries joined the Euro zone, and takes a value of 1 after they joined the Euro zone

2.6.4 Excluding the insignificant control variables

When I exclude all insignificant variables in the benchmark model, the results are still robust, as shown in Table 2.7 Columns (7) and (8).

2.6.5 Excluding one country at a time

To exclude the possibility that the results are driven by one country. I exclude one country from the sample at a time and conduct the same estimation. The main results are generally robust to omitting individual countries. The most notable change is when South Korea is omitted. South Korea has a history of using relatively small but frequent policy adjustments in LTV caps and DTI caps. When South Korea is excluded from the sample, the first lag of the demand-side policy index is no longer significantly different from zero. However, longer lags of the demand-side policy index are still positive and significant, and have similar magnitude as the benchmark model for both dependent variables, as shown in Table 2.8.[14]

Table 2.8: Robustness check: excluding South Korea

Dependent variable: SB growth				
	(1)	(2)	(3)	(4)
Demand MAP				
lag 1	0.753			
	(0.527)			
lag 2		1.248*		
		(0.622)		
lag 3			1.275*	
			(0.659)	
lag 4				0.984**
				(0.455)
Supply MAP				
lag 1	0.005			
	(0.356)			
lag 2		0.243		
		(0.308)		
lag 3			0.163	
			(0.299)	
lag 4				0.239
				(0.307)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[14]When the dependent variable is the relative shadow banking growth, excluding South Korea and Malta would both lead to insignificant first lag of demand-side policy index. However, lags 1-3 of the demand-side policy index are jointly significant in both cases.

2.7 Chapter conclusion

In this chapter, I study the impact of macroprudential policies on shadow banking activities. The main findings are as follows. First, the effectiveness of demand-side macroprudential policies, namely LTV caps and DTI caps, is mitigated by regulation arbitrage and systemic risk-transfer through the shadow banking system. Second, there is no evidence of policy mitigation for the supply-side policies with two exceptions. Sector-specific capital requirements are found to be able to effectively suppress shadow banking credit expansion, while loan-loss provisionings could be counter-productive as they could lead to more active shadow banking credit intermediation and risk-shifting.

Facing the challenge of regulatory arbitrage, a possible solution could be to use a combination of different policy tools together. It would be interesting to explore what combination of macroprudential policy tools are the most effective. This is beyond the scope of this research but may be an avenue for future studies.

It is important to recognize that the ultimate objective of macroprudential policies is to reduce the build-up of systemic risk and safeguard the overall financial system. My results strongly suggest that, to design, adopt and evaluate policies from the macroprudential toolkit, policymakers should take a broad perspective and consider how well the policy tools could address the key externalities and market failures that can lead to the build-up of systemic risk in both the traditional banking system and the shadow banking system.

Chapter 3

House prices and household debt in Australia: understanding the relationship

3.1 Introduction

After the financial liberalization of the 1980s and the subsequent sharp decline in nominal interest rates and inflation as monetary policy switched to inflation targeting in the early 1990s, both house prices and household debt grew rapidly relative to income in Australia. As Goodhart and Hofmann (2007) emphasize, mutual reinforcing boom-bust cycles in credit and housing markets may increase the likelihood of financial fragility. Deviations of house prices and debt from their long-run fundamentals raise the possibility of future financial instability as a house-price correction would pose stress on both banks and households. Furthermore, high leverage and house prices may stretch the household balance sheet too far and weaken the resilience of households to future economic shocks (Lowe, 2017).

This chapter aims to empirically investigate the short-run and long-run

interactions among Australian house prices and their drivers, with a particular focus on household debt. Employing a quarterly dataset from 1990 to 2016, I conduct cointegration analysis to estimate the long-run equilibrium relationship and then analyze short-run interactions among Australian house prices and the drivers of house price movements, namely household debt, housing stock, household disposable income, and the real interest rate, in a Structural Vector Error Correction Model (SVECM).

There are several dimensions to the main findings of this chapter. First, in the long-run equilibrium analysis, household debt and housing supply are found to be the significant long-run determinants of the equilibrium level of house prices. The cost of financing and the household disposable income only affect the equilibrium house prices indirectly through the credit channel. The speed of adjustment of Australian house prices towards the equilibrium is found to be sluggish relative to that of other countries in comparable studies.

Second, in the investigation of short-run dynamics, Australian house prices and household debt are found to be mutually reinforcing. Such a two-way interaction suggests the potential for a boom and bust cycle in the housing market may undermine the resilience of households as well as financial stability. A credit condition tightening shock leads to lower household debt burden and higher housing affordability. Such results suggest that if macroprudential policies act in a similar manner as an exogenous tightening in credit conditions, they may help reinforce the resilience of the economy.

Finally, when monetary policy is incorporated into the framework, it is found that a contractionary policy rate shock would suppress house price inflation, but may be at the cost of higher household debt. High-leveraged households, who cannot access further borrowings, may have difficulties smoothing the shock. It suggests that there could be potential build-up in systemic risk if monetary policy "leans against the wind" to address house price inflation. In particular, it may threaten the resilience of highly indebted households.

This study contributes to the literature in several aspects. First, to the best of my knowledge, this is the first study that empirically investigates the Australian housing market focusing on the linkage between house prices and household debt with a SVECM framework. The importance of the credit channel in determining house prices is highlighted.

Second, compared to similar studies in the literature that primarily focus on investigating the response of house prices to various shocks, this study takes a step further and explores the interactions between house prices and the macroeconomic fundamentals including household borrowings.

Third, this study let the results be driven by data to the largest possible extent by adopting the identification technique of Pagan and Pesaran (2008), so as to avoid imposing unnecessary restrictions. Essentially, compared to other studies, I impose minimal restrictions to identify the model and therefore allow for contemporaneously interactions between house prices and household debt. There have been mixed approaches used to identify the dynamic effects of structural shocks to the housing market in the literature. However, the contemporaneous interaction between house prices and household debt is restricted in one way or another. Some assume sticky house prices that do not respond to changes in household borrowings contemporaneously (Oikarinen 2009, Hofmann 2004), whereas others make the opposite assumption (Anundsen and Jansen 2013, Berki and Szendrei 2017). I make neither.

Fourth, I analyze the main factors affecting housing market development over time using a historical decomposition. Notably, it is found that credit condition shocks and housing demand shocks are the main drivers of the house price boom before and after 2000. Housing demand shocks contributed the most to the raising house prices since 2013.

Finally, I contribute to the literature by investigating the role of monetary policy in the interaction between the housing market and household borrowings.

The remainder of this chapter is structured as the following. Section 3.2 provides a review of relevant literature. Section 3.3 provides the empirical framework and the benchmark model. Section 3.4 provides the sensitivity analysis which extends the model to incorporate monetary policy. Section 3.5 concludes.

3.2 Literature review

My research is related to a growing body of empirically studies on house prices, particularly focusing on the linkage between house prices and household debt.

There are numerous studies analyzing house price movements. Typically econometric models are used to compute the fundamental house price, which is determined by demand-side factors, such as real disposable income, the user cost of capital, as well as demographic, and supply-side factors, such as housing stock; *e.g.,* Meen (2002) and Muellbauer and Murphy (1997). Girouard et al. (2006) provides a literature review on empirical studies of house price determination for the majority of the OECD economies.

However, the roles of credit conditions and household borrowings arguably have not had enough attention paid to them in this type of framework. After the 2007-2008 financial crisis, which originated in the mortgage and related market, academics and policy economists have become more concerned about the extent of interdependence between the housing market and the credit market and how it may affect the financial stability.

Some early works, such as Goodhart et al. (2004), studied and documented the coincidence of the credit cycle and the housing market cycle. Goodhart and Hofmann (2007) summarized the channels on how house prices and bank lendings affecting each other. On the one hand, to what extent the households are borrowing-constrained will impact the demand of housing, while on the other hand, house prices may impact household borrowings via wealth effects.

Household borrowings are informative about several aspects of housing market development, such as market confidence and the expectations of both banks and households. The aggregate level of household borrowings also influences the resilience of households to various potential economic risks. Barakova et al. (2003) present empirical evidence on the importance of credit constraints on the demand of housing properties. Jin and Zeng (2004) also find that the existence of liquidity constraints would amplify the impact of monetary shocks on house prices in a DSGE model.

House prices may impact household borrowings via the wealth effect. First, since properties usually are the collaterals of mortgages, higher house prices would increase the net-worth of households, thereby expanding the household borrowing capacity and reducing the default risk of banks, leading to further credit expansion. Iacoviello (2004) find strong collateral effects on household wealth by expanding borrowing capacity in a dynamic general equilibrium model framework. Second, a house price appreciation may lead to higher demand for credit, as

households may perceive themselves to have higher lifetime wealth and want to borrow more to smooth consumption. Finally, higher house prices would lead to an expansion in bank assets and increase banks' willingness to originate new loans.

Recently, there has been a growing body of empirical studies on the nexus of house prices and household debt. However, mixed evidence about their interaction has been found, as the analysis are different in terms of whether they are about the long-run or the short-run, and whether they are country-specific or cross-country studies. There are also differences in the econometric framework and country-specific attributes, such as institutions and regulations.

Using a panel of 20 countries over 1985 to 2001, Hofmann (2004) find the existence of one cointegration relationship between house prices and bank lending, and the bidirectional effects in the short run. Brissimis and Vlassopoulos (2009) also find similar evidence for mortgage lending and house prices for Greece over 1993 to 2005. Oikarinen (2009) finds evidence that house prices are affected by household borrowings in the long run for Finland over 1975 to 2006, while the two-way interaction in the short run strengthened after the financial deregulation. In contrast, Gerlach and Peng (2005) find house prices affect private sector debt but not the other way around in the short run for Hong Kong over 1984 to 2001. Semlali and Collyns (2002) find a very strong contemporaneous effect of the credit channel to property price inflation in four East Asia countries: Hong Kong, Korea, Singapore and Thailand. They conclude that bank lending contributed considerably to the Asian property bubble in the 1990s.

Goodhart and Hofmann (2008) use a fixed-effect panel VAR model to assess the links between money, credit, house prices and economic activities in 17 industrialized countries over 1970-2006. They find evidence of a significant multi-directional link between house prices, broad money, private credit and the macroeconomy. They also find such link to be stronger for a sub-sample 1985-2006, which basically covers the periods following the financial liberalizations in industrialized countries. Using a number of econometric approaches and a relatively short sample period, namely 1996-2002, Fitzpatrick and McQuinn (2007) find a long-run mutually reinforcing relationship between house prices and mortgage credit in Ireland. Anundsen and Jansen (2013) investigate Norway 1986-2008 and find mutually reinforcing interaction between house prices and credit, both in the long run and the short run.

In summary, the interaction between house prices and household debt is critical to the stability and resilience of the financial system. However, current empirical evidence is mixed and country specific.

This chapter also relates to a strand of the empirical literature on the Australian housing market. Australia, like many other industrialized countries, experienced house price boom after the liberalization of the financial system. Empirical studies about the Australian housing market rarely focused on the linkage between house prices and household debt post 1990s.

Abelson et al. (2005) use an asymmetric VECM model covering 1970-2003 quarterly to investigate the determinants of real house prices in Australia. Including a large number of endogenous variables, they find more than four cointegration vectors in their long-run analysis. They conclude that the long-run real house prices are determined positively by the real disposable income, CPI and negatively by the unemployment rate, real mortgage rates, equity prices and the housing stock. They also find a reasonably fast speed of adjustment of house prices to the long-run equilibrium, at approximately 21% each quarter, excluding the early 1970s. In contrast, this research finds some notably different results by incorporating the credit channel that interacts with the Australian housing market and using a more recent quarterly dataset covering 1990 to 2016. I identify the drivers for equilibrium house prices and find only one cointegration relationship exists. The speed of adjustment of house prices to its long-run equilibrium is lower (6.2%), although the time period covered differs.

Fry et al. (2010) incorporate a housing sector into the macroeconomic Structural Vector Autoregression (SVAR) model of Dungey and Fry (2009) for Australia 2002 to 2008, and estimate the model with a set of long-run restrictions on the housing market. They find strong evidence of overvaluation in Australian real house price over 2002-2008. Specifically, they identify the benchmark house price level as the rational forecast, which they refer as the 'market fundamental' house price. They find two main periods of overvaluation - pre-2006 and post-2006 - where the overvaluation is mainly driven by housing demand shocks in the first period and by good market shocks in the second period. The cointegration analysis and historical decomposition of this chapter yield similar conclusion for Australia housing market in this particular period.

Kohler and Van Der Merwe (2015) identifies that the house price boom from 1990s to mid-2000s is associated with significant increases in the debt-to-income ratio of Australian households. Otto (2007) investigates Australian capital cities over 19862005 and finds that economic factors could explain around 40%-60% of the variation in house price growth. The mortgage rate is found to be an important driver for house price growth, but the size of the effect differs substantially across different capital cities. This chapter takes the analysis a step further and finds that the impact of mortgage rate on the equilibrium house price is through the credit channel and shows that monetary policy leaning against the wind may actually be counter-productive to financial instability.

Saunders and Tulip (2019) build an empirical model of the Australian housing market 1987Q1-2018Q2 and quantifies the interrelationships between construction, vacancies, rent and house prices. Saunders and Tulip (2019) use sets of single-equations and conduct identification through lags and *a priori* reasoning. Their model suggests low interest rates were important contributors to the recent rapid growth in house prices and construction activities. Covering a similar sample period, I investigate the housing market with a particular focus on the linkage between house prices and household debt.

On the development of Australia household indebtedness, Atalay et al. use micro-level household data and find approximately one quarter of the growth in household debt over 2002-2014 can be explained by rising house prices, mostly driven by the wealth effect and the collateral effect for collateral and liquidity constrained households.

Finally, Berkelmans (2005) investigates the relationships of total credit with other key macroeconomic variables by estimating a SVAR model for Australia over 1983Q4-2003Q4. He finds the level of total credit respond negatively and slowly to changes in monetary policy, and monetary policy could stabilize the economy in responding to a credit shock. In contrast, this study finds evidence against the usefulness of using monetary policy to pursue financial stability.

3.3 Empirical analysis

In section 3.3.1, I briefly describe the data. In Section 3.3.2, I conduct cointegration analysis to examine the long-run relationship between house prices and their drivers. In section 3.3.3, I investigate the short-run dynamics of the housing market by identifying the structural shocks and estimating the impulse responses. Section 3.3.4 presents the empirical results and interpretation. Section 3.3.5 analyze the main drivers of the housing market development over time using a historical decomposition.

3.3.1 Data

The sample covers the period 1990Q1 to 2016Q3 quarterly. The benchmark model includes five variables, with the housing supply (h), household disposable income (hdi), household debt ($debt$) and real house prices (hp) being endogenous, and the real interest rate (r) which is assumed to be exogenous.[15] All variables are in real terms, and are in logarithmic form except the real interest rate. The unit of the endogenous variables is per household. A detailed description of the variables is listed in Appendix Table B1.

I test the orders of integration of the series with the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test. The detailed results of these unit root tests are reported in Appendix Table B2. Overall, the test results suggest that the housing supply, household disposable income, household debt and real house prices are of order 1, while real interest rate is stationary in the sample period. In the benchmark model, I treat the real interest rate as an I(1) variable, assuming it explains house price levels in the long run. The real interest rate is a proxy for the real user costs of capital, which is one of the determinants of fundamental house prices in both theory and many empirical work (Meen, 2002; Muellbauer and Murphy, 1997; Malpezzi, 1999). Such treatment is commonly adopted by empirical studies on modelling the long-run house prices, such as Oikarinen (2009).

[15]The assumption of exogenous real interest rate in the benchmark model follows the literature such as Anundsen and Jansen (2013) and Gerlach and Peng (2005). This assumption is relaxed in the Section 3.4.

The benchmark VECM model has the following reduced form:

$$\Delta Y_t = \alpha\beta' Y^*_{t-1} + \sum_{i=1}^{p} \phi_i \Delta Y^*_{t-i} + c + \epsilon_t \tag{3.1}$$

where Y is the vector containing the four endogenous variables $[h, hdi, debt, hp]$. Y^* contains the four endogenous variables and the exogenous real interest rate r. c is the intercept. $\beta' Y^*$ is the cointegration vector and α is the loading matrix. I also include a constant and a linear trend in the cointegrating relation to accommodate for the possibility of the presence of a deterministic trend.

3.3.2 Cointegration analysis

A systematic approach is adopted to determine and estimate the cointegration relation.

I first estimate an unrestricted VAR model in the levels of $[h, hdi, debt, hp]$, taking r as exogenous. The optimal lag length of the VAR model is 2 according to the Schwarz Information Criterion. The VECM model then has lag of order 1 as all the endogenous variables are in first difference terms.

I then conduct the trace test of Johansen (1988) to determine the rank of cointegration, allowing for an intercept and a deterministic trend in the cointegrating relationship.[16] As shown in Table 3.1, the result suggests only one cointegration vector exists. The cointegration equation can be written as the following form.

$$ec_t = \beta_1 hp_t + \beta_2 h_t + \beta_3 hdi_t + \beta_4 debt + \beta_5 r_t + const + trend \tag{3.2}$$

ec_t is the error correction term at time t. $const$ is a constant and $trend$ is the linear trend. Since the rank of cointegration is one, by normalizing the coefficient of the real house price index, it can be written as a long-run equilibrium house price

[16] A linear trend is included to handle the possibility that variables do not share a common deterministic trend. When omitting the trend, the constant will become significant and the estimated coefficients of other variables change slightly.

equation:

$$hp_t = -\beta_2 h_t - \beta_3 hdi_t - \beta_4 debt - \beta_5 r_t - const - trend + ec_t \tag{3.3}$$

The cointegration equation is estimated by the method of Fully Modified Ordinary Least Squares (FMOLS) (Phillips, 1995).[17] The results are presented in Table 3.2.

Table 3.1: Trace Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value[1]
None *	0.31	89.92	73.13
At most 1	0.26	49.79	50.08
At most 2	0.09	17.87	30.91
At most 3	0.07	7.29	15.33

* denotes rejection of the null hypothesis at the 0.05 level
[1]Critical values are adjusted for the case of 4 endogenous variables and 1 exogenous variable. The critical values are obtained from Table 13 of Doornik (2003)

Table 3.2: Estimated cointegration relation

	hp	h	hdi	debt	r	Constant	Trend
Long-run coefficients							
β	1	6.315***	0.014	-1.574***	0.002	-8.950***	-0.002
Standard error		1.585	0.215	0.199	0.006	3.259	0.001
Loading factor							
α	**-0.062****	-0.001	-0.006	0.021			
Standard error	0.030	0.003	0.034	0.023			

** denotes rejection of the null hypothesis at the 5% level
*** denotes rejection of the null hypothesis at the 1% level

The estimation results suggest that in the long run, an 1% increase in the housing stock per household leads to the equilibrium house prices being 6.32% lower, and an 1% increase in household debt leads to an 1.57% increase in the equilibrium house prices. In other words, it suggests that increasing housing supply will dampen the

[17]I used the default option of no lags in Eviews when calculating the long-run covariance. Prewhitening the data with AIC selected lags does not affect the results.

house prices in the long run, while higher household debt is associated with higher long-run equilibrium house prices.

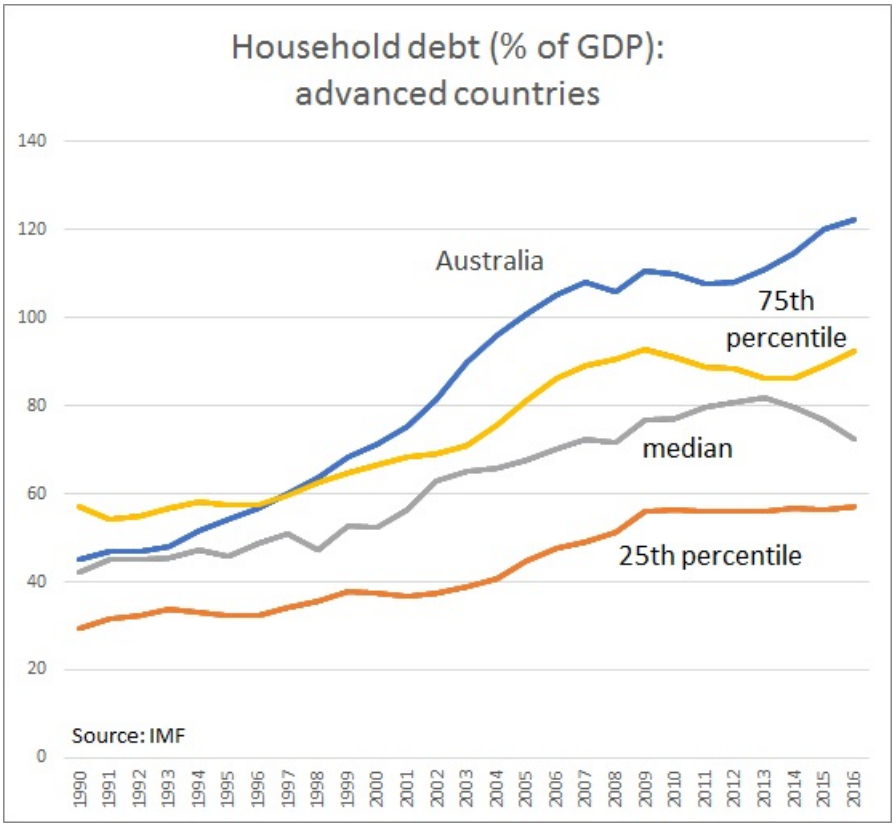
Intuitively, both a higher household disposable income and a lower real interest rate would lead to higher housing demand and therefore have a positive impact on house prices. However, they have no statistical significance when household debt is present in the estimation. Alternatively, if household debt is omitted from the cointegration equation, the disposable income and interest rate regain their expected signs and significance. In contrast, omitting either the real interest rate or household disposable income from the cointegration relation does not change the other estimated parameters. To test whether the housing supply channel may play a role, I estimate the equation omitting the housing stock variable and find no significant changes to the other estimated parameters. These results imply that changes in household disposable income and the real interest rate affect the house prices through the credit channel in the long run.

In some comparable studies, Oikarinen (2009) and Anundsen and Jansen (2013) also find similar insignificant real interest rate in their long-run house price equations for Finland and Norway. This is also in line with the result of Hofmann (2004), who find a long-run negative relationship between credit and real interest rate in many industrialized countries.

Some country-specific studies do find that household disposable income significantly contributes to higher equilibrium house prices in the presence of household debt in their cointegration equations (Turk, 2015; Oikarinen, 2009; Anundsen and Jansen, 2013; Berki and Szendrei, 2017). Such results are in line with Girouard et al. (2006), who found that Australia, unlike many other OECD countries, experienced a higher household debt burden after the common housing market boom in early 1990s. Alternatively, the general increase in indebtedness of OECD countries, due in part to the financial deregulation, was mostly offset by lower borrowing rates, resulting in households not devoting a greater share of income to debt service than before on average. As Figure 3.1 demonstrates, the increase in household debt relative to GDP in Australia since the 1990s has been relatively large by international standards.

One distinctive feature of Australia is that the stock in the rental market is mostly owned by households, unlike many other countries that have rental stock mainly owned by commercial corporations. Australian households do not only borrow to

Figure 3.1: Household debt (% of GDP) in advanced countries



*The advance countries included are: Australia, Belgium, Canada, Finland, France, Germany, Hungary, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Turkey, United Kingdom, United States

finance their own home, but also take on loans to purchase investment properties. This is especially the case after the government announced a significant capital gain tax reduction in 1999, which motivated investment in the housing market. Households pursuing house ownership for investment purpose explains why household disposable income affects equilibrium house prices only through the channel of household borrowings in Australia.

The long-run equilibrium house price equation may also be intepreted from the perspective of housing market supply and demand. As hp and h represent house prices and the quantity of housing stock, the inverse of the coefficient on h, which equals -0.16, could be seen as the long-run elasticity of housing demand. It suggests that at the aggregate level housing demand is relatively inelastic in the long run. Furthermore, the estimated elasticity of demand with respect to the debt is 0.25, which is comparable to findings of Caldera and Johansson (2013) that the long-run income elasticity for Australia over 1970-2009 equals 0.21. In comparison, Abelson

et al. (2005) find the income elasticity of demand for Australia over 1970-2003 to be 0.42.

As presented in Table 3.2, the estimated loading factor of house prices is 6.2% quarterly. This result is comparable to Oikarinen (2009), who finds that the speed-of-adjustment of house prices to their long-run equilibrium is 7.2% quarterly in Finland for the sample 1970-2006; Turk (2015) also estimates the coefficient to be 8.3% in Sweden for 1980-2015. Anundsen and Jansen (2013) find the speed-of-adjustment of house prices is 17.5% in Norway for 1986-2008. In the context of Australia, Abelson et al. (2005) investigate the housing market between 1970-2003 and find a much faster speed-of-adjustment of Australia house prices at 21% each quarter. Compared to the above studies, it appears that the speed-of-adjustment when house prices deviate from their long-run equilibrium has become much more sluggish after the financial liberalization.

3.3.3 Short-run structural analysis

To investigate the dynamics of the housing market, I adopt the techniques of Pagan and Pesaran (2008) to identify the structural shocks without imposing unnecessary restrictions on the parameters. The SVECM model is exactly-identified so as to let the result be driven by the data to the largest possible extent.

3.3.3.1 Empirical specification

The key idea of Pagan and Pesaran (2008) is that the permanent/transitory decomposition of shocks can be used for the identification of structural models. It shows that structural equations for which there are known permanent shocks must have no error-correction terms present in them. If the model is estimated with the Instrumental Variables (IV) method, the error-correction terms could be used as instruments when estimating the parameters of these variables with permanent shocks in their structural equations.

Specifically, a system with n endogenous I(1) variables and r cointegration vectors must have r transitory shocks and $n - r$ permanent shocks. According to Pagan and Pesaran (2008), in the $n - r$ structural equations with permanent shocks, the loading factors of the lagged error correction terms must equal to zero. Therefore, if

we have the knowledge of the structural shocks being permanent or transitory, long-run restrictions could be imposed *a priori* and aid the identification of structural equations.

The benchmark model contains the first difference of the four I(1) endogenous variables in the order of $[h, hdi, debt, hp]$ and one exogenous variable $[r]$. There are four shocks in the system: housing supply shock ($\epsilon_{h,t}$), household disposable income shock ($\epsilon_{hdi,t}$), household debt shock ($\epsilon_{debt,t}$) and house price shock ($\epsilon_{hp,t}$). Section 3.3.2 has established that only one cointegration vector exists. Therefore the system must have 3 permanent shocks and only 1 transitory shock.

I assume that the shocks of the first three variables are permanent shocks. The housing supply shock is permanent as the existence of newly constructed property is physical and not expected to be demolished in the short run. The shock on household disposable income is taken to be permanent, representing a supply-side shock on economic development. The household debt shock is taken to be permanent to represent changes in credit conditions, such as banks tightening or easing the borrowing constraints. I take the house price shock to be a demand shock and it is the only transitory shock in the system. As Table 3.2 shows, only the loading factor in the house price equation is significantly different from zero. None of the other endogenous variables reacts to house price disequilibrium.

Following Pagan and Pesaran (2008), I start by reformulating the SVECM system into a SVAR system containing the first difference of the first three endogenous variables with permanent shocks ($\Delta h, \Delta hdi, \Delta debt$) and the error correction term (ec).

Denote $\zeta_t = [h, hdi, debt, hp]'$. Φ_0 is the coefficient matrix of $\Delta\zeta_t$. $exog$ represents the exogenous variable, while c is the constant term. The SVECM has the following format.

$$\Phi_0 \Delta\zeta_t = \alpha \times ec_{t-1} + lags + exog + c + \epsilon_t \tag{3.4}$$

Denote $\zeta_1 = [h, hdi, debt]', \zeta_2 = [hp]'$. Φ^0_{11} and Φ^0_{12} are the coefficient matrices of $\Delta\zeta_{1t}$ and $\Delta\zeta_{2t}$ respectively. The first 3 equations with permanent shocks must have

their loading factors of the lagged error-correction terms being zero:

$$\Phi_{11}^0 \Delta\zeta_{1t} + \Phi_{12}^0 \Delta\zeta_{2t} = \alpha_1 \times ec_{t-1} + lags + exog + c + \epsilon_{1t} \tag{3.5}$$

$$= \mathbf{0} * ec_{t-1} + lags + exog + c + \epsilon_{1t} \tag{3.6}$$

The equation of the variable with transitory shocks is the only equation that has the term ec_{t-1}:

$$\Phi_{21}^0 \Delta\zeta_{1t} + \Phi_{22}^0 \Delta\zeta_{2t} = \alpha_2 \times ec_{t-1} + lags + exog + c + \epsilon_{2t} \tag{3.7}$$

Rearranging the cointegration equation and taking first difference yields an expression for $\Delta\xi_{2t}$.

$$ec_t = \beta_1'^* \zeta_{1t} + \beta_2'^* \zeta_{2t} \Rightarrow \zeta_{2t} = (\beta_2'^*)^{-1}(ec_t - \beta_1'^* \zeta_{1t}) \tag{3.8}$$

$$\Rightarrow \Delta\zeta_{2t} = (\beta_2'^*)^{-1}(\Delta ec_t - \beta_1'^* \Delta\zeta_{1t}) \tag{3.9}$$

Substituting Equation 3.9 into Equation 3.6 enables the equations with permanent shocks to be written as:

$$A_{11}^0 \Delta\zeta_{1t} + A_{12}^0 \Delta ec_t = lags + exog + c + \epsilon_{1t} \tag{3.10}$$

In Equation 3.10, A_{11}^0 is the coefficient matrix of $\Delta\zeta_{1t}$. A_{12}^0 is the coefficient of Δec_t.

Likewise, substituting Equation 3.9 into Equation 3.7 and writing Δec_t as $ec_t - ec_{t-1}$, the equation with transitory shocks becomes:

$$A_{21}^0 \Delta\zeta_{1t} + A_{22}^0 ec_t = lags + exog + c + \epsilon_{2t} \tag{3.11}$$

In Equation 3.11, A_{21}^0 is the coefficient matrix of $\Delta\zeta_{1t}$. A_{22}^0 is the coefficient of ec_t.

Denote $Z = [\Delta h, \Delta hdi, \Delta debt, ec]'$. The SVAR system can then be expressed as the following form by normalizing the left-hand-side. Φ is the matrix of the

contemporaneous impulse responses to the structural shocks.

$$Z_t = lags + exog + c + \Phi\epsilon_t \tag{3.12}$$

By replacing Δhp with ec_t, we have a SVAR system of $[\Delta h, \Delta hdi, \Delta debt, ec]$, while all the shocks are still the original SVECM structural shocks.

With 4 endogenous variables in the system, at least 6 restrictions are required to identify the model.

By adopting the approach of Pagan and Pesaran (2008), I can free up to three zero contemporaneous restrictions from the model by fixing the nature of the structural shocks *a priori*. In the reformulated equations with permanent shocks, it is the first difference of the error correction term that gets in these equations, reflecting no permanent impact from the transitory house price shock to the other variables. These are three implicit long-run restrictions. I impose three more short-run restrictions to the matrix Φ. It is assumed that the housing stock does not respond to changes in household disposable income and household debt contemporaneously. As changes in household income and debt are not directly and immediately observable, it takes time for property developers to make decisions to augment housing supply and for constructors to finish building properties. Household disposable income is also assumed not to respond to household debt changes contemporaneously. In summary, the benchmark model is exactly identified with the following restrictions:

$$\text{Long-run restrictions}: \begin{array}{c} \\ \Delta h \\ \Delta hdi \\ \Delta debt \\ ec \end{array} \begin{array}{c} \begin{array}{cccc} \epsilon_h & \epsilon_{hdi} & \epsilon_{debt} & \epsilon_{hp} \end{array} \\ \begin{bmatrix} * & * & * & 0 \\ * & * & * & 0 \\ * & * & * & 0 \\ * & * & * & * \end{bmatrix} \end{array}$$

$$\text{Short-run restrictions}: \quad \begin{array}{c} \\ \Delta h \\ \Delta hdi \\ \Delta debt \\ ec \end{array} \begin{array}{c} \begin{array}{cccc} \epsilon_h & \epsilon_{hdi} & \epsilon_{debt} & \epsilon_{hp} \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & * \\ * & 1 & 0 & * \\ * & * & 1 & * \\ * & * & * & 1 \end{bmatrix} \end{array}$$

Similar studies identify the structural shocks by imposing a recursive structure of zero restrictions in the contemporaneous response. This approach, however, will restrict the contemporaneous interaction between house prices and household debt. The choice of assuming no instantaneous impact of house price changes to household debt or assuming the opposite depends on the variable order in the system and is subjective.

For example, Oikarinen (2009) assumes household borrowings have no contemporaneous impact on house prices, while Anundsen and Jansen (2013) and Berki and Szendrei (2017) make the opposite assumption that household borrowings do not respond to house price changes contemporaneously.

Intuitively, house prices are likely to be sensitive to changes in credit conditions contemporaneously; for example, in Australia, the inclusion of a "subject to finance" clause in the contracts of sale of real estate is common. Tightened credit conditions are likely to lead to more rejections in loan approvals and suppress active housing market transactions and house prices within one quarter. Household debt may also be sensitive to changes in the housing market. For example, a negative demand shock to the housing market is likely to affect the confidence of both investors and sellers, reducing market turnover and keeping households from undertaking further borrowings.

The advantage of my identification strategy is that there are no long-run or short-run restrictions to the interaction between house prices and household debt. I impose a minimal number of restrictions so that the results could be driven by data to the largest possible extent.

3.3.4 Short-run dynamics: empirical results

The benchmark model is estimated with the method of Maximum Likelihood Estimation (MLE). As the model is just identified, this is the same as using the IV approach. An intercept is included in the structural equations. In the impulse response analysis, I investigate the dynamic impact of one percent positive shocks. The impulse responses of the levels of variables are presented.

To better understand the implication for the financial stability, the responses of house prices and household debt relative to household disposable income are also presented. The debt-to-income ratio represents the degree of household indebtedness. A higher debt-to-income ratio indicates higher debt burden of households. The house-price-to-income ratio represents housing affordability, i.e., higher house-price-to-income ratio means houses are less affordable to households. The rest of the chapter uses the expression "debt burden" and "housing affordability" to refer to the debt-to-income ratio and the price-to-income ratio respectively.

In the benchmark model, the impulse responses of the endogenous variables to structural shocks are presented in Figures 3.2 to 3.5. Shaded areas are the corresponding one-standard-deviation asymptotic confidence bands.

3.3.4.1 Housing supply shock

The impact of an 1% increase in the housing stock per household is shown in Figure 3.2. As expected, a positive housing supply shock leads to permanently higher housing stock and permanently lower house prices.

The response for household disposable income might be the result of more active economic activity in construction and other relevant industries, mixed with higher rental income that makes households wealthier. The initial decrease in income might relate to a more competitive rental market that reduce the rental income of households in the short run.

The level of household debt immediately increases and stays at a permanently higher level, suggesting that as more housing stock becomes available, households would take more debt to finance their purchase.

The responses of the debt-to-income ratio and house-price-to-income ratio suggest that, while increasing housing supply could lead to better housing affordability, it will also lead to higher debt burden for Australian households. Since household indebtedness is already high in Australia, policymakers may need to take the possible impact on the financial stability into consideration when deciding whether to relax the restrictive zoning and planning policies to increase housing supply.

3.3.4.2 Household disposable income shock

The impact of an 1% household disposable income shock is shown in Figure 3.3. As expected, permanently higher income relaxes the borrowing constraints and allow households to take on more debt. The higher debt level is more than offset by the increase in income, leading to a permanently lower debt burden. Similarly, while real house prices is higher, possibly due to a higher housing demand as a result of the higher income, housing affordability has improved.

3.3.4.3 Credit condition shock

A permanent shock to household debt is interpreted as a credit condition shock, such as when banks increase the allowed loan-to-value ratio or debt-to-income ratio to grant households easier access to mortgage borrowing. Figure 3.4 gives the dynamic impact of an 1% permanent increase in household debt.

As expected, an increase in household debt leads house prices to increase instantaneously and stay permanently higher above the initial equilibrium. looser borrowing constraints make credit more accessible to households, increase housing demand and bid up real house prices. Household disposable income is also permanently higher. This might be the result of higher household rental income and more active construction activity stimulating the economy.

Both debt-to-income ratio and house-price-to-income ratio increase instantaneously and permanently, suggesting a higher debt burden and lower housing affordability. It appears that higher household indebtedness and house prices more than offset the positive impact on household disposable income.

3.3.4.4 House price shock

A house price shock is a transitory shock that drives up house prices and demand for credit. When the housing supply is relatively inelastic, a higher housing demand would drive up house prices. Higher house prices make credit more accessible to borrowing-constricted households.

As Figure 3.5 shows, household debt responds to an 1% house price shock by an instantaneous small decrease, but then immediately starts to grow and becomes elevated before it slowly returns to the steady state. This is in line with the result of Hofmann (2004), who finds innovations in property prices have highly positive and significant dynamic effect on bank lendings.

As houses are usually used as the collateral for mortgages, higher house prices would increase banks' willingness to approve loans and make credit more accessible to borrowing-constrained households. Therefore, cycles in the house market could transmit to the credit market through household borrowing, while a high level of household leverage may pose great risk to the financial stability when the cycle is in its downturn phase. The interaction between house prices and household debt also has implication on household consumption. The study of Windsor et al. (2015) on Australia households finds that relaxed borrowing constraints is the dominant source of higher house prices driving up household consumption, especially for younger households.

The housing stock experiences temporary growth as expected. According to Tobin (1969), the rate of investment should be related to the value of capital relative to its replacement costs. As Tobin's Q is usually used to model the supply of property market, it implies the construction activity of the housing market depends on house prices relative to construction costs. Since higher housing demand is not likely to cause higher construction costs (at least in the short run), an increase in house prices would escalate construction activity and raise housing supply, which may also contribute to a higher level of debt.

As the house price shock may have opposite impact to the supply and demand in the rental market, the response of household disposable income could be a result of mixed effects. The higher house-price-to-income ratio suggests a lower housing affordability for households when house prices increase due to greater demand. The

debt-to-income ratio also suggests that higher house prices lead to higher household debt burden.

Figure 3.2: Housing supply shock (Permanent)

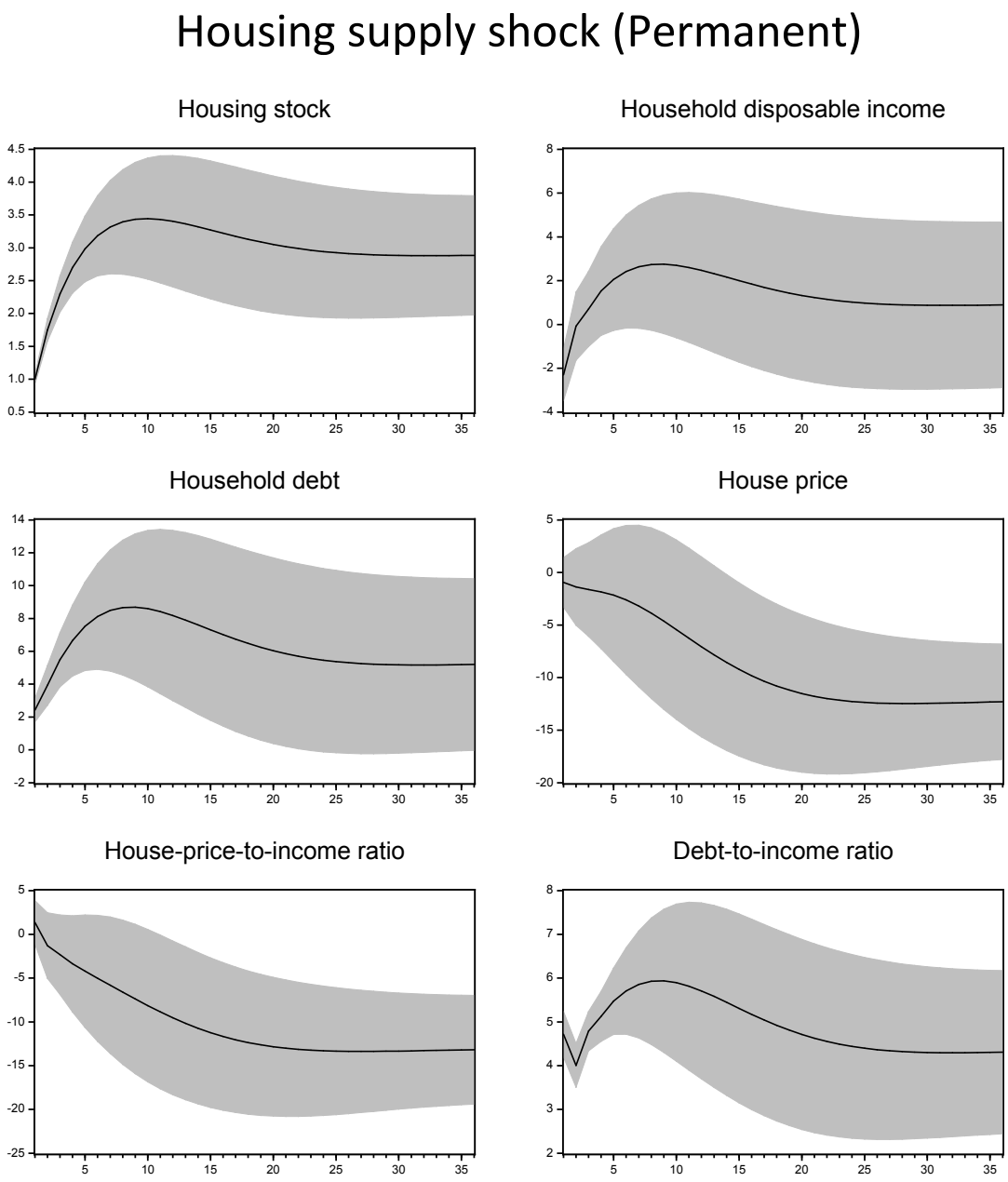


Figure 3.3: Household income shock (Permanent)

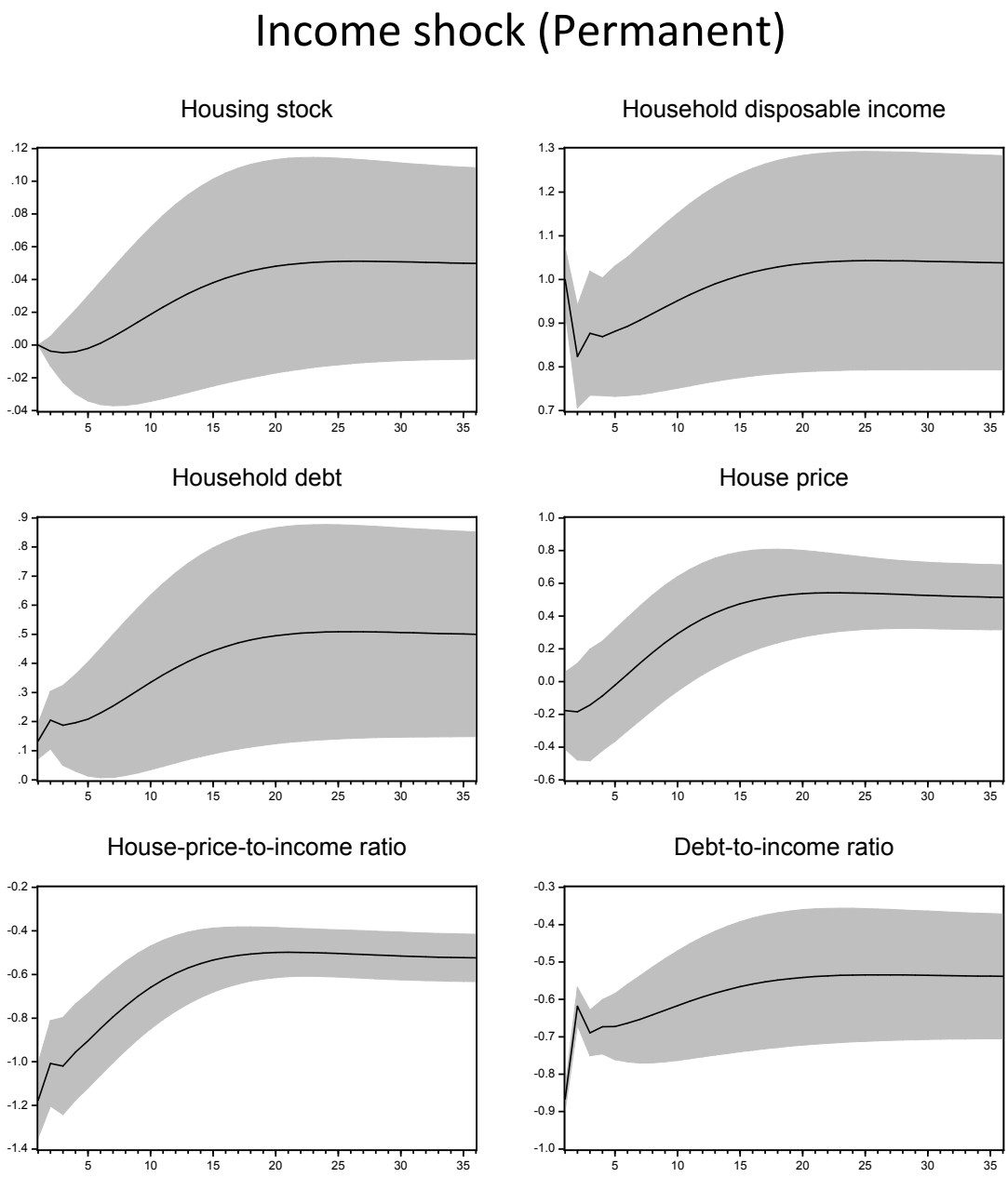


Figure 3.4: Credit condition shock (Permanent)

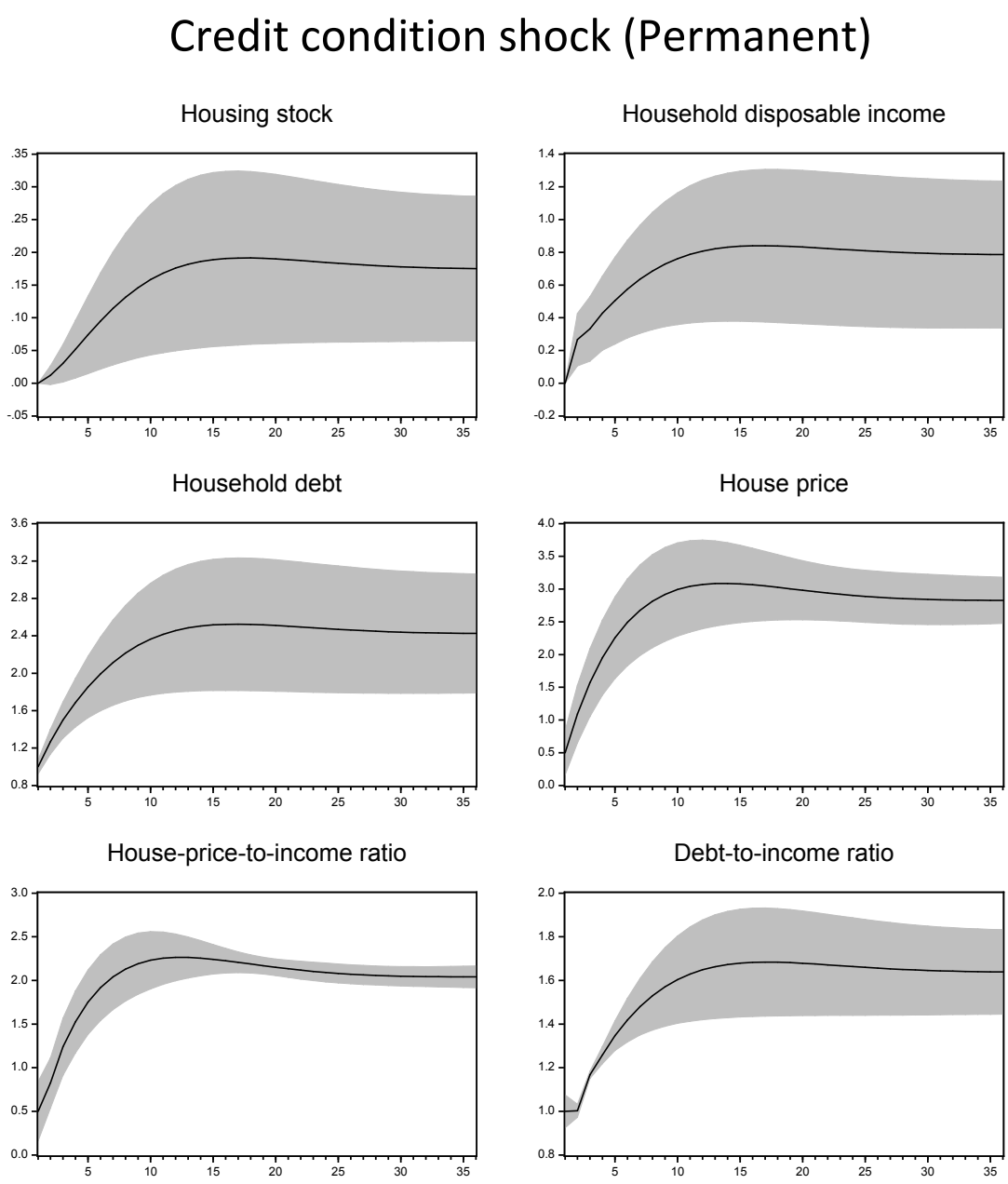
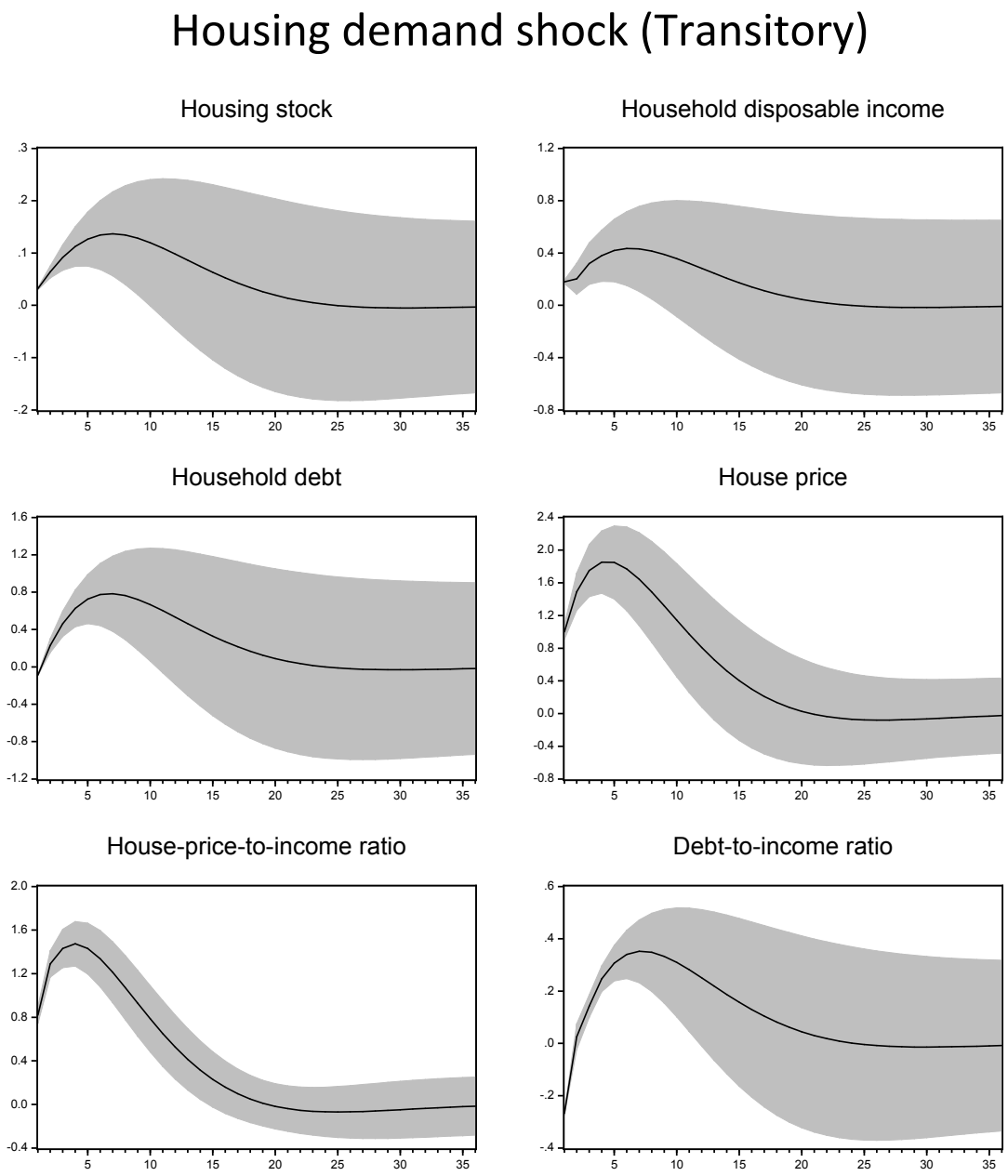


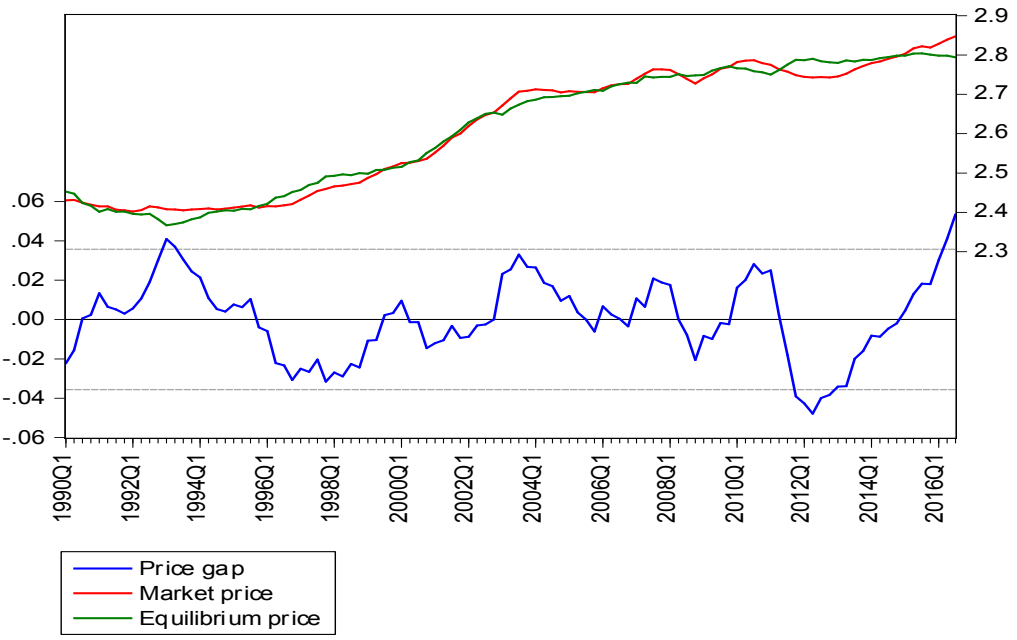
Figure 3.5: Housing demand shock (Transitory)



3.3.5 Deviation from the house price equilibrium and historical decomposition: Australia 1990-2016

The house price gap, which is the difference between the real house price and the equilibrium house price is shown in Figure 3.6. Roughly five periods can be identified in terms of persistent positive or negative shocks. The discussion is accompanied by Figure 3.7 and Figure 3.8, which illustrate the contribution of various shocks to the changes in house prices and in household debt in Australia over 1990-2016. In both figures, changes of house prices and household debt are detrended.

Figure 3.6: The house price gap: deviation from the estimated equilibrium house price



The first time period is from 1990 to 1995, where the market prices are above their long-run equilibrium. This period is characterized by consecutive falls in the nominal interest rate and the real rate. The recession and relatively tight credit conditions were weighing on house prices. The household debt level started to increase in 1993, which is also the time that market prices started to fall back to their long-run equilibrium.

The second period is from 1995 to 2002. House prices are estimated to be mainly below their equilibrium. This period is characterized by continuously decreasing cost of financing, sluggish housing supply, and rapid growing household debt and house prices. During this period, house price growth significantly outpaced the growth in household income. Bloxham et al. (2010) discussed several factors influencing housing market developments in this period. These include (1) the low and stable inflation environment which reduced the cost of financing; (2) financial innovations that eased lending standards; and (3) a capital gain tax reduction in September 1999 that encouraged investment in housing.

As shown in Figures 3.7 and 3.8, before 2000, credit condition shocks were the main drivers of house price growth as well as household debt growth. It suggests that the loosened credit conditions granted households easier access to borrowings. These credit flows into the housing market drove up house prices. Such a result is in line with Ellis (2005), who sets up a model to demonstrate that a reduction in inflation and thus nominal interest rate leads to a higher level of debt, in the presence of borrowing constraints. After 2000, housing demand shocks became the

Figure 3.7: Historical decomposition of house price growth - benchmark model

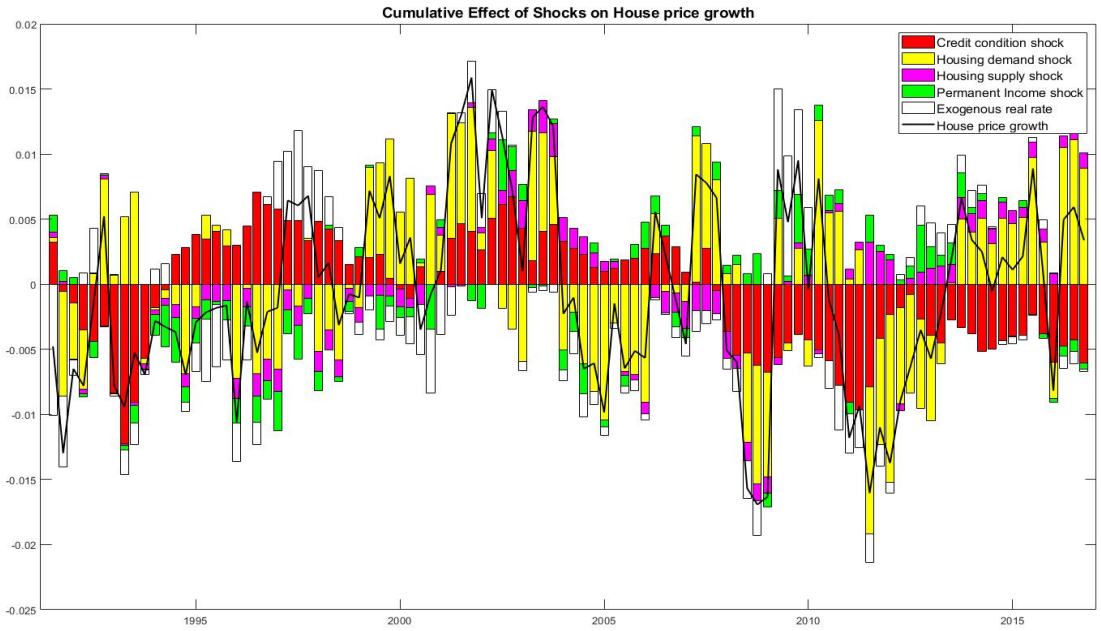
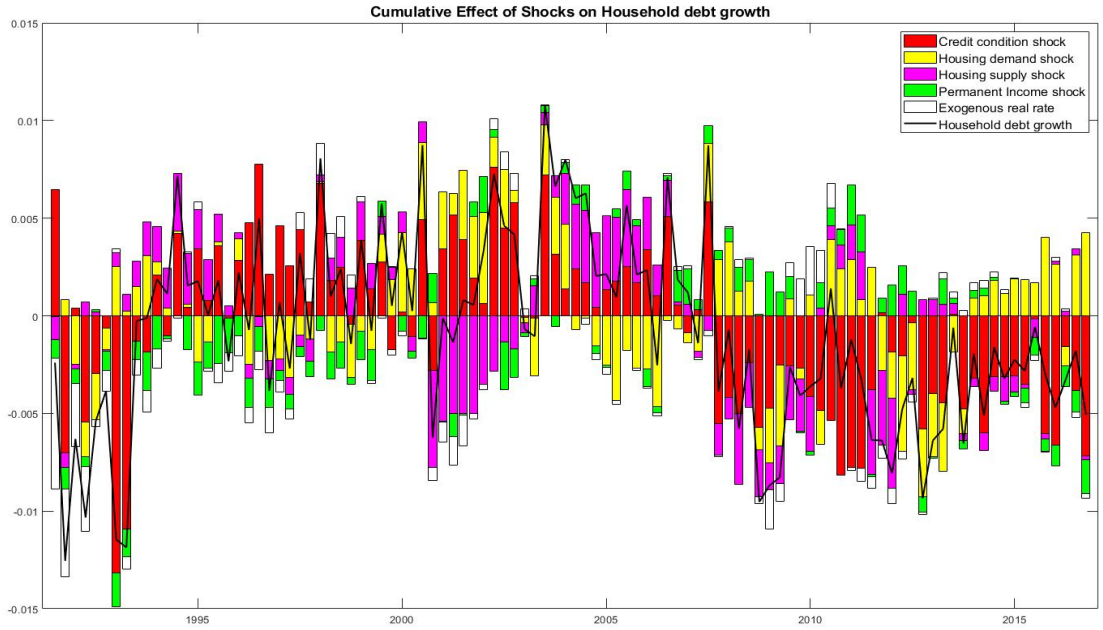


Figure 3.8: Historical decomposition of household debt growth - benchmark model



main drivers of house price growth. The significant reduction in the capital gain tax rate by the Federal Government in September 1999 might be one contributing factor to the booming housing demand, as lower capital gain tax would motivate more investment in the housing market.

Housing demand shocks started to contribute to the growth of household debt in addition to the credit condition shocks after 2000, suggesting the increased housing demand may come from investors pursuing capital gain rather than owner occupiers.

The third period is from 2002 to 2008. House prices were mainly above their equilibrium until the 2007-2008 global financial crisis. This period is characterized by a large rise in the terms of trade, and a growing household income and debt. In Figure 3.7, we can see that in the first half of this period, the overheated housing market was driven by higher market demand and loosened credit conditions. From 2002 to 2004, the Reserve Bank of Australia (RBA) conducted the "open mouth operations" due to their concerns on the rapid growth in house prices and credit. It involved senior officials making public statement and trying to draw attention to

the risks in the housing market and household indebtedness (Bloxham et al., 2010). Monetary policy was also tightened several times in 2002 and late 2003. This is in line with the gradually closing price gap after 2003 in Figure 3.6. However, household debt was still accumulating rapidly in this period. After 2004, housing supply shocks became another main contributors to the growth in household debt, indicating households took on more debt to finance new property purchases.

My result over this period is in line with Fry et al. (2010), who find strong evidence of overvaluation in Australian real house prices over 2002-2008 in their estimated 7-variable macroeconomic SVAR model with a housing sector. Using different approaches to identify the market fundamental house prices, Fry et al. (2010) and my study both distinguish two periods: before and after 2006. They find the overvaluation is mainly driven by housing demand shocks in the first period and by good market shocks in the second period. My results from cointegration analysis and historical decomposition over this period mainly agree with Fry et al. (2010), as illustrated in Figure 3.6 and Figure 3.7. One notable difference is I also find strong housing demand shocks contributed to the housing market for a few quarters just before the 2007-2008 financial crisis.

The next period is from 2008 to 2011. This is the post-crisis period that the market prices fluctuated around the equilibrium prices. The historical decomposition in Figure 3.7 demonstrates that fluctuations were mainly driven by housing demand in this period. The tightened credit conditions put downward pressure on the house prices as well as on household debt in this period.

The last time period is from 2012 to 2016, which is the rest of the sample. The majority of this period experienced a boom in house prices. The market prices stayed below the equilibrium until 2015Q1. This period is characterized by consecutively decreasing cash rate as well as the real rate. House price growth was mainly driven by house demand shocks. The negative price gap closed on 2015, and has been positive since then.

Since 2014, a series of macroprudential policy measures were implemented. The specific policies are described in Orsmond and Price (2016). The macroprudential tightening actions, represented by the consecutive negative credit condition shocks after 2014 in Figure 3.7 and 3.8, have contributed to restraining the growth in house prices and in household debt.

3.4 Sensitivity analysis

3.4.1 Incorporating monetary policy

As Section 3.3.4 shows, the short-run dynamic interactions between Australian house prices and household debt are mutually reinforcing. This suggests that the boom-bust cycles in the housing market will augment fluctuations in the credit cycle, thereby possibly challenging the resilience of households to economic shocks. This raises the question as to the role of monetary policy. In this section, I aim to investigate the role of monetary policy in the interaction between house prices and household debt.

The benchmark model follows the literature and takes the real interest rate as an exogenous I(1) variable, so that it can be treated as one of the long-run drivers of the equilibrium house prices. As I discussed in Section 3.3.2, the coefficient of the real interest rate is not statistically different from zero in the estimated cointegration equation. There is no change to the estimation of other parameters if the real rate is omitted from the cointegration equation. Therefore, the real interest rate can be safely excluded from the long-run equation.

Furthermore, the assumption of the interest rate being I(1) implies that its shocks must be permanent. It must have a non-zero long-run effect on at least one another I(1) variable. If the theory of money neutrality holds, the interest rate should be treated as an I(0) variable so that monetary policy shocks are transitory. I also include the underlying inflation (π) to the system, which also is an I(0) variable.

In a nutshell, to model monetary policy into the benchmark model, I replace the real interest rate (r) with the policy rate (i), make it endogenous in the system and take it as I(0) variable in order to have transitory monetary shocks. The unit root tests in Table A2 also support the policy rate to be I(0).

The extended model has six endogenous variables $[h, hdi, debt, hp, \pi, i]$, with the first four being I(1) and the last two being I(0). The reformulated SVAR model has the following variables in this order of $[\Delta h, \Delta hdi, \Delta debt, ec, \pi, i]$. In addition to the restrictions imposed in the benchmark model, at least 9 more restrictions are needed to identify the model. If the shocks of I(0) variables are to have transitory effects, they must have no permanent impact on any other variables. Hence I impose another

6 long-run restrictions so that the shocks of the I(0) variables have no permanent impact on the I(1) variables. In the short run, I assume the core inflation and the policy rate have sticky responses to housing demand shocks, and a policy rate shock has no instantaneous impact on household income, as it may take time for the policy rate changes to affect household income through its impact on the labour market and other economic activities. Therefore, the extended model is exactly identified with the following restrictions:

$$\text{Long-run restrictions:} \quad \begin{array}{c} \\ \Delta h \\ \Delta hdi \\ \Delta debt \\ ec \\ \pi \\ i \end{array} \begin{array}{c} \begin{array}{cccccc} \epsilon_h & \epsilon_{hdi} & \epsilon_{debt} & \epsilon_{hp} & \epsilon_\pi & \epsilon_i \end{array} \\ \begin{bmatrix} * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & 0 & 0 & 0 \\ * & * & * & * & * & * \\ * & * & * & * & * & * \\ * & * & * & * & * & * \end{bmatrix} \end{array}$$

$$\text{Short-run restrictions:} \quad \begin{array}{c} \\ \Delta h \\ \Delta hdi \\ \Delta debt \\ ec \\ \pi \\ i \end{array} \begin{array}{c} \begin{array}{cccccc} \epsilon_h & \epsilon_{hdi} & \epsilon_{debt} & \epsilon_{hp} & \epsilon_\pi & \epsilon_i \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & * & * & * \\ * & 1 & 0 & * & * & 0 \\ * & * & 1 & * & * & * \\ * & * & * & 1 & * & * \\ * & * & * & 0 & 1 & * \\ * & * & * & 0 & * & 1 \end{bmatrix} \end{array}$$

3.4.2 Monetary policy shocks

Figure 3.9 demonstrates the impulse responses to a contractionary monetary policy shock, which is defined as a 25 basis points increase in the policy rate. The impulse responses of a cost-push shock, which is defined as a 25 basis points increase in the core inflation, is shown in Appendix Figure B1. The unit of the impulse responses for policy rate and core inflation is percentage point, and for all the other variables it is percentage change. The impulse responses of $h, hdi, debt, hp$ to the shocks are similar to the estimation results in Section 3.3.4, as shown in Appendix Figures B2-B5.

The impulse response of the core inflation indicates the existence of a price puzzle. The price puzzle is very difficult to avoid when using SVARs to model Australian economy, as discussed by Bishop et al. (2017).[18]

As expected, an increase in the policy rate leads to lower house prices, as higher cost of financing would reduce housing demand. A lower house-price-to-income ratio is indicative of a contractionary monetary shock which would then increase housing affordability for households.

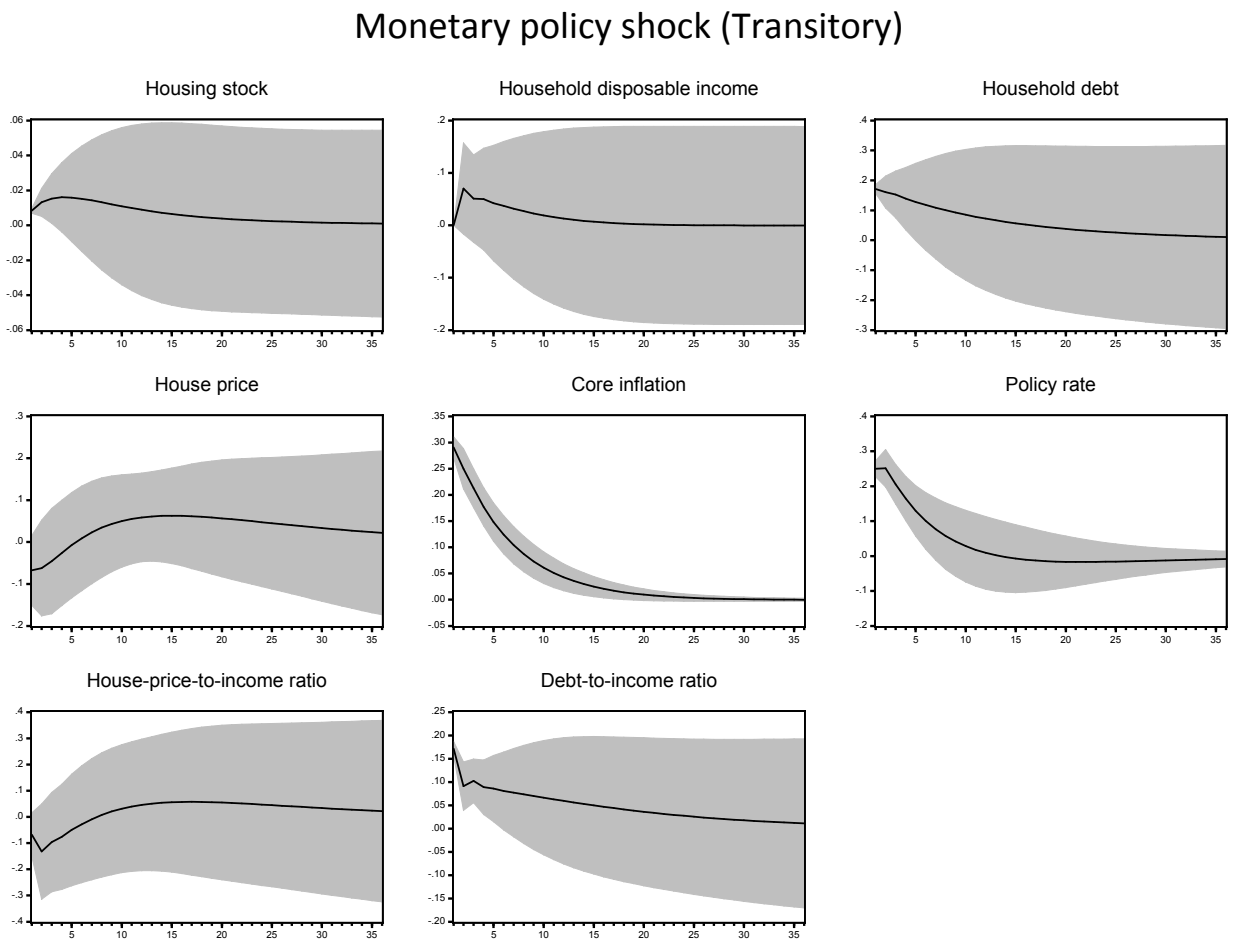
The level of household debt immediately increases following a contractionary monetary policy shock. This result is different from Berkelmans (2005), who studies the interaction between credit and monetary policy in Australia over 1983Q4-2003Q4, and finds that the level of total credit would drop after a positive cash rate shock. My analysis finds that the impact effect on the growth of debt is so large that it more than offsets the negative impact on household debt in the following periods, resulting in household debt level staying above the steady state for a prolonged period before it returns to the long-run equilibrium. In this study, household debt includes both mortgage debt and consumer debt and thus it reflects the overall leverage of household. Similarly, Romer and Romer (1990) and Bernanke and Blinder (1992) find the level of bank loans immediately increases after the contractionary monetary policy shock. It is likely that with a higher interest rate, already highly leveraged Australian households may find it harder to pay down their existing loans and may need further borrowing to smooth the impact of shock.

The dynamic response of the debt-to-income ratio suggests that a contractionary monetary policy shock results in deeper household indebtedness. The initial rise in the debt burden can be considered risky to less resilient household. It would be difficult for households whose borrowing constraints are binding to obtain more loans and smooth the negative effects of the shock. They may consequently have to sharply cut spending so as to avoid insolvency. This is the case that is of concern for the Reserve Bank of Australia, as Lowe (2017) points out.

There has been much debate on whether monetary policy should be used to address asset prices inflation and financial stability. Many see a greater role for monetary

[18]Examples of finding the existence of a price puzzle in Australian SVARs include Phan (2014) and Beechey and Österholm (2008). The SVAR models developed by Dungey and Pagan (2000) and Dungey and Pagan (2009) do not exhibit a price puzzle, but they omit the interest rate from the inflation equation.

Figure 3.9: Monetary policy shock (Transitory) - extended model



policy, at least occasionally, to lean against the financial cycle upswings (e.g. BIS, 2014). Many take an opposite view and believe monetary policy should play a minimal role in asset markets (e.g. Svensson, 2017). It is macroprudential policies that should be incorporated into the policy framework and target financial imbalance and systematic risk. Bordo and Jeanne (2002) set up a stylized model and suggest the linkages between monetary policy, assets price (property price or stock price) and financial stability are complex and non-linear. Therefore, the feasibility of using monetary policy to safeguard financial stability is in doubt. Svensson (2017) finds that a higher policy rate may slow down the growth of nominal debt, but it also slows down the growth of the price level. As both the numerator and the denominator of real debt are affected in the same direction, the effect could be small or even of the opposite sign. Therefore, he argues that the costs of leaning against the wind monetary policy may exceed benefits by a substantial margin.

My analysis finds that a higher policy rate leads to higher real household debt level, along with lower house prices, thus further worsening the household leverage in the short run. This result suggests that a potential danger of using contractionary monetary policy to "lean against the wind", is that it may negatively impact on already highly leveraged households and pose risk to the financial system.

In contrast with the impact of the credit condition shocks, it appears that tightening both credit condition and monetary policy could both suppress excessive growth in house price and improve housing affordability. However, tighter credit conditions could moderate household indebtedness, whereas a higher policy rate could lead to the opposite result. In summary, if we consider macroprudential policies acting like exogenous credit condition tightening shocks, the empirical evidence in this study suggests that macroprudential policy which directly limits the ability for households to access credit might be preferable to a monetary policy of "leaning against the wind".

3.4.3 Historical decomposition with monetary policy

Figures 3.10 and 3.11 illustrate the contribution of monetary policy shocks and cost-push shocks to the house price changes and household debt changes for Australia over 1990-2016, in addition to the shocks discussed in Section 3.3.5.

Monetary policy shocks have contributed to the growth in house prices from 1997 to 2000. The low policy rate is a big contributor to the housing market development after late 2012. At the end of 2011, the RBA announced a decrease in the policy rate and ended the consecutive increasing policy rate in place since 2009Q3. After that, both policy rate and the real interest rate started to drop.

The contribution of other shocks to the growth in house prices and in household debt is generally consistent with the historical decomposition results of the benchmark model in Section 3.3.5.

There is one notable difference though. After taking the monetary policy shocks into account, the contribution of housing demand shocks in restraining house price growth after 2012 are smaller compared to the benchmark model. It indicates that a large part of the high housing demand in this period is a result of the low cost of financing. This is in line with Saunders and Tulip (2019), who find that the low interest rates explain much of the rapid growth in house prices over the past few years.

Figure 3.10: Historical decomposition of house price growth - extended model

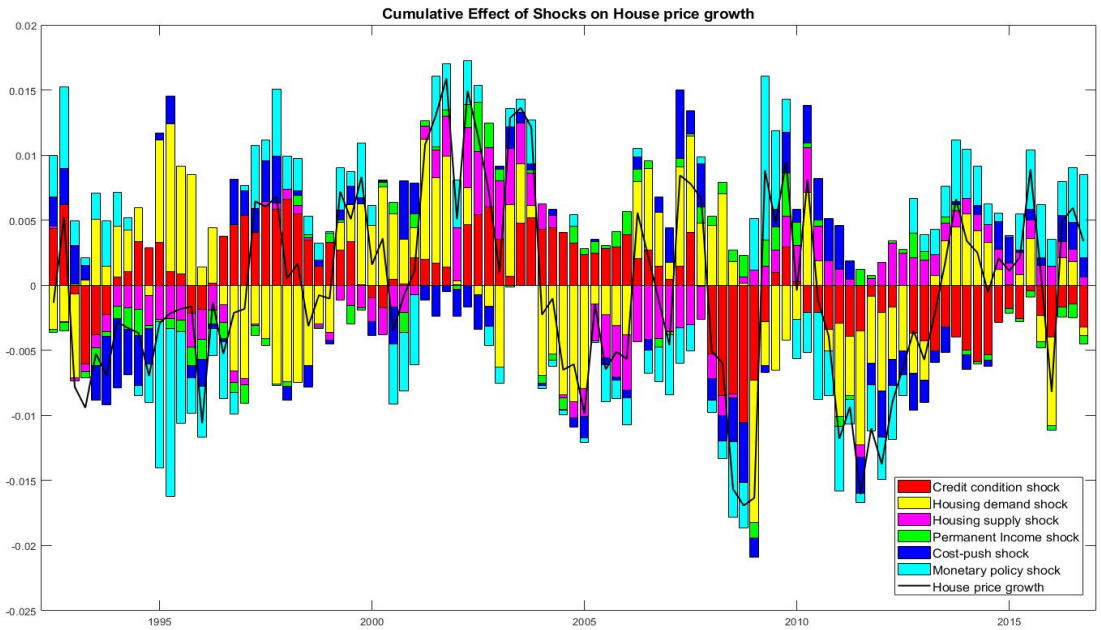
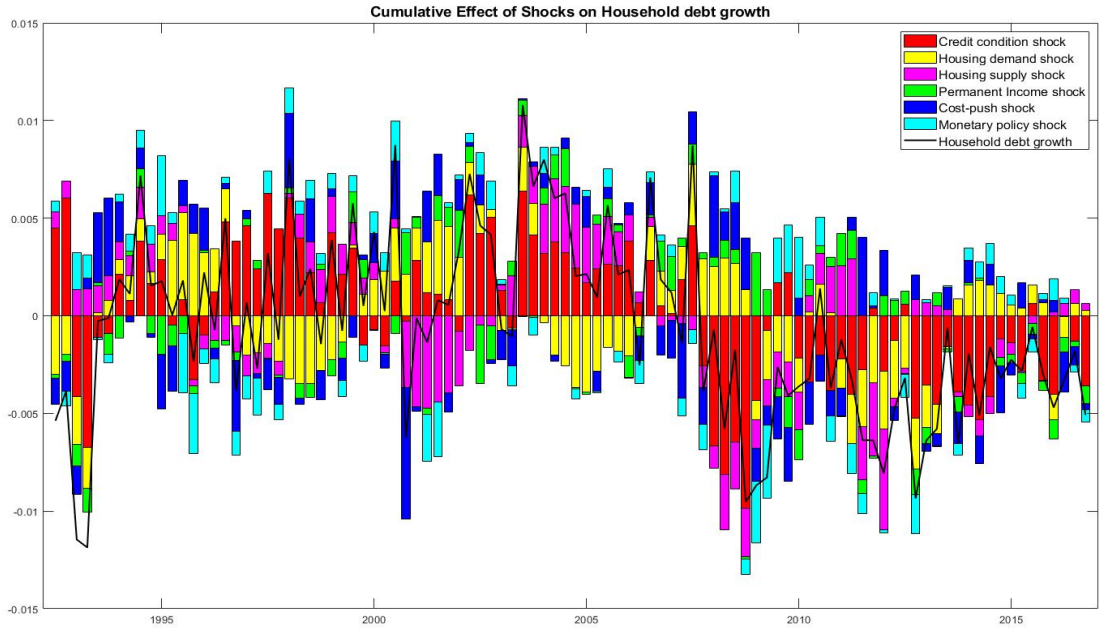


Figure 3.11: Historical decomposition of household debt growth - extended model



3.5 Chapter conclusion

This chapter analyzes the long-run relationship and short-run dynamics among house prices and their determinants in Australia, particularly focusing on household debt, using a Structural Vector Error Correction Model framework. Using a quarterly dataset from 1990 to 2016, the cointegration analysis suggests that household debt and housing supply are the two significant drivers of the long-run equilibrium house prices. Household disposable income and the real interest rate affect equilibrium house prices through the credit channel.

The short-run dynamic impact of various structural shocks is also investigated. This chapter makes a difference in the identification strategy by using the technique of Pagan and Pesaran (2008), so as to impose fewer restrictions than other similar studies. The interaction between house prices and household debt is driven mainly by information in the data to the greatest extent possible. The analysis suggests that house prices and household debt are mutually reinforcing.

Such an interaction is likely to exacerbate the boom and bust cycle of the financial system, thus posing greater risk to financial stability and threatening the resilience of households to future shocks. Credit condition tightening shocks are found to be capable of improving housing affordability as well as reducing household leverage.

An examination of the deviation of house prices from their long-run equilibrium and the historical decomposition identified the various drivers of the growth in house prices in the sample period. It appears that the Australian housing market boom after 1995 was mainly fueled by credit condition shocks, while the recent growth in house prices after 2012 was mainly driven by the increased housing demand and the low cost of financing.

The investigation on the role of monetary policy shows that a contractionary monetary policy shock may unfavourably increase household indebtedness. Meanwhile, a credit condition shock that tightens the borrowing constraint could lead to both lower house prices and lower household debt burden. Thus, if macroprudential policies act like exogenous credit condition tightening shocks, this chapter suggests that the use of macroprudential policy might be preferable to a monetary policy of leaning against the wind. However, as there are many possible macroprudential policy instruments, the issue of policy selection is outside the scope of this study. Further research is required to examine the welfare implications of these different policies.

Chapter 4

Towards better banking crisis prediction: Could an automatic variable selection process improve the performance?

4.1 Introduction

As a result of the devastating economic and social consequences of the 2007-08 global financial crisis, interest has grown in the prediction of systemic banking crises. Better Early Warning Systems (EWS) are called for to guide the activation of regulatory policies and guard against potential systemic events. These EWS may draw on, for example, the remarkable similarities found in the data preceding financial crises (Reinhart and Rogoff, 2009).

The multivariate logit framework has emerged as one of the most popular models in the context of global early warning systems. Intuitively, multivariate early warning models for systemic banking crises should include variables that can

capture the build-up of systemic risk and imbalances in the financial system. A wide range of potential variables exist, and different studies select different sets of indicators, often based on economic intuition. However, if the early warning models' primary focus is prediction, it is unclear which set of predictors should be included in the model so as to optimize the *out-of-sample* forecasting performance. Reflecting the wide range of possible predictors, it is also difficult to determine which of the numerous possible interaction terms should be included by standard model selection approaches. To the best of my knowledge, there has not yet been any guideline or principle to systematically formalize the variable selection process, specifically for the multivariate logit model in the literature about global early warning system for systemic banking crises.

Studies such as those by Alessi and Detken (2018) and Tanaka et al. (2016) propose the use of a novel machine learning technique - the "Random Forest" - to construct a completely automatic early warning system for systemic banking crisis prediction. However, it may not be superior to the conventional multivariate logit model for two major reasons. First, while the machine learning model has excellent *in-sample* fit, its *out-of-sample* performance is still unclear so far. Second, it may be challenging to interpret Random Forest models, which is important for policy communication. Indeed, interpretability and transparency are essential if the early warning system is to inform policy.

In summary, on the one hand, it is very important, but yet difficult in practice, to select the right set of predictors from a large pool of available variables. One the other hand, it is essential to keep the early warning system transparent and interpretable if it is to have policy impact.

Motivated by the need to jointly address these two issues, this study proposes applying the LASSO method with cross-validation to automate the variable selection process in order to improve the performance of the conventional multivariate logit model in predicting systemic banking crises. Specifically, LASSO, originally proposed by Tibshirani (1996), provides a model selection mechanism that eliminates standardized variables with small coefficients, thereby maintaining the important predictors that contribute the most to the model's forecasting performance.

The results of the recursive out-of-sample prediction evaluation demonstrate that the predictive performance of the multivariate logit model can be significantly

improved via automatic variable selection by the LASSO method with cross-validation approach, which I refer to as the LASSO logit model. The LASSO logit model identifies the most important predictors for the systemic banking crises to be domestic credit growth, the domestic and global credit to GDP gaps, real house price growth, and the real effective exchange rate. By focusing on enhancing only the variable selection process, the proposed model can utilize information from the lags and interaction terms that are not typically included in the conventional multivariate logit model to improve the forecasting performance, while maintaining the capability for effective policy communication.

This chapter contributes to the strand of early-warning literature of systemic banking crises by highlighting the importance of a systematic variable selection process and proposing the use of LASSO with cross-validation as a feasible, transparent and interpretable method to automate this process, and hence improve the out-of-sample forecasting performance.

There are two reasons to justify why we need a systematic variable selection process. First, the choice of early warning indicators and risk indicators, together with the transformations used, such as the growth rate, deviation from the long-run trend, choices of global variables, the number of lags and interaction terms, can all have a significant impact on the performance of the model (Davis and Karim, 2008; Duca and Peltonen, 2013). However, as systemic banking crises are rare events in history, only a small number of covariates can realistically be included in the model. If one attempts to incorporate many early warning indicators and their different variations to improve the model performance, it may lead potentially to over-fitting a model that fits the limited *in-sample* crises too well but loses its predictive power for out-of-sample crises. For example, a couple of lags and interaction terms could easily lead to perfect *in-sample* prediction of the multivariate logit model, but perform poorly in a different sample.

Second, the optimal set of explanatory variables may depend on the objective of the early warning model, which is not always clear. If the model aims to serve an explanatory purpose, then the specification should be one that gives the best *in-sample* interpretation. If the model aims to serve a forecasting purpose, then the selection of predictors should optimize the *out-of-sample* performance. Even with the same modelling technique, a set of variables that provides good *in-sample* properties may not obtain the best *out-of-sample* prediction performance. This issue is closely related to over-fitting a particular sample as discussed previously.

Furthermore, even if the objective of the early warning model is to forecast the occurrence of the systemic events, the model itself must still maintain good interpretability. Communication is of key importance to the policymakers. A good early warning system should not only have good predictive ability, but also be such that policymakers and the public can interpret it. Models which are viewed by policymakers as being a "black-box" may only have limited impact on policy despite their impressive forecasting performance. This is particularly relevant as the recently proposed machine learning methods: the Random Forest methods, which overcame the variable selection issue, but might sacrifice too much in terms of model interpretability and transparency.

The LASSO with cross-validation approach is proposed for two reasons. First, using LASSO with cross-validation to automate the variable selection process can help to identify which variables are most important to be included in the model. It is specifically designed to address the over-fitting issue and enhance the prediction accuracy. Second, relative to the strand of more complicated machine learning techniques such as the "Random Forest", LASSO has a transparent mechanism. The users have full control over the extent of penalization on extreme parameter values with a single penalty parameter. Indeed, every detail of LASSO is interpretable and controllable. Problematic aspects of some applications of cross-validation, mentioned by Hastie et al. (2009) and Bussiere and Fratzscher (2006), such as the same data being used for model selection and evaluation, are avoided. In this study, cross-validation is only used to fine-tune the hyperparameter of the LASSO loss function, and therefore model selection. Different data is ultimately used for model estimation and evaluation.

The remainder of the chapter is organized as the follows. Section 4.2 reviews the relevant literature. Section 4.3 describes the data. Section 4.4 introduces the empirical framework and the evaluation criteria. Section 4.5 presents and discusses the out-of-sample prediction results. Section 4.6 conducts the sensitivity analysis. Section 4.7 concludes the analysis presented here.

4.2 Literature review

Numerous studies on early warning models of systemic events prediction have been published since the 1990s. There are mainly two mainstream modelling approaches,

namely the signal extraction approach, originated by Kaminsky and Reinhart (1999), and the multivariate probability approach, such as the multivariate logit econometric model, developed by Demirgüç-Kunt and Detragiache (1998) and Demirgüç-Kunt and Detragiache (2000).

The idea of the signal extraction approach is to warn of a potential systemic event if some leading indicators exceed their previously defined threshold level. Building on the work of Kaminsky and Reinhart (1999), authors such as Borio and Lowe (2002), Borio and Drehmann (2009) and Alessi and Detken (2011) further develop models based on the signal extraction approach.

The multivariate probability approach assumes the probability of crisis occurrence to be a function of explanatory variables. A multivariate logit model can be used to fit the data and transform the estimated crisis probability into a binary indicator of systemic banking crises. It could be used to study the impact of various risk drivers on historical systemic events as well as provide predictions of future crises.

Demirgüç-Kunt and Detragiache (2005) emphasize the importance of interpretability of the early warning system and argue the multivariate logit model is more useful for policymakers to identify the factors associated with the occurrence of crisis. While the multivariate logit model can be used to identify the common drivers of systemic banking crises, it cannot identify the heterogeneous drivers for each country. Davis and Karim (2008) find the signal extraction approach is better for developing a country-specific early warning system, while multivariate logit models are the most appropriate approach for a global early warning system. Recent papers such as Duca and Peltonen (2013) and Behn et al. (2013), further develop and apply the multivariate logit framework to identify important early warning indicators and assess predictive performance. They find the global variables and their interactions with domestic variables are important predictors of systemic banking crises.

Demirgüç-Kunt and Detragiache (2000) highlight importance of considering the relative preference of policymakers between missed crises and false alarms in evaluating the early warning system. Alessi and Detken (2011) and Sarlin (2013) further improve modelling policymakers' preferences to capture such a trade-off by defining a loss function for the policymakers.

In the early warning literature of multivariate logit model, it is common to make the dependent crisis variable binary and omit the in-crisis observations once a crisis occurs. This treatment aims to avoid the "post-crisis bias" discussed by Bussiere and

Fratzscher (2006). Once a crisis occurs, it will impact on the dynamic of explanatory variables and create endogeneity issue from both the crisis itself and the policies implemented to mitigate the crisis. The behaviour of economic variables during the crisis would be significantly different from the tranquil times. Since systemic banking crises are rare events, many studies drop these "in-crisis" observations that are not informative about crisis prediction to eliminate the possibility of endogeneity (Duca and Peltonen, 2013; Behn et al., 2013; Davis and Karim, 2008). Dawood et al. (2017) take a step further. They use the multinomial logit model to predict the occurrence of a crisis as well as its duration in the literature about sovereign crisis. Furthermore, they find the predictive performance of multinomial logit model is worse than the binary logit model.

Recently, novel machine learning methods have been proposed as a strong alternative statistical approach to construct early warning signals for systemic events. Manasse and Roubini (2009) pioneer the use of Classification and Regression Tree to predict sovereign debt crisis. Alessi and Detken (2018) and Tanaka et al. (2016) propose the use of the Random Forest technique to construct a completely automatic early warning system for systemic banking crisis prediction.

Introduced by Breiman (2001), the Random Forest method is a much more sophisticated machine learning method based on classification trees. The classification tree is an algorithm of binary recursive partitioning, which is an iterative process of splitting the data into binary partitions and then further splitting it up at each branch. The Random Forest consists of many individual decision trees so as to get a more accurate prediction. It is a popular modern classification tree ensemble technique that achieves great *in-sample* prediction performance and overcomes the issue of variable pre-selection. Tanaka et al. (2016) propose the use of it to predict failures at the level of individual banks while Alessi and Detken (2018) focus on predicting the systemic banking crises at country level. Both studies argue that the Random Forest method achieves better predictive performance than the conventional approaches.

However, there has been no general consensus on whether it is actually superior to the conventional multivariate logit model for two major reasons.

First, machine learning methods often attain excellent *in-sample* fit, but the *out-of-sample* predictive performance in the context of crisis prediction remains unclear. Neither Alessi and Detken (2018) nor Tanaka et al. (2016) conduct a

systematic *out-of-sample* forecast exercise to compare the performance of the Random Forest model to the conventional models. Only a few papers conduct horse races of different early warning models to evaluate whether machine learning models could achieve better *out-of-sample* forecasting performance in crisis prediction, and they find mixed evidence.

Holopainen and Sarlin (2017) expand the idea of applying machine learning methods and conduct a horse race of the conventional statistical models with a few different machine learning methods other than the Random Forest, such as artificial neural networks, support vector machines, k-nearest-neighbors and decision trees. They find the machine learning models generally outperform the conventional multivariate logit model in their recursive out-of-sample forecasting exercise. Expanding on the work done by Holopainen and Sarlin (2017), Beutel et al. (2018) refine the horse race in several dimensions, such as the construction of datasets, robustness checks, and bootstrap and hyperparameter selection schemes. They find machine learning methods perform worse compared to simple logit models in recursive out-of-sample evaluations.

Second, while interpretability and transparency are essential for an early warning system to inform policy, it may be challenging to interpret machine learning models such as the Random Forest approach to the extent necessary for effective policy communication. As acknowledged by Alessi et al. (2015), the Random Forest model is inherently a black box model. It would be hard to defend its predictions, particularly if one wants to use it to support the activation of possibly unpopular policies. There have been some studies in the discipline of computer science attempting to interpret the results of Random Forests. Applications on rare crisis prediction, especially when the time dimension must be considered, however, are still at a developmental stage.

When it comes to fine-tuning the hyperparameters, there could be a potential transparency issue associated with cross-validation that may lead to problematic model evaluation. As Hastie et al. (2009) point out, the cross-validation procedure must be correctly applied to the entire sequence of modelling steps. If a single cross-validation procedure is used for model tuning and model estimation and evaluation, it would lead to misreporting of the performance measures which would seriously overstate the performance of machine learning models. Using examples from applied work in political science, Neunhoeffer and Sternberg (2019) stress that such problematic cross-validation procedure could be hard to identify only by

reading the paper. Neither Tanaka et al. (2016) nor Alessi and Detken (2018) mention the details of how they specifically conduct cross-validation with their Random Forest models.

In sum, due to the mixed evidence with respect to the out-of-sample predictive ability, their low interpretability and the potential transparency issues, the prospect of practically using machine learning techniques to serve the early warning purpose in a policy setting is arguably limited at present.

This study proposes the use of LASSO with cross-validation to only automate the variable selection process of the conventional multivariate logit model to achieve better forecasting performance in systemic banking crisis prediction. To avoid the criticism raised by Hastie et al. (2009) and Neunhoeffer and Sternberg (2019), I use cross-validation only for hyperparameter selection in LASSO and perform the standard recursive out-of-sample forecasting exercise to evaluate models. This approach would automatically select the most important predictors to enhance the predictive performance. As one of the simplest, yet powerful, variable selection methods, it also retains transparency and interpretability for effective policy communications. A limitation is that the LASSO approach may not identify some of the non-linearities found to be important by more sophisticated machine learning methods.

The LASSO with cross-validation method has been applied in the context of early warning system of different disciplines. It is worth noting that an ECB working paper, Lang et al. (2018), apply this method to study bank stress from 1999Q1 to 2014Q4. This study differs from Lang et al. (2018) in three aspects. First, Lang et al. (2018) focus on the stress events of individual banks such as state aid cases, distressed mergers, defaults and bankruptcies, while this study focuses on predicting the systemic banking crises at a country level.[19] Second, while macro-financial indicators are included, their paper aims to use LASSO with cross-validation to select relevant predictors from a large set of bank-specific risk drivers related to financial statements. In this study, the LASSO with cross-validation approach is also used to capture the non-linear interactive relationship between variables and information hidden in the lags. Last, their analysis attempts to predict the "pre-distress events" while my research aims to predict the occurrence of systemic banking crises.

[19]Lang et al. (2018) define the "state aid cases" as direct capital injections, asset protection measures and loans/guarantees other than guaranteed bank bonds.

4.3 Data

4.3.1 Systemic banking crisis database

The systemic banking crisis database in this study covers 23 OECD countries during the period 1970Q1 to 2018Q3. Table 4.1 summarizes the identified systemic banking crises and their starting and ending date for each country.

The systemic banking crisis dataset used in this study is mainly based on Laeven and Valencia (2018), which updates a widely used global systemic banking crisis database developed by Laeven and Valencia (2013). I also supplement the database with the work of Detken et al. (2014). Their database updates and amends the database of Babecký et al. (2014) for European countries under the framework of the European Systemic Risk Board on the basis of country experts' judgement.[20] Focusing on systemic banking crises associated with domestic credit and financial cycles in European countries, it enriches the systemic banking dataset by including past crises in European countries that are not recorded by Laeven and Valencia (2018).[21] This is in line with the purpose of early warning models to identify the extreme vulnerable states of the financial system and to inform policy actions.

4.3.2 The explanatory variables

In order to predict the systemic banking crises, we need to select a range of indicators that can capture the sources contributing to the build-up of the systemic risk and macro-financial vulnerabilities. The selection of key variables in this study broadly follows the discussion of Behn et al. (2013) and Duca and Peltonen (2013).

In the benchmark model, I include the same variables as the best performed model (model 5) of Behn et al. (2013). Domestic and global credit growth and credit gaps are included to capture the credit market development. Credit growth is the year-to-year rate, while the credit gap is calculated as the deviation of the credit-to-GDP ratio from its long-run backward-looking trend.

[20] This database also includes would-be crises, which are the cases where systemic banking crises were likely to occur had it not been for policy action or external events that dampened the financial cycle. These "would-be" crises are not added to my dataset.

[21] This includes the following crises: Italy 1994-1995, Germany 2000-2003, the UK 1973-1975 and 1991-1995, Spain 1982-1985, France 1994-1995, and Denmark 1987-1993.

Table 4.1: Systemic banking crisis: summary

Country	Crisis	Start	End	Start	End	Start	End	Tranquil period	Crisis periods	Crisis share(%)
Australia	0							195	0	0.00%
Austria	1	2008q4	2012q4					178	17	8.72%
Belgium	1	2008q4	2012q4					178	17	8.72%
Canada	0							195	0	0.00%
Denmark	2	1987q1	1993q4	2008q3	2012q4			149	46	23.59%
Finland	1	1991q3	1995q4					177	18	9.23%
France	2	1994q1	1995q4	2008q1	2009q4			179	16	8.21%
Germany	2	2000q1	2003q4	2008q1	2009q4			171	24	12.31%
Greece	1	2008q1	2012q4					175	20	10.26%
Ireland	1	2008q1	2012q4					175	20	10.26%
Israel	1	1977q1	1984q2					195	0	0.00%
Italy	2	1994q1	1995q4	2008q3	2009q4			181	14	7.18%
Japan	1	1997q4	2001q4					178	17	8.72%
South Korea	1	1997q4	1998q4					190	5	2.56%
Netherlands	1	2008q1	2009q4					187	8	4.10%
New Zealand	0							195	0	0.00%
Norway	1	1991q4	1993q4					186	9	4.62%
Portugal	1	2008q3	2012q4					177	18	9.23%
Spain	2	1982q2	1985q3	2009q2	2013q2			164	31	15.90%
Sweden	2	1990q3	1993q4	2008q3	2009q4			175	20	10.26%
Switzerland	1	2008q3	2009q4					189	6	3.08%
UK	3	1973q4	1975q4	1991q1	1995q2	2007q1	2011q4	148	47	24.10%
US	2	1988q1	1988q3	2007q4	2011q4			175	20	10.26%

It is worth noting the credit gap is calculated using the modified Beverage-Nelson (BN) filter proposed by Kamber et al. (2018). Many studies in the literature, such as Behn et al. (2013) and Alessi and Detken (2018), use an one-side Hodrick-Prescott (HP) filter with a very high smoothing parameter, $\lambda = 400,000$, to capture the long-run trend of the credit-to-GDP ratio, following the suggestion of Drehmann et al. (2011) that the financial cycle should be considered four times longer than the business cycle. This approach is recommended by the European Systemic Risk Broad[22] and the Basel Committee (BIS, 2010). However, this approach is subject to the critiques of Orphanides and Norden (2002) and Edge and Meisenzahl (2011), namely that the real-time output gap estimates by HP filter are unreliable.

The modified BN filter by Kamber et al. (2018) particularly addresses the key critique of Orphanides and Norden (2002). The output gap estimated by the modified BN filter is both reliable, in the sense of more accurate in out-of-sample forecasting and subject to smaller revisions, and intuitive, in the sense that in the sense of "being persistent, large in amplitude, and generally moving procyclically in terms of the NBER reference cycle" (Kamber et al., 2018).

Macroeconomic related variables such as the real GDP growth rate and inflation are included in the benchmark model to capture broad trends in the real sector, which may be closely related to the credit and financial cycle. Furthermore, the short-term rate and term spread are included in the pool of candidate variables to capture the risk appetite, as low cost of funding and large term spread may encourage risk-seeking activities for investors.

Asset prices usually show strong growth preceding systemic banking crises. Equity price growth and house price growth are therefore included in the benchmark model to capture the booms and busts in asset prices, which are tightly connected to systemic events as documented by Reinhart and Rogoff (2009). The house-price-to-income ratio, house-price-to-rental ratio, and the deviation of these ratios from their long-run trends are also included as variables that can capture imbalance in the housing market; they are suggested to be good predictors for systemic events in the relevant literature (Aldasoro et al., 2018; Duca and Peltonen, 2013; Alessi and Detken, 2018).

[22]Recommendation of the European Systemic Risk Broad of 18 June 2014 on guidance for setting countercyclical buffer rates(ESRB/2014/1).

According to the discussion by Kaminsky and Reinhart (1999) on "twin crises", namely currency crises and banking crises, these became closely linked following the financial liberalization in many advanced countries in the 1980s. The current account relative to GDP and real effective exchange rate are included to capture imbalances in the external sectors that may contribute to the financial vulnerability. Davis et al. (2016) finds the marginal effect of credit growth on the probability of banking crises greatly depends on the size of the current account deficit to GDP ratio. Their findings suggest the inclusion of both the current account relative to GDP and its interaction terms with credit growth and credit gap. Reinhart and Rogoff (2009) also find that a widening current account imbalance preceded banking crises in OECD countries.

Furthermore, I include global variables to allow global imbalances to affect domestic financial stability through channels such as financial linkages and trade (Kaminsky and Reinhart, 2000). The global variables are calculated as the average of the US, UK, Japan and the Euro area. Following Behn et al. (2013), I include global variables for credit growth, the credit gap, real GDP growth, inflation, real house price growth, and equity price growth.

Interaction terms are generally found to be very important in the literature on early warning models of systemic banking crises as they can improve the model's performance (e.g. Davis and Karim, 2008; Behn et al., 2013; Duca and Peltonen, 2013). The best performing model of Behn et al. (2013) includes four interaction terms, which are the mutual interactions between the domestic and global credit growth and credit gap. However, as there is a large pool of variables and transformations, many interaction terms are possible. For example, Duca and Peltonen (2013) even included second-order interaction terms in their benchmark model. The proposed LASSO logit model will do the work of automatically selecting the most important interaction terms from the pool of all interaction terms between predictors so as to improve the forecasting performance of the early warning system.

Considering more lags of the possible explanatory variables, which may contain information that can help with the prediction, further widens the list of possible covariates to be included into the early warning system. In practice, however, it can be troublesome to include more lags in the conventional multivariate logit model. Since systemic banking crises are rare events, the classes of the binary dependent variable are heavily imbalanced, as the data structure contains a major

portion of null values ("0"s) and relatively few observations of "1"s. This naturally restricts the number of covariates that can be included in the model. Incorporating more explanatory variables may lead to a serious over-fitting problem and, in the extreme, even perfect prediction. However, for models intended primarily for predictive purposes we would want to only include variables which result in the best out-of-sample forecasting performance, as an over-fitted model would undermine the effectiveness of the early warning system.

This study proposes to use LASSO with cross-validation approach to automate the variable selection process to address this particular issue. LASSO essentially is a way of conducting model selection when there are many possible covariates. From a large pool of candidate variables, transformations, interaction terms and lags, the LASSO with cross-validation method is used to select a handful of predictors that can jointly maximize the out-of-sample forecasting performance. The specific methodology adopted is discussed in the next section. The details of the explanatory variables are described in Appendix Table C1.

4.4 Empirical framework and automatic variable selection

4.4.1 Multivariate logit model

Following the literature, models are estimated in the multivariate logit framework. In the benchmark model, the probability of a systemic banking crisis for country i at time t follows the logistic distribution function.

$X_{i,t-h}$ is the vector of h-period lagged explanatory variables which are individual indicators for financial vulnerability. The specific lag may vary across variables so not all variables need to be at time $t-h$. The multivariate logit model can be written below:

$$\ln \frac{Pr(Y_{i,t}=1)}{1-Pr(Y_{i,t}=1)} = domestic_{i,t-h}\beta_1 + global_{i,t-h}\beta_2 + interaction_{i,t-h}\beta_3 + c + \epsilon_{i,t} \tag{4.1}$$

The right-hand side of the logit equation includes domestic variables, global variables, interaction variables and a constant. β_1, β_2 and β_3 are the vectors of coefficients for corresponding variables. To compare the performance of models with a benchmark model, I follow Behn et al. (2013) and choose the specification of their model (5), which is the best performed model in their study, as the benchmark model in this study. It includes domestic and global credit growth and credit gaps, the mutual interactions of the four credit variables, inflation, domestic and global GDP growth, equity price growth, and house price growth.

4.4.1.1 Setup of the dependent variable

There are two important steps to construct the dependent variable. First, I set the dependent variable to 1 in the beginning of the systemic event and to 0 otherwise. In the literature of EWS, the common practice is to set an early warning horizon and make the dependent variable be 1 in several quarters or years preceding the systemic events and be 0 otherwise. Then a discrete choice model, typically a logit model, is used to predict the defined "pre-crisis" periods (Duca and Peltonen, 2013; Behn et al., 2013).

This approach implicitly assumes that all observations are independent conditional on covariates, but the assumption of conditional independence is violated by the construction of the dependent variables. The dependent variable would be inherently serial correlated for each country as most of it would be "0"s. Considering the purpose of early warning system, warning signals should be issued to reflect the transition from tranquil periods to the deteriorated crisis-incoming periods. If the dependent variable includes a list of sequential"1"s in the "pre-crisis" periods, it will mechanically produce autocorrelation in these "1"s. It implies the warning signals are not issued independently, but depend on whether warning signals are issued in the previous period. This approach would lead to first-order autocorrelation in the residual and model misspecification. Intuitively this could be handled by incorporating the lagged dependent variable to capture the dynamic response. However, this approach is not feasible in the context of predicting systemic events, because crises are not really "discrete choices" and the timing of crises cannot be predetermined.

To overcome this issue, my approach is to make the model directly predict the starting period of systemic banking crises rather than the pre-crisis periods.

Specifically, the model aims to catch the point of transition from tranquil periods to systemic banking crises, while the extent of "early warning" is reflected in the interpretation and evaluation of the generated signals. Using this approach, the evidence that the model is correctly specified is if that there is no serial correlation in the residuals.[23]

Second, following common practice in the literature, for each country I drop all the subsequent time periods that has an on-going crisis from the sample. This treatment is for two reasons. Once a crisis occurs, it would be followed by crisis deepening periods and economics recovery periods. The economic variables would be significantly affected by the crisis, the policies to moderate the crisis and people's sentiment and expectations. This create an endogeneity problem in the model. The behaviour of economic variables during the crisis would be significantly different from the tranquil times during the adjustment process of the economy before reaching a more sustainable level or growth path. This is the so-called "post-crisis bias" problem discussed by Bussiere and Fratzscher (2006). To avoid the endogeneity problem and the post-crisis bias, it is common to drop the in-crisis periods from the sample in the literature of early warning systems, such as Duca and Peltonen (2013), Behn et al. (2013) and Davis and Karim (2008).

Nevertheless, by omitting all the in-crisis periods that are not informative on the transition from tranquil times to the systemic events, this study aims to predict the occurrence of a systemic banking crisis. Crisis duration is outside the scope of this research. Eventually, the dependent variable is binary as all the tranquil periods have the value of 0 and the periods that are the beginning of the crises have the value of 1.

4.4.1.2 Fixed effects or not?

In the literature about using the multivariate logit model to predict systemic events, there are two different estimation strategies regarding whether the country fixed

[23]Cumby-Huizinga panel serial correlation tests are conducted for the linear probability models under the two approaches of dependent variable construction over the full sample. Both models have the same specification as the benchmark model. The null hypothesis of no first order serial correlation in the error is not rejected at the 5% level of significance with the starting periods of crises serving as the dependent variable. In contrast, if the dependent variable is defined as the pre-crisis periods, there is serial correlation in the error, suggesting serious model misspecification. The results are robust to varying sample size and heteroskedasticity.

effects are considered or not. One strand of studies estimates the pooled logit model without country fixed effects (Demirgüç-Kunt and Detragiache, 1998; Davis and Karim, 2008; Duca and Peltonen, 2013). Their motivation for excluding the fixed effects is to avoid the selection bias. By including country fixed effects, all the countries that never experienced systemic banking crisis in the sample have to be excluded from the estimation as the country-specific dummy would be perfectly correlated with the banking crisis dummy for these countries. The estimation may thus be biased due to the omission of these countries. On the other hand, Behn et al. (2013) incorporate the fixed effect in their model nevertheless with the belief that the importance of addressing the unobserved time-invariant heterogeneity across countries outweighs the selection bias.

With *in-sample* analysis, Van den Berg et al. (2008) argue that it is unlikely that systemic events are homogeneously caused by identical factors. In contrast, with an extensive *out-of-sample* forecasting exercise, Fuertes and Kalotychou (2006) find a very weak association between *in-sample* fit and *out-of-sample* forecast performance in the context of early warning system for sovereign debt crisis. They find the fixed-effect model describes the data better but has very poor performance in out-of-sample prediction. Similarly, Dawood et al. (2017) also find that fixed-effect models fit the data better but the pooled logit models without fixed effects perform significantly better when it comes to out-of-sample forecasting. Since the objective of this study is to focus on crisis events prediction, I decided it is the best to use the pooled logit model without fixed effects in the main analysis. In the sensitivity analysis, I find the main results are still robust if the models incorporate country fixed effects.

4.4.2 LASSO with cross-validation

This study proposes to use LASSO with cross-validation to select the variables to be included in the logit model specification for forecasting.

Among many machine learning techniques that could be used to enhance the variable selection process, LASSO is a relatively simple and straight forward one. In contrast with other techniques with higher model complexity, LASSO is recommended and applied for two reasons. First, it is designed specifically for variable selection by addressing the over-fitting issue and enhancing the prediction

accuracy. Second, LASSO is transparent and statistically closer to the conventional modelling approaches in comparison to a range of more complicated machine learning techniques.

Designed for the purpose of variable selection, the idea of LASSO regression is to drop the variables with small coefficients to zero and thus only select variables that make a significant contribution to the model's performance.

In a generic form, the ordinary logit regression with binary response can be written as follows:

$$Pr(y_i = 1) = \pi_i = \frac{e^{y_i \beta}}{1 + e^{y_i \beta}} \tag{4.2}$$

The generic log-likelihood function can be written as in the following form accordingly:

$$L(\beta) = \sum_{i=1}^{n} \Big[y_i \log(\pi_i) + (1 - y_i) \log(1 - \pi_i) \Big] = \sum_{i=1}^{n} \Big[y_i x_i \beta - \log(1 + e^{x_i} \beta) \Big] \tag{4.3}$$

In the standard logit regression, the parameter β are estimated by maximizing the log-likelihood function $L(\beta)$. In the LASSO regression, the log-likelihood function is penalized with an additional term.

$$L_{\lambda}^{lasso}(\beta) = L(\beta) - \lambda \sum_{j=1}^{p} ||\beta||_1 \tag{4.4}$$

The choice of the penalty parameter, λ, is critical when LASSO is applied for variable selection. A higher penalty parameter indicates more coefficients of variables would shrink to zero and therefore less variables are selected to be in the model. As the purpose of this study focuses on prediction rather than model interpretation, it is favourable to only select those predictors with substantial coefficients to improve the prediction performance. The penalty parameter λ should be fine-tuned to fulfil

this purpose. I use K-fold cross-validation method to select the optimal penalty parameter λ that can maximize the out-of-sample prediction accuracy.

K-fold cross-validation is one of the most popular resampling techniques to evaluate the effectiveness of models in the machine learning literature. It is conducted by randomly splitting the sample into K-folds of approximately equal size. One fold is taken out as the *out-of-sample* validation fold while the other K-1 folds are used as training folds to estimate the model. The estimated parameters from the K-1 folds are used to predict the dependent variable in the one validation fold. This procedure is repeated for K times until every fold has served as the evaluation fold. The optimal λ is selected to be the one that the model is estimated with which minimizes the estimated deviance, which measures the goodness of fit and represents the accuracy of the prediction.

It is important to note that the entire sample is *not* used in the cross-validation. A portion of the data is withheld so that the model's predictive performance can be evaluated with data not used in selecting its specification.

As the dependent variable is binary and the number of "1" is relatively rare, I conduct 5-fold stratified cross-validation to select the optimal λ. Typical K-fold cross-validation is conducted with K=10 or K=5 to obtain good bias-variance trade-off as suggested by James et al. (2013). Since systemic banking crises are very rare events, the heavily imbalanced class size of the binary dependent variable makes 10-fold cross-validation infeasible, otherwise there will not be enough observations of crises in each fold. Hence the cross-validation is performed with 5 folds. The cross-validation is stratified so that every fold has approximately the same proportion of observations of values of different classes, that is, the number of "1"s and "0"s are approximately the same across folds.

While the method of K-fold cross-validation is frequently applied in the recent novel studies of adopting machine learning techniques to build early warning systems (e.g. Alessi and Detken, 2018; Holopainen and Sarlin, 2017), the validity of the cross-validation method should not be considered as guaranteed. Cross-validation usually requires the data to be independent and identically distributed. However, if the data has time series structure with inherent possible serial correlation, the process of randomly reshuffling the observations will break the feature of time dependence and could lead to questionable results.

It is critical to adopt the correct cross-validation method when constructing early warning systems for crisis prediction. The application of the standard K-fold cross-validation with time-series data is justified by Bergmeir et al. (2018). They find that a normal K-fold cross-validation procedure is valid if the residuals of the model are uncorrelated. In other words, if the model under-fits the data, it would lead to serially correlated errors.

4.4.3 Model evaluation criteria

The criteria of model evaluation are of key importance in the prediction of systemic banking crises. This study follows Sarlin (2013) and adopts the measure of usefulness as the criteria to evaluate the usefulness of the model. This usefulness measure extends the one developed by Alessi and Detken (2011) and takes both: (i) the preference of the policymakers between Type I errors (missing the crises) and Type II errors (False alarms); and (ii) the imbalanced frequency of the tranquil times and the crisis events into consideration.

This approach is built upon the "signalling approach" that was originally developed by Kaminsky et al. (1998) and Kaminsky and Reinhart (1999), which is widely used in crisis prediction. To do so, the contingency matrix is constructed (see Table 4.2).

Table 4.2: The contingency matrix

	Crisis event (within 6 quarters)	Tranquil period
Signal	True Positive *Correct signal*	False Positive *False alarm (Type II error)*
No signal	False Negative *Missed crisis (Type I error)*	True Negative *Correct silence*

The early warning indicator issues a signal whenever the indicator passes a certain threshold. If a signal is issued by the model, that period is predicted to be the starting period of a systemic banking crisis. If there is no signal given, the period is predicted to be a tranquil period. The share of Type I error is the number of missed crisis events relative to the total number of crisis events, which is represented as $T_1 = \frac{FN}{TP+FN}$. The share of Type II error is the number of false alarms relative to the total tranquil periods, which is represented as $T_2 = \frac{FP}{FP+TN}$. The hitting rate is

therefore represented as $1 - \frac{FN}{TP+FN}$, which is the share of correctly predicted crises relative to the total number of crises.

There are two issues related to the prediction of the starting periods of systemic banking crises. First, some degree of ambiguity is inevitable in the documentation of the starting period of systemic banking crisis. There may be no consensus on the exact quarter of a banking crisis becoming systemic. Second, the prediction of systemic events should serve the purpose of early warning eventually, leaving time to inform and implement relevant policies. To accommodate these issues, a signal is taken to be a correct signal if it is issued within 6 quarters before an actual crisis starting period.

When evaluating the forecasting performance of the model, policymakers may value differing outcomes in the contingency matrix differently. In order to take the policymaker's relative preference for Type I and Type II errors into account, a loss function is defined following Sarlin (2013).

$$L(\mu) = \mu T_1 P_1 + (1 - \mu) T_2 P_2 \tag{4.5}$$

P_1 and P_2 are the unconditional probabilities of the vulnerable pre-crisis periods and tranquil periods, respectively. μ is the policymakers' preference on the trade-off between issuing false alarm (Type II errors) and missing crises (Type I errors). It can be seen that the loss of policymakers is a weighted average of type I and type II errors based on their preference for misclassification captured by the parameter μ, adjusting for the imbalance of classes in the panel.

The usefulness of model is defined as

$$U = min[\mu P_1, (1 - \mu) P_2] - L(\mu) \tag{4.6}$$

μP_1 is the policymakers' loss if a model never issues a crisis signal, and $(1 - \mu)P_2$ is the policymakers' loss if a model always issues crisis signals. $min[\mu P_1, (1 - \mu)P_2]$ is therefore the loss if the model is ignored. The usefulness U represents the absolute gain for the policymakers by using the model compared to the case if they completely ignore the model. Hence, U is expected to be positive for any useful model.

I further define the relative usefulness U_r as the ratio of the absolute usefulness

relative to a perfectly performing model that achieves maximum possible usefulness. The relative usefulness U_r normalizes the usefulness U to be bounded between 0 and 1.

$$U_r = \frac{U_a}{\min[\mu P_1, (1-\mu)P_2]} \tag{4.7}$$

The performance of different models is evaluated by calculating and comparing their relative usefulness U_r. A higher U_r indicates a relatively more useful model.

4.5 Out-of-sample forecasting: practice and evaluation

In order to evaluate and compare the performance of the benchmark logit model and the LASSO logit model, this section performs an *out-of-sample* forecasting evaluation on predicting the occurrence of systemic banking crises.

The full sample must be split into the training dataset and the evaluation dataset. The training set is the sample used to select the model specification with LASSO. The evaluation set is the sample that is used to evaluate the *out-of-sample* performance of the selected model. The base training set covers the periods 1970Q1-2004Q4, while the evaluation set covers 2005Q1-2009Q4. Since there is no systemic banking crisis occurring after the 2010s, I restrict the evaluation period to test the models' ability to predict the 2007-08 global financial crisis period.

There are two distinct parts in the practice. Firstly, using the training dataset, the LASSO with cross-validation method is used to select the most important predictors from the pool of candidate variables. To do this, K-fold cross-validation is performed to find the best tuning parameter λ. Secondly, I produce recursive *out-of-sample* forecasts with the selected variables over the evaluation dataset. The forecasts are then evaluated and compared to the performance of the benchmark model. The *out-of-sample* forecasting exercises are performed in a pseudo-real-time manner. In each time period the information set only contains knowledge that is available up to that particular time period. To reiterate, fresh data is used to evaluate the model.

It worth noting that the specification of the LASSO logit model is pinned down with the base training periods 1970Q1-2004Q4 and this particular model is then recursively estimated over the evaluation period. Although it is possible to let LASSO choose a new model specification at each period with more up-to-date information, it would be hard for policymakers to communicate to the public with a model that keeps changing every quarter. Therefore, it was decided to not frequently respecify the model specification for the sake of consistency in communication.

4.5.1 Variable selection with the training set

The first part of the practice is to select the most important predictors using Lasso with cross-validation using the training dataset. To evaluate whether the automatic variable selection would enhance the forecasting performance, we need to compare the LASSO logit model with the benchmark model. As mentioned in Section 4.4.1, the benchmark model includes all the explanatory variables of the best performing model of Behn et al. (2013) (their model 5) and a constant. All the covariates in the benchmark model are lagged one period, following Behn et al. (2013).

The information in longer lags is usually not used for the standard multivariate logit model in relevant literature. For example, adding lags up to four quarters to the explanatory variables would already make the benchmark model produce perfect prediction. The proposed LASSO with cross-validation technique utilizes such information by selecting only the important predictors in the longer lags. To make this point, I repeat the automatic variable selection using the same pool of candidate variables but with different lag orders.

Model 1 has the selected predictors chosen from a pool of candidate variables that include only one period lag, just like the benchmark model. Model 2 contains selected predictors from candidate variables with their lags up to 4 quarters. Table 4.3 summarizes the selected predictors by Model 1 and Model 2.

It must be made clear that the handful of predictors selected by the automatic variable selection process with cross-validation are those that can achieve the best *out-of-sample* forecasting outcomes. This is appropriate given the goal of developing an early warning system. However, it is inappropriate to interpret and analyze these as a causal relationship when using predictive models. Nevertheless,

the automatic variable selection process can deliver valuable information on what the most important early-warning predictors are among a large number of variables and indices. With different sample and different candidate variables, LASSO with cross-validation may select different predictors. If some predictors are frequently selected, even in different forms such as different lag order or interaction terms, they should be considered as key indicators that need particular attention and monitoring by the policymakers. Model 1 and Model 2 share five common key indicators, namely credit growth, credit gap, global credit gap, real effective exchange rate and real house price growth.

Before progressing to the next step, it is essential to check if the selected models are correctly specified. There is no automatic guarantee that no serial correlation will exist in the residuals. Serial correlation test should be performed not only to the training sample but also to the full sample because the model will be recursively estimated over the evaluation periods. The serial correlation test results are listed in Table 4.4.

Model 1 has no autocorrelated error in its residuals over the base training sample 1970Q1-2004Q4. However, in the recursive prediction exercise, as we keep expanding the size of the training sample, Model 1 starts to have autocorrelation in its residuals when the training sample rolls over the 2007-08 financial crisis. By restricting the lag order of the candidate variables to 1, the LASSO with cross-validation approach selects only 4 variables. It can be used within the base training sample 1970Q1-2004Q4, but could be overly parsimonious when the sample size is extended. Therefore, Model 1 would be misspecified if we use it after the 2007-08 financial crisis.

This problem may be solved if we use an extended training dataset to reselect the variables, but that would be unnecessary as we can simply expand the pool of candidate variables and select better models. With variables selected from a larger pool of candidate variables, Model 2 does not have this problem. Nevertheless, the forecasting practice is conducted for both Model 1 and Model 2.

Table 4.3: LASSO with cross-validation selected variables

Model 1	Model 2
lag 1	lag 1
credit growth × credit gap	real house price growth
real effective exchange rate × real house price growth	global credit growth × global credit gap
credit growth × global credit gap	real effective exchange rate × real house price growth
credit gap × global credit gap	credit gap × global credit gap
	lag 3
	credit growth × credit gap
	credit growth × current account to GDP
	lag 4
	current account to GDP × global equity price growth
	global credit gap × global inflation
$\lambda = 6.867$	$\lambda = 6.021$

Table 4.4: Cumby-Huizinga test for first order serial correlation

	p-value
Model 1	
Training set (1970Q1-2004Q4)	0.4310
Training set+Evaluation set(1970Q1-2009Q4)	0.0185**
Model 2	
Training set (1970Q1-2004Q4)	0.4290
Training set+Evaluation set(1970Q1-2009Q4)	0.8990

4.5.2 Forecasting results and performance evaluation

To compare and evaluate the predictive ability of the candidate models, the *out-of-sample* exercise is carried out recursively in the following way:

1. Start with the base training sample 1970Q1-2004Q4, estimate the model on the data that contains information that is only available up to that period. Predict the probability of a systemic banking crisis that is about to happen in the next period, which is out-of-sample.

2. Compute the *in-sample* relative usefulness U_r given the policy preference μ for all thresholds from 0 to 1. Apply the threshold that yield the highest relative usefulness to the predicted probability of a crisis in the next period and generate a "real-time" warning signal of 0 or 1.

3. Expand the training set by 1 period forward and repeat steps 1-3 recursively.

4. Collect the warning signals produced over the entire evaluation period and calculate the relative usefulness based on the number of false signals and missed crises.

Relevant studies such as Behn et al. (2013) and Lang et al. (2018) set the value of μ as 0.9. This is due to the consideration that the cost of missing a systemic event is far larger than issuing false alarm about an incoming crisis, which would at least call for more attention to the current distress of banks. As discussed by Sarlin (2013), setting the policy parameter μ as 0.9 and adjusting for the unconditional probability of systemic events is equivalent to the approach of setting $\mu = 0.5$ without adjusting for the unconditional probability of systemic events.[24] To ensure the forecasting results are robust to varying policy preference, in addition to setting the policy preference parameter μ as 0.9, the performance of the models selected by LASSO with cross-validation will be evaluated with the policy preference parameter μ set at two values: 0.8 and 0.7, which indicates policymakers' relatively stronger preference to avoid false alarm rather than missing crises.

In addition to the measure of the relative usefulness, the noise to signal ratio is also calculated for each model to supplement the forecasting evaluation from an objective perspective that does not take the policymakers' preference into account. The noise to signal ratio is calculated as the ratio of type II error to the hitting rate. A smaller noise to signal ratio indicates more precise prediction, regardless of the policymakers' preference.

[24] This approach has been used by Alessi and Detken (2018) and Duca and Peltonen (2013).

Table 4.5: Main results: forecast evaluation

	Benchmark			Model 1 LASSO lag 1			Model 2 LASSO lag 1-4			Model 3 LASSO lag 1-4 with the linear terms		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Policy preference (μ)	0.9	0.8	0.7	0.9	0.8	0.7	0.9	0.8	0.7	0.9	0.8	0.7
Relative usefulness	0.48	0.18	-0.09	0.67	0.47	0.27	0.64	0.55	0.51	0.50	0.33	0.22
Noise to signal ratio	0.16	0.16	0.14	0.04	0.03	0.02	0.04	0.02	0.01	0.08	0.05	0.04
Hitting rate	0.72	0.72	0.65	0.73	0.56	0.32	0.69	0.61	0.54	0.60	0.43	0.32
Type I error	0.28	0.28	0.35	0.27	0.44	0.68	0.31	0.39	0.46	0.40	0.57	0.68
Type II error	0.11	0.11	0.09	0.03	0.02	0.01	0.03	0.01	0.00	0.05	0.02	0.01

Table 4.5 summarizes the results of the recursive *out-of-sample* forecasting practice. There are several notable results.

Regardless of varying the policy preference parameter, Model 1 (LASSO lag 1) and Model 2 (LASSO lag 1-4) always outperform the benchmark model as they achieve higher relative usefulness in all cases. They also generate far less false alarms compared to the benchmark model. The LASSO with cross-validation selected models all have a very low noise to signal ratio, indicating their prediction is more precise than the benchmark model.

For each model, as the policy preference parameter μ becomes smaller, there would be more weight in the loss function on type I errors but less on type II errors, and result in lower relative usefulness. This suggests policymakers would benefit from more warning signals so as to avoid the huge cost associated with systemic events.

At $\mu = 0.7$, the relative usefulness of the benchmark model is negative, suggesting this model is not useful for policymakers to predict the 2007-08 systemic banking crises at all. In comparison, Model 1 and Model 2 have positive usefulness in all cases.

The relative usefulness of Model 2 is only slightly lower than Model 1 at $\mu = 0.9$, but it outperforms Model 1 at lower μ. It also achieves lower noise to signal ratio. It is quite obvious that the results of the benchmark model and Model 1 are relatively sensitive to varying policy preference. As μ becomes smaller, their relative usefulness drastically falls. In contrast, Model 2 achieves a much more stable forecasting performance under varying policy preferences. Consider that the benchmark model and Model 1 only include one period lagged variables, while Model

2 includes predictors of longer lags, it is very likely that longer lags of the covariates contain valuable information that help reinforce the stable performance of the model. This finding further justifies the use of LASSO with cross-validation to automate the variable selection process in order to extract as much information as possible for better prediction. The robustness of this finding is investigated in the sensitivity analysis section.

In Model 1 and Model 2, if any interaction term is selected, it is included in the model but not the linear terms. As the ultimate objective is to achieve better forecasting performance rather than model interpretation, the implication of including the linear terms of the interaction terms is unclear. Columns (10) to (12) of Table 4.5 report the results of Model 3, which extends Model 2 by including the linear terms for the selected interaction terms. By including the linear terms, Model 3 performs strictly worse than Model 2 in all cases.[25]

Overall, the results suggest that the automatic variable selection process of LASSO with cross-validation is useful to extract information that may not be accessible by the standard multivariate logit models. Thus more useful, more stable and more precise predictive results are generated.

4.5.3 Forecast horizon

The focus of my modeling approach is to capture and predict the key transition of variable dynamics from the tranquil periods to the systemic events. The feature of such a key transition is most apparent in the very period preceding the outbreak of a systemic banking crisis. The variable selection process is carried out accordingly and the out-of-sample forecasting exercise in Section 4.4.2 is essentially a one-period ahead prediction.

In practice, the policymakers may need a longer forecast horizon to allow time for policy selection and implementation so as to reduce the probability of a crisis occurring. To make sure the LASSO with cross-validation approach could contribute to the purpose of an early warning system, I extend the forecast horizon and conduct h-step ahead direct forecasting exercise to evaluate the performance for the benchmark model and Model 2, which contains selected predictors from a

[25]The same practice is conducted for Model 1, which is found to perform better without including the linear terms.

pool of candidate variables with lags up to four quarters. Table 4.6 presents the prediction results with forecast horizon being 4, 8, and 12 quarters ahead. The policy preference parameter μ is set to 0.9.[26]

Table 4.6: Varying forecast horizon

	Model 2 LASSO lag 1-4			Benchmark		
Forecast horizon	t+4	t+8	t+12	t+4	t+8	t+12
Relative usefulness	0.59	0.56	0.35	0.49	0.19	0.15
Noise to signal ratio	0.06	0.07	0.11	0.16	0.35	0.21
Hitting rate	0.69	0.67	0.46	0.76	0.81	0.28
Type I error	0.31	0.33	0.54	0.24	0.19	0.72
Type II error	0.04	0.05	0.05	0.12	0.28	0.06

As expected, with a longer forecast horizon, the prediction of both models become less useful and noisier. It reflects the difficulty of predicting the breakout of systemic events for longer periods ahead. Nevertheless, the LASSO selected model still outperforms the benchmark model in all cases.

In the above exercise, Model 2 contains variables selected to optimize the one-step ahead forecasting results, yet it maintains good predictive performance in h-step ahead forecast. It is possible for one to select variables that optimize h-step ahead forecast performance and then conduct the exercise. However, this approach would omit too much valuable information considering that the variable dynamics just preceding the banking crises would be particularly important. Hence the former approach is used to conduct h-step ahead forecast exercise.

4.5.4 Implications for monitoring to preserve financial stability

As discussed in Section 4.5.1, the LASSO with cross-validation approach selects the predictors that jointly have the best out-of-sample predictive performance.

[26] I also conduct the same exercise with policy preference μ being 0.8 and 0.7. The robustness of the results still holds.

Regardless of the lag order and the interaction terms, the frequently selected variables should be considered as the key early warning indicators that reflect existing and future financial vulnerability. By closely monitoring these early warning indicators, policymakers would have a better understanding for adopting appropriate policies and for timing the implementation to mitigate the build-up of systemic risk, subsequently reducing the probability of potential systemic banking crises.

Table 4.7 presents the selected early warning indicators when the candidate variables contain different orders of lags across different sample size. Columns (1) and (2) present the individual indicators by Model 1 and Model 2 using the pre-2005 sample. In Table 4.3, these indicators are selected to have various forms and order of lags, and are used to conduct the forecasting performance evaluation in Section 4.5.2. Columns (3) and (4) present the indicators selected by the LASSO with cross-validation method using the same set of candidate variables as in Columns (1) and (2) but with the full sample (1970Q1-2008Q3). The common selected key indicators are marked in bold.

Table 4.7: LASSO+CV selected indicators

	Pre-2005 sample		Full sample	
	lag 1	lag 1-4	lag 1	lag 1-4
Variable category				
Credit	**credit gap** **credit growth** **global credit gap**	**credit gap** **credit growth** **global credit gap** global credit growth	**credit gap** **credit growth** **global credit gap** global credit growth	**credit gap** **credit growth** **global credit gap** global credit growth
Housing market	**real house price growth**	**real house price growth** house-price-to-rental gap house-price-to-income gap	**real house price growth** house-price-to-rental gap house-price-to-rental ratio global house price growth	**real house price growth** house-price-to-rental gap house-price-to-rental ratio global house price growth
External sector	**real effective exchange rate**	**real effective exchange rate** current account to GDP	**real effective exchange rate** current account to GDP	**real effective exchange rate** current account to GDP
Macroeconomics		global inflation short rate	global inflation equity price growth inflation term spread	global inflation equity price growth

As shown in Table 4.7, allowing for different lag orders of the candidate variables to be selected across different samples, five indicators are commonly selected by the LASSO with cross-validation approach, namely domestic credit growth and credit gap, global credit gap, real effective exchange rate and real house price growth. It is important to understand how the development of these indicators may undermine financial stability.

Credit-related variables, unsurprisingly, are selected as the most important predictors of systemic banking crises. Domestic credit growth and credit gap capture the systemic risk associated with domestic credit market development. Prolonged excessive credit growth is often observed preceding episodes of financial instability, especially the 2007-08 global financial crisis. In the expansionary phase of the financial cycle, rapid credit expansion is accompanied by credit risk quickly building up for banks and non-bank financial institutions. This reflects rising market confidence and financial institutions becoming optimistic; consequently, they are willing to accept higher risks and increase leverage. Active credit intermediation would also increase the degree of interconnectedness of the whole financial system. Banks and shadow banks, domestic financial institutions and foreign investors would be much more integrated. The impact of an adverse shock to a single bank is likely to spread through other financial intermediaries and become amplified. Studying the experience of 14 developed countries over 140 years, Jordà et al. (2011) conclude that excessive credit growth poses key risk to the financial system, and view credit growth as the best single predictor of financial instability. By monitoring credit growth, policymakers would likely know when to adopt adequate policies to avoid the credit market getting overheated.

The credit gap, which is defined as the gap between the credit-to-GDP ratio and its long-run trend, is widely acknowledged as one of the most useful early warning indicators for banking crises in a range of studies (Drehmann and Tsatsaronis, 2014; Behn et al., 2013; Borio et al., 2002). The credit gap identifies the excessive portion of credit from the level justified by the development of fundamental economic factors. Recommended by Basel III, policymakers should use credit gap as a guide to inform the setting of countercyclical macroprudential policies, such as adjusting countercyclical capital buffers to banks.

The global credit gap captures the systemic risk associated with imbalances in the development of world-wide credit. The degree of global financial integration has deepened considerably in recent years. Adverse shock to non-domestic financial institutions could spread across many countries especially those with active cross-border credit flow, and threaten the stability of the domestic banking system.

The inclusion of the other two commonly selected variables, namely real house price growth and the real effective exchange rate, indicates the importance of property market and the external sector to the stability of the banking system.

The development of property markets has played a prominent role in previous systemic banking crises, especially the 2007-2008 financial crisis. During an asset price boom, a large amount of bank and non-bank credit flows into the property market and drives up house prices and household leverage. Though mortgages are usually perceived to be safe assets by banks since they are backed by tangible collateral, the potential credit risk, liquidity risk and concentration risk associated with concentrated mortgage portfolio of banks should not be underestimated. Excessive house price growth may potentially cause an asset price bubble and lead to a boom-bust cycle in the property market, thereby threatening the resilience of the financial system. Macroprudential policies that target the demand side of the housing credit such as putting caps on the loan-to-value ratio and debt-to-income ratio may be considered by policymakers to dampen the cycle.

The real effective exchange rate reflects the market sentiment and expectation of investors to domestic economic development. It also captures the imbalance of the external sector and the pressure associated with a surge in capital inflows, which typically fuel a house price boom. Sudden adjustments could lead to an unexpected significant loss in the balance sheet of domestic and foreign financial institutions, while the loss is likely to spread across the financial system and exacerbate financial instability. Frankel and Saravelos (2012) conduct a meta-analysis of 83 papers in the financial crisis literature and find that the real effective exchange rate stands out as one of the most useful leading indicators in explaining crisis incidence across different countries and episodes in the past. While advanced countries usually have much more resilient external sectors than developing countries, one should not ignore the build-up of vulnerabilities in these external sectors.

Apart from the five key indicators that I discussed in detail, global credit growth, house-price-to-rental gap, current account to GDP and global inflation are also frequently selected. They have proved to be very important in early warning systems. Briefly, global credit growth captures the impact of global credit expansion to the domestic banking system. The house-price-to-rental gap is an indicator of the housing market's strength. Excessive increases in the house-price-to-rental gap suggest properties are overvalued and there is potential danger of housing market correction. The inclusion of current account to GDP ratio further highlights the importance of the external sector to the financial sector's stability. It is interesting to find that the global level of inflation is taken to be an important predictor for a banking crisis. Ciccarelli and Mojon (2010)

study the global co-movement of inflation in detail and find that on average global inflation accounts for 70% of the variability of inflation in industrialized countries from 1960 to 2008. It captures both the trend in the global price level and the fluctuations at global business cycle frequencies. As a proxy for the inflation expectations, it has good predictive ability in forecasting domestic inflation by capturing slow-moving trends in inflation rates (Ciccarelli and Mojon, 2010).

4.6 Sensitivity analysis

I conduct the following tests to ensure the robustness of my results.

4.6.1 Longer lags of candidate variables

One may doubt if the stable performance of Model 2 (LASSO logit lag 1-4) comes from utilizing information in the longer lag of the covariates. I expand the pool of candidate variables with up to 8 lags and apply the LASSO with cross-validation approach to get Model 4. The five common key variables are once again selected, indicating their importance to the early warning system of systemic banking crises. There is no serial correlation in the residuals. The predictive performance is presented in Table 4.8. While Model 4 still strictly outperforms the benchmark model and Model 1, the results suggest that further expanding the lag order of the candidate variables does not lead to better predictive performance. These results are still relatively insensitive to varying policy preference parameter.

Table 4.8: Longer lags of candidate variables

	Model 4 LASSO lag 1-8			Benchmark		
	(1)	(2)	(3)	(4)	(5)	(6)
μ	0.9	0.8	0.7	0.9	0.8	0.7
Relative usefulness	0.62	0.48	0.40	0.48	0.18	-0.09
Noise to Signal Ratio	0.04	0.04	0.01	0.16	0.16	0.14
Hitting rate	0.68	0.58	0.43	0.72	0.72	0.65
Type I error	0.32	0.42	0.57	0.28	0.28	0.35
Type II error	0.03	0.02	0.00	0.11	0.11	0.09

4.6.2 Models with fixed effects

As discussed in Section 4.4.1, to avoid the selection bias of dropping countries from the sample, I follow the mainstream of the early warning literature and conduct the analysis without fixed effects. Nevertheless, I conduct the same recursive *out-of-sample* forecasting practice to the fixed-effect model to ensure the superior predictive performance of my approach still holds regardless of the inclusion of fixed effect or not. To include the fixed effects, Australia, Canada and New Zealand are omitted from the sample because they never experienced any systemic banking crises during the sample period. Table 4.9 summarizes the results.

Selecting candidate variables up to four lags and eight lags respectively, both Model 2 and Model 4 have achieved higher relative usefulness and lower noise to signal ratio than the benchmark model in all cases of policy preference. The LASSO logit models still strictly outperform the benchmark model even if we take the unobserved time-invariant heterogeneity of countries into account. In this case, however, Model 4 yields better and more stable predictive result compared to Model 2.

Table 4.9: *Out-of-sample* performance of logit models: with fixed effects

	Benchmark			Model 2 LASSO lag 1-4			Model 4 LASSO lag 1-8		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
μ	0.9	0.8	0.7	0.9	0.8	0.7	0.9	0.8	0.7
Relative usefulness	0.29	0.08	-0.19	0.48	0.37	0.26	0.68	0.50	0.42
Noise to Signal Ratio	0.27	0.20	0.18	0.05	0.05	0.05	0.04	0.02	0.01
Hitting rate	0.60	0.60	0.60	0.53	0.47	0.38	0.74	0.56	0.47
Type I error	0.40	0.40	0.40	0.47	0.53	0.62	0.26	0.44	0.53
Type II error	0.16	0.12	0.11	0.03	0.02	0.02	0.03	0.01	0.01

4.7 Chapter conclusion

This chapter proposes the use of LASSO with cross-validation approach to automate the variable selection process of the conventional multivariate logit econometric framework. Through formalizing and automating the variable selection process, the most important information, which may not be easily

identified and accessed by subjective variable pre-selection, can be extracted to achieve better systemic banking crisis prediction.

The empirical analysis covers a set of 23 OECD countries with quarterly data. Through a classic pseudo-real-time recursive *out-of-sample* forecasting exercise, I evaluate the predictive performance of a benchmark multivariate logit model with specification from Behn et al. (2013) against the LASSO logit model with automatic variable selection. The evaluation criteria take policymakers' preferences into account. The results suggest that better predictive performance can be achieved by using the proposed LASSO with cross-validation approach to enhance the variable selection process of the conventional multivariate model. Such results are robust to varying policymakers' preference, forecast horizon, lag length of candidate variables and the different treatment of the fixed effects.

As a simple and straight forward variable selection method, the conventional early warning model with this add-on would retain good interpretability and transparency to effectively communicate with policymakers and guide policy activation. Five variables, namely credit growth, the domestic and global credit gaps, real house price growth and the real effective exchange rate, are identified as the most important key indicators of systemic banking crises. This study further highlights the importance of not only considering the domestic indicators, but also variables that can capture imbalance in the global economy and the interactive relationship of these variables.

Chapter 5

Concluding Remarks

The devastating consequences of historical financial crises have highlighted the critical importance of a stable and sound financial system. It is important to understand how systemic risk accumulates, spreads and materializes in the financial system. Policymakers need to thoroughly analyze how the build-up of financial vulnerabilities could be mitigated when designing the appropriate preventive macroprudential measures. While it is inherently difficult to prevent further systemic events from occurring again, macroprudential authorities should continuously assess systemic risk in the financial sector by identifying and monitoring relevant early warning indicators. This thesis provides insights into the build-up of vulnerabilities outside the traditional banking system, the implications of interactions between house prices and household debt, and how to better identify the most relevant predictors so as to improve the forecasting performance of a conventional early warning model.

In Chapter 2, I study the impact of macroprudential policies on shadow banking activities and the implication to financial stability. It is found that the effectiveness of demand-side macroprudential policies, namely LTV caps and DTI caps, is mitigated by regulation arbitrage and systemic risk-transfer through the shadow banking system. There is no evidence of the effectiveness of general supply-side policies being affected by the shadow banking system, except in two cases. The implementation of loan-loss provisionings is associated with more active shadow banking credit intermediation and risk-shifting, which is

counter-productive. In contrast, I find tightening sector-specific capital requirements could reduce credit growth in the shadow banking system. In all, these results demonstrate the importance of assessing the consequences of macroprudential policies for the entire financial system.

In Chapter 3, I analyze the short-run and long-run interactions among Australian house prices and their drivers, with a particular focus on household debt, using a SVECM framework. Using a quarterly dataset from 1990 to 2016, I find that household debt and housing supply are the two significant drivers of long-run equilibrium house prices. Alternatively, household disposable income and the real interest rate affect equilibrium house prices through the credit channel. This study adopts a different identification strategy to the existing literature by using the technique of Pagan and Pesaran (2008), so as to impose fewer restrictions. The interaction between house prices and household debt therefore is driven mainly by information in the data to the greatest extent possible. The analysis of the short-run dynamics suggests that house prices and household debt in Australia are mutually reinforcing. Such an interaction is likely to amplify the boom and bust cycle of the financial system, thus posing greater risk to financial stability and making highly indebted households more vulnerable to future adverse shocks.

I also identify the various drivers of house price growth in the sample period by examining the deviation of house prices from their long-run equilibrium and a historical decomposition. I find that the Australian housing market boom in the later 1990s was mainly fueled by credit condition shocks, while the recent growth in house prices after 2012 was mainly driven by a higher housing demand and a lower cost of financing.

By investigating the role of monetary shocks, I find that a contractionary monetary policy shock, while dampening house prices, may unfavourably increase household indebtedness. Alternatively, a credit condition shock that tightens the borrowing constraint could lead to both lower house prices and lower household leverage. Thus, if macroprudential policies act like exogenous credit condition tightening shocks, my findings suggest that the use of macroprudential policy might be preferable to a monetary policy of leaning against the wind of asset price misalignments.

In Chapter 4, I propose automating the variable selection process of the multivariate logit early warning model using the LASSO with cross-validation method. This method can develop a model which extracts important information

that may not be easily identified and accessed by subjective variable pre-selection, thereby improving the performance of predicting systemic banking crises. Employing a quarterly dataset of 23 OECD countries, I evaluate the predictive performance of the LASSO logit model with automated variable selection and find it strongly outperforms the benchmark model from the literature. My results are robust to varying policymakers' preferences, the forecast horizon, the lag length of candidate variables and the inclusion or exclusion of the fixed effects.

This variant of the conventional framework retains good interpretability and transparency of the early warning system, which is essential for communicating with policymakers and guiding policy activation. Five variables are identified to be the most important key predictors of systemic banking crises, namely credit growth, the domestic and global credit gaps, real house price growth and the real effective exchange rate. This study emphasizes the importance of identifying and monitoring the most important early warning indicators to guide the activation of policies to reinforce financial stability.

Overall, financial stability is of critical importance for sustainable economic growth. In-depth analyses into all components of the financial system are required in order to promote a stable and sound financial system and to prevent systemic events from occurring. The effect of macroprudential regulation to the overall financial sector needs to be carefully assessed. Vulnerabilities stemmed from the interactions between different sectors of the financial market should also be recognized and addressed by appropriate measures. Reliable early warning systems should be developed and employed to identify economic weaknesses and vulnerabilities to give policymakers a clearer picture of when and how to take preventive measures to mitigate any emerging systemic risk. By addressing these dimensions of financial stability, the three chapters of this thesis shed light on how to better safeguard the financial system.

References

Abelson, P., Joyeux, R., Milunovich, G., and Chung, D. (2005). Explaining house prices in Australia: 1970–2003. *Economic Record*, 81:S96–S103. 39, 45, 46

Ahmed, A. S., Takeda, C., and Thomas, S. (1999). Bank loan loss provisions: a reexamination of capital management, earnings management and signaling effects. *Journal of Accounting and Economics*, 28(1):1–25. 28

Aiyar, S., Calomiris, C. W., and Wieladek, T. (2014). Does macro-prudential regulation leak? Evidence from a UK policy experiment. *Journal of Money, Credit and Banking*, 46(s1):181–214. 11

Akinci, O. and Olmstead-Rumsey, J. (2017). How effective are macroprudential policies? an empirical investigation. *Journal of Financial Intermediation*. 8, 10, 11, 21, 23, 24, 25, 26

Aldasoro, I., Borio, C. E., and Drehmann, M. (2018). Early warning indicators of banking crises: expanding the family. *BIS Quarterly Review, March*, pages 29–45. 80

Alessi, L., Antunes, A., Babecky, J., Baltussen, S., Behn, M., Bonfim, D., Bush, O., Detken, C., Frost, J., Guimaraes, R., Havranek, T., Joy, M., Kauko, K., Mateju, J., Monteiro, N., Neudorfer, B., Peltonen, T. A., Rusnak, M., Marques Rodrigues, P. M., Schudel, W., Sigmund, M., Stremmel, H., Smidkova, K., van Tilburg, R., Vasicek, B., and Zigraiova, D. (2015). Comparing different early warning systems: Results from a horse race competition among members of the macro-prudential research network. *MPRA Paper*, (No.62194). 76

Alessi, L. and Detken, C. (2011). Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy*, 27(3):520–533. 74, 88

Alessi, L. and Detken, C. (2018). Identifying excessive credit growth and leverage. *Journal of Financial Stability*, 35:215–225. 71, 75, 77, 80, 87, 94

Anundsen, A. K. and Jansen, E. S. (2013). Self-reinforcing effects between housing prices and credit. *Journal of Housing Economics*, 22(3):192–212. 4, 36, 38, 41, 44, 46, 50

Atalay, K., Barrett, G., Edwards, R., and Yu, C. Household indebtedness and housing prices in Australia. *University of Sydney Economics Working Paper Series*. 40

Babeckỳ, J., Havránek, T., Matěju, J., Rusnák, M., Šmídková, K., and Vašíček, B. (2014). Banking, debt, and currency crises in developed countries: Stylized facts and early warning indicators. *Journal of Financial Stability*, 15:1–17. 78

Bakk-Simon, K., Borgioli, S., Giron, C., Hempell, H. S., Maddaloni, A., Recine, F., and Rosati, S. (2011). Shadow banking in the euro area: an overview. *ECB occasional paper*, (133). 13

Barakova, I., Bostic, R. W., Calem, P. S., and Wachter, S. M. (2003). Does credit quality matter for homeownership? *Journal of Housing Economics*, 12(4):318–336. 37

Beechey, M. and Österholm, P. (2008). A Bayesian vector autoregressive model with informative steady-state priors for the Australian economy. *Economic Record*, 84(267):449–465. 64

Behn, M., Detken, C., Peltonen, T. A., and Schudel, W. (2013). Setting countercyclical capital buffers based on early warning models: would it work? *ECB Working Paper*, (No. 1604). 74, 75, 78, 80, 81, 83, 84, 85, 91, 94, 99, 103

Bergmeir, C., Hyndman, R. J., and Koo, B. (2018). A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Computational Statistics and Data Analysis*, 120:70–83. 88

Berkelmans, L. (2005). Credit and monetary policy: An Australian SVAR. *Reserve Bank of Australia Research Discussion Papers*, (No. 2005-06). 40, 64

Berki, T. and Szendrei, T. (2017). The cyclical position of housing prices: A VECM approach for Hungary. *MNB Occasional Papers*. 36, 44, 50

Bernanke, B. S. and Blinder, A. S. (1992). The Federal Funds rate and the channels of monetary transmission. *American Economic Review*, 82(4):901–921. 64

Beutel, J., List, S., and Von Schweinitz, G. (2018). An evaluation of early warning models for systemic banking crises: Does machine learning improve predictions? *Deutsche Bundesbank Discussion Paper*. 76

Bikker, J. A. and Metzemakers, P. A. (2005). Bank provisioning behaviour and procyclicality. *Journal of International Financial Markets, Institutions and Money*, 15(2):141–157. 28

BIS (2010). *Guidance for national authorities operating the countercyclical capital buffer*. Basel Committee on Banking Supervision, BIS. 80

BIS (2014). *Bank for International Settlements 84th Annual Report*. Bank for International Settlements. 66

Bishop, J., Tulip, P., et al. (2017). Anticipatory monetary policy and the price puzzle. *Reserve Bank of Australia Research Discussion Paper*, (No. 2017-02). 64

Blanchard, O., DellAriccia, G., and Mauro, P. (2010). Rethinking macroeconomic policy. *Journal of Money, Credit and Banking*, 42(s1):199–215. 6

Bloxham, P., Kent, C. J., and Robson, M. (2010). Asset Prices, Credit Growth, Monetary and Other Policies: An Australian Case Study. *Reserve Bank of Australia Research Discussion Paper*, (No. 2010-06). 59, 61

Boot, A. W. and Ratnovski, L. (2016). Banking and trading. *Review of Finance*, 20(6):2219–2246. 10

Bordo, M. D. and Jeanne, O. (2002). Monetary policy and asset prices: does "benign neglect"make sense? *International Finance*, 5(2):139–164. 66

Borio, C., Lowe, P., et al. (2002). Assessing the risk of banking crises. *BIS Quarterly Review*, 7(1):43–54. 99

Borio, C. E. and Drehmann, M. (2009). Assessing the risk of banking crises–revisited. *BIS Quarterly Review, March*, pages 29–46. 74

Borio, C. E. and Lowe, P. W. (2002). Asset prices, financial and monetary stability: exploring the nexus. *BIS Working Paper*. 74

Breiman, L. (2001). Random forests. *Machine Learning*, 45(1):5–32. 75

Brissimis, S. N. and Vlassopoulos, T. (2009). The interaction between mortgage financing and housing prices in Greece. *The Journal of Real Estate Finance and Economics*, 39(2):146–164. 38

Brunnermeier, M. K., Crockett, A., Goodhart, C. A., Persaud, A., and Shin, H. S. (2009). *The fundamental principles of financial regulation*, volume 11. International Center for Monetary and Banking Studies. 7

Bussiere, M. and Fratzscher, M. (2006). Towards a new early warning system of financial crises. *Journal of International Money and Finance*, 25(6):953–973. 73, 74, 84

Caldera, A. and Johansson, Å. (2013). The price responsiveness of housing supply in OECD countries. *Journal of Housing Economics*, 22(3):231–249. 45

Cerutti, E., Claessens, S., and Laeven, L. (2017). The use and effectiveness of macroprudential policies: new evidence. *Journal of Financial Stability*, 28:203–224. 7, 10, 11, 23, 25, 26

Cerutti, M. E. M., Correa, M. R., Fiorentino, E., and Segalla, E. (2016). Changes in prudential policy instrumentsa new cross-country database. *IMF Working Paper*, No. 16/110. 9, 16

Chinn, M. D. and Ito, H. (2008). A new measure of financial openness. *Journal of Comparative Policy Analysis*, 10(3):309–322. 22

Ciccarelli, M. and Mojon, B. (2010). Global inflation. *The Review of Economics and Statistics*, 92(3):524–535. 100, 101

Cizel, J., Frost, J., Houben, A., and Wierts, P. (2019). Effective macroprudential policy: Cross-sector substitution from price and quantity measures. *Journal of Money, Credit and Banking*, 51(5):1209–1235. 7, 12

Claessens, S. (2015). An overview of macroprudential policy tools. *Annual Review of Financial Economics*, 7(1):397–422. 7, 12, 16

Claessens, S., Ghosh, S. R., and Mihet, R. (2013). Macro-prudential policies to mitigate financial system vulnerabilities. *Journal of International Money and Finance*, 39:153–185. 7, 11, 15, 26

Crowe, C., DellAriccia, G., Igan, D., and Rabanal, P. (2013). How to deal with real estate booms: Lessons from country experiences. *Journal of Financial Stability*, 9(3):300–319. 8, 11, 12, 26

Cummings, J. R. and Durrani, K. J. (2016). Effect of the basel accord capital requirements on the loan-loss provisioning practices of australian banks. *Journal of Banking and Finance*, 67:23–36. 28

Davis, E. P. and Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial Stability*, 4(2):89–120. 72, 74, 75, 81, 84, 85

Davis, J. S., Mack, A., Phoa, W., and Vandenabeele, A. (2016). Credit booms, banking crises, and the current account. *Journal of International Money and Finance*, 60:360–377. 81

Dawood, M., Horsewood, N., and Strobel, F. (2017). Predicting sovereign debt crises: an early warning system approach. *Journal of Financial Stability*, 28:16–28. 75, 85

De Nicoló, M. G., Favara, G., and Ratnovski, L. (2012). Externalities and macroprudential policy. *International Monetary Fund Staff Discussion Notes*, (12/05). 7

Demirgüç-Kunt, A. and Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. *IMF Staff Papers*, 45(1):81–109. 74, 85

Demirgüç-Kunt, A. and Detragiache, E. (2000). Monitoring banking sector fragility: a multivariate logit approach. *The World Bank Economic Review*, 14(2):287–307. 74

Demirgüç-Kunt, A. and Detragiache, E. (2005). Cross-country empirical studies of systemic bank distress: a survey. *National Institute Economic Review*, 192(1):68–83. 74

Detken, C., Weeken, O., Alessi, L., Bonfim, D., Boucinha, M. M., Castro, C., Frontczak, S., Giordana, G., Giese, J., Jahn, N., et al. (2014). Operationalising

the countercyclical capital buffer: indicator selection, threshold identification and calibration options. *European Systemic Risk Board (ESRB) Occasional Paper Series*, (No.5). 78

Doornik, J. (2003). Asymptotic tables for cointegration tests based on the gamma-distribution approximation. Nuffield College, University of Oxford. Unpublished Note. 43

Drehmann, M., Borio, C. E., and Tsatsaronis, K. (2011). Anchoring countercyclical capital buffers: the role of credit aggregates. *BIS Working Paper*. 80

Drehmann, M. and Tsatsaronis, K. (2014). The credit-to-gdp gap and countercyclical capital buffers: questions and answers. *BIS Quarterly Review March*. 99

Duca, M. L. and Peltonen, T. A. (2013). Assessing systemic risks and predicting systemic events. *Journal of Banking and Finance*, 37(7):2183–2195. 72, 74, 75, 78, 80, 81, 83, 84, 85, 94

Dungey, M. and Fry, R. (2009). The identification of fiscal and monetary policy in a structural VAR. *Economic Modelling*, 26(6):1147–1160. 39

Dungey, M. and Pagan, A. (2000). A structural VAR model of the Australian economy. *Economic record*, 76(235):321–342. 64

Dungey, M. and Pagan, A. (2009). Extending a SVAR model of the Australian economy. *Economic Record*, 85(268):1–20. 64

Edge, R. M. and Meisenzahl, R. R. (2011). The unreliability of credit-to-gdp ratio gaps in real-time: Implications for countercyclical capital buffers. *International Journal of Central Banking*, 7(4):261–298. 80

Ellis, L. (2005). Disinflation and the dynamics of mortgage debt. *BIS Working Paper*, 22:5–20. 59

Fitzpatrick, T. and McQuinn, K. (2007). House prices and mortgage credit: Empirical evidence for Ireland. *The Manchester School*, 75(1):82–103. 38

Fonseca, A. R. and Gonzalez, F. (2008). Cross-country determinants of bank income smoothing by managing loan-loss provisions. *Journal of Banking and Finance*, 32(2):217–228. 28

Frankel, J. and Saravelos, G. (2012). Can leading indicators assess country vulnerability? evidence from the 2008–09 global financial crisis. *Journal of International Economics*, 87(2):216–231. 100

Fry, R. A., Martin, V. L., and Voukelatos, N. (2010). Overvaluation in Australian housing and equity markets: wealth effects or monetary policy? *Economic Record*, 86(275):465–485. 39, 61

FSB (2011). *Macroprudential Policy Tools and Frameworks: Update to G20 Finance Ministers and Central Bank Governors*. Financial Stability Board. 7

FSB (2012). *Strengthening the Oversight and Regulation of Shadow Banking: Progress Report to G20 Ministers and Governors*. Financial Stability Board. 7, 10

Fuertes, A.-M. and Kalotychou, E. (2006). Early warning systems for sovereign debt crises: The role of heterogeneity. *Computational Statistics and Data Analysis*, 51(2):1420–1441. 85

Geanakoplos, J. (2010). The leverage cycle. *NBER Macroeconomics Annual*, 24(1):1–66. 10

Gerlach, S. and Peng, W. (2005). Bank lending and property prices in Hong Kong. *Journal of Banking and Finance*, 29(2):461–481. 38, 41

Girouard, N., Kennedy, M., Van Den Noord, P., and André, C. (2006). Recent house price developments: the role of fundamentals. *OECD Economics Department Working Papers*, (No. 475). 37, 44

Goodhart, C. (2008). The boundary problem in financial regulation. *National Institute Economic Review*, 206(1):48–55. 7, 11

Goodhart, C. and Hofmann, B. (2007). *House prices and the macroeconomy: implications for banking and price stability*. Oxford University Press. 3, 34, 37

Goodhart, C. and Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1):180–205. 38

Goodhart, C., Hofmann, B., and Segoviano, M. (2004). Bank regulation and macroeconomic fluctuations. *Oxford Review of Economic Policy*, 20(4):591–615. 37

Goodhart, C. A., Kashyap, A. K., Tsomocos, D. P., and Vardoulakis, A. P. (2012). Financial regulation in general equilibrium. *NBER Working Paper*, No. 17909. 29

Hahm, J.-h., Shin, H. S., and Shin, K. (2013). Noncore bank liabilities and financial vulnerability. *Journal of Money, Credit and Banking*, 45(s1):3–36. 15

Harutyunyan, A., Massara, M. A., Ugazio, G., Amidzic, G., and Walton, R. (2015). Shedding light on shadow banking. (15/1). 9, 13, 14, 15

Hastie, T., Tibshirani, R., and Friedman, J. (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Springer. 73, 76, 77

Hofmann, B. (2004). The determinants of bank credit in industrialized countries: do property prices matter? *International Finance*, 7(2):203–234. 36, 38, 44, 53

Holopainen, M. and Sarlin, P. (2017). Toward robust early-warning models: A horse race, ensembles and model uncertainty. *Quantitative Finance*, 17(12):1933–1963. 76, 87

Iacoviello, M. (2004). Consumption, house prices, and collateral constraints: a structural econometric analysis. *Journal of Housing Economics*, 13(4):304–320. 37

Jackson, P. (2013). Shadow Banking and New Lending Channels Past and Future. In Balling, M. and Gnan, E., editors, *50 Years of Money and Finance: Lessons and Challenges*, SUERF 50th Anniversary Volume Chapters, chapter 11, pages 377–414. SUERF - The European Money and Finance Forum. 21, 25

James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). *An Introduction To Statistical Learning*, volume 112. Springer. 87

Jin, Y. and Zeng, Z. (2004). Residential investment and house prices in a multi-sector monetary business cycle model. *Journal of Housing Economics*, 13(4):268–286. 37

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3):231–254. 42

Jordà, Ò., Schularick, M., and Taylor, A. M. (2011). Financial crises, credit booms, and external imbalances: 140 years of lessons. *IMF Economic Review*, 59(2):340–378. 99

Kamber, G., Morley, J., and Wong, B. (2018). Intuitive and reliable estimates of the output gap from a beveridge-nelson filter. *Review of Economics and Statistics*, 100(3):550–566. 80

Kaminsky, G., Lizondo, S., and Reinhart, C. M. (1998). Leading indicators of currency crises. *IMF Staff Papers*, 45(1):1–48. 88

Kaminsky, G. L. and Reinhart, C. M. (1999). The twin crises: the causes of banking and balance-of-payments problems. *American Economic Review*, 89(3):473–500. 74, 81, 88

Kaminsky, G. L. and Reinhart, C. M. (2000). On crises, contagion, and confusion. *Journal of International Economics*, 51(1):145–168. 81

Kaufmann, D., Kraay, A., and Mastruzzi, M. (2011). The worldwide governance indicators: methodology and analytical issues. *Hague Journal on the Rule of Law*, 3(2):220–246. 30

Kohler, M. and Van Der Merwe, M. (2015). Long-run trends in housing price growth. *RBA Bulletin*, pages 21–30. 39

Kuttner, K. N. and Shim, I. (2016). Can non-interest rate policies stabilize housing markets? evidence from a panel of 57 economies. *Journal of Financial Stability*, 26:31–44. 2, 7, 8, 9, 10, 11, 16, 21, 23, 26

Laeven, L. and Majnoni, G. (2003). Loan loss provisioning and economic slowdowns: too much, too late? *Journal of Financial Intermediation*, 12(2):178–197. 28

Laeven, L. and Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, 61(2):225–270. 21, 22, 78

Laeven, M. L. and Valencia, M. F. (2018). Systemic banking crises revisited. *IMF Working Paper 18/206*. 78

Lang, J. H., Peltonen, T. A., and Sarlin, P. (2018). A framework for early-warning modeling with an application to banks. *ECB Working Paper*. 77, 94

Lim, C. H., Costa, A., Columba, F., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T., and Wu, X. (2011). Macroprudential policy: what instruments and how to use them? lessons from country experiences. *IMF Working Paper*, pages 1–85. 2, 11, 16

Lowe, P. (2017). Household debt, housing prices and resilience. *Economic Analysis and Policy*, 55:124 – 131. 34, 64

Malpezzi, S. (1999). A simple error correction model of house prices. *Journal of Housing Economics*, 8(1):27–62. 41

Manasse, P. and Roubini, N. (2009). rules of thumb for sovereign debt crises. *Journal of International Economics*, 78(2):192–205. 75

Meen, G. (2002). The time-series behavior of house prices: a transatlantic divide? *Journal of Housing Economics*, 11(1):1–23. 37, 41

Mian, A. and Sufi, A. (2011). House prices, home equity-based borrowing, and the us household leverage crisis. *American Economic Review*, 101(5):2132–56. 3

Muellbauer, J. and Murphy, A. (1997). Booms and busts in the UK housing market. *The Economic Journal*, 107(445):1701–1727. 37, 41

Neunhoeffer, M. and Sternberg, S. (2019). How cross-validation can go wrong and what to do about it. *Political Analysis*, 27(1):101–106. 76, 77

Oikarinen, E. (2009). Interaction between housing prices and household borrowing: the Finnish case. *Journal of Banking and Finance*, 33(4):747–756. 4, 36, 38, 41, 44, 46, 50

Orphanides, A. and Norden, S. v. (2002). The unreliability of output-gap estimates in real time. *Review of Economics and Statistics*, 84(4):569–583. 80

Orsmond, D. and Price, F. (2016). Macroprudential policy frameworks and tools. *RBA Bulletin*, pages 75–86. 61

Otto, G. (2007). The growth of house prices in australian capital cities: What do economic fundamentals explain? *Australian Economic Review*, 40(3):225–238. 40

Pagan, A. R. and Pesaran, M. H. (2008). Econometric analysis of structural systems with permanent and transitory shocks. *Journal of Economic Dynamics and Control*, 32(10):3376–3395. 36, 46, 47, 49, 68, 105

Phan, T. (2014). Output composition of the monetary policy transmission mechanism: Is Australia different? *Economic Record*, 90(290):382–399. 64

Phillips, P. C. B. (1995). Fully modified least squares and vector autoregression. *Econometrica*, 63(5):1023–1078. 43

Reinhart, C. M. and Rogoff, K. S. (2009). *This Time Is Different: Eight Centuries Of Financial Folly*. Princeton University Press. 70, 80, 81

Romer, C. D. and Romer, D. H. (1990). New evidence on the monetary transmission mechanism; comments and discussion. *Brookings Papers on Economic Activity*, (1):149. 64

Sarlin, P. (2013). On policymakers loss functions and the evaluation of early warning systems. *Economics Letters*, 119(1):1–7. 74, 88, 89, 94

Saunders, T. and Tulip, P. (2019). A model of the Australian housing market. *Reserve Bank of Australia Discussion Paper Series*, (2019-01). 40, 67

Semlali, M. A. S. and Collyns, M. C. (2002). *Lending Booms, Real Estate Bubbles and the Asian Crisis*. Number 2-20. International Monetary Fund. 38

Shiller, R. J. (2013). *Finance and the good society*. Princeton University Press. 14

Shin, H. S. and Shin, K. (2011). Procyclicality and monetary aggregates. *NBER Working Paper*, (w16836). 13, 14

Shleifer, A. and Vishny, R. W. (2010). Unstable banking. *Journal of Financial Economics*, 97(3):306–318. 10

Svensson, L. E. (2017). Cost-benefit analysis of leaning against the wind. *Journal of Monetary Economics*, 90:193–213. 66

Tanaka, K., Kinkyo, T., and Hamori, S. (2016). Random forests-based early warning system for bank failures. *Economics Letters*, 148:118–121. 71, 75, 77

Tibshirani, R. (1996). Regression shrinkage and selection via the LASSO. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1):267–288. 71

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money, Credit and Banking*, 1(1):15–29. 53

Tucker, P. (2012). Shadow banking: thoughts for a possible policy agenda. Speech at the European Commission High Level Conference, Brussels. 11

Turk, R. (2015). Housing price and household debt Interactions in Sweden. *IMF Working Paper*, (WP/15/276). 44, 46

Valckx, N., Amidzic, G., Arregui, N., Blankenheim, J., Ehrentraud, J., Gray, D., Harutyunyan, A., Kiff, J., Kim, Y., Krznar, I., et al. (2014). Shadow banking around the globe: How large, and how risky? *IMF Global Financial Stability Report*, 10:65–104. 11, 13, 20

Van den Berg, J., Candelon, B., and Urbain, J.-P. (2008). A cautious note on the use of panel models to predict financial crises. *Economics Letters*, 101(1):80–83. 85

Vandenbussche, J., Vogel, U., and Detragiache, E. (2015). Macroprudential policies and housing prices: a new database and empirical evidence for central, eastern, and southeastern europe. *Journal of Money, Credit and Banking*, 47(S1):343–377. 18

Windsor, C., Jääskelä, J. P., and Finlay, R. (2015). Housing wealth effects: Evidence from an Australian panel. *Economica*, 82(327):552–577. 53

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press. 10, 23

Zhang, L. and Zoli, E. (2016). Leaning against the wind: macroprudential policy in asia. *Journal of Asian Economics*, 42:33–52. 12, 21, 26

Appendix A

Appendix Chapter 2

Table A1: Variable definition and data sources

Variable	Source	Description
Real GDP growth	OECD	Quarterly growth
Short-term real interest rate	IFS	Three-month interbank rate
Long-term real interest rate	IFS	Ten-year government bonds
Term spread		Calculated as the gap between the long-term rate and the short-term rate
Systemic banking crisis dummy	Laeven and Valencia (2013)	
Chinn-Ito financial openness index	Chinn and Ito (2008)	Normalized to 1-100, annual

Appendix B

Appendix Chapter 3

Table B1: Variable definition and data sources

Abbrevation	Variable	Description	Source
h	housing stock	Per household, in logs. Chain volume measures. The following capital accumulation equation is used to estimate the quarterly data, while the end-year housing stock data is directly taken from the end-year net capital stock from the ABS. h_t=(1- quarterly depreciation rate)*h_{t-1}+gross fixed capital formation$_{t-1}$, (that is, residential investment$_{t-1}$) for the gap within a year. The depreciation rate is calculated as (consumption of fixed capital in dwellings)/(net capital stock of the last year)*100.	ABS
hp	real house price index	In logs, deflated by underlying CPI. Hedonic home value index. Eight Capital City Aggregate Dwellings. I backed out the series using quarterly growth from ABS measure for 1990Q1-1995Q4 to get longer time coverage	Corelogic
hdi	household disposable income	Per household, in logs, seasonally adjusted, deflated by underlying CPI. After tax, before the deduction of interest payments, includes income of unincorporated enterprises	RBA
debt	real household debt	Per household, in logs, deflated by underlying CPI	ABS
r	real interest rate	Calculated as nominal mortgage rate - inflation expectation	RBA
i	policy rate	Nominal policy rate, 3 months average	RBA
π	underlying inflation	Trimmed-mean inflation, seasonally adjusted. 2002-2017 from ABS, and the rest is back out with growth rate from the RBA.	ABS, RBA
tot	terms of trade	Seasonally adjusted. Calculated as export price/import price*100	ABS
	number of household	Interpolated from the three censuses (1986, 1991, 1996) where household is counted approximately by the private occupied dwelling before 1994. After 1994, The annual/biannual data from ABS 4130.0-Housing Occupancy and Costs are linearly interpolated	ABS

Table B2: Unit root tests for the order of integration

Test on levels (5% p-value)[a]			
	ADF	PP	Characteristic[b]
h	0.384	0.87	t
hdi	0.425	0.427	t
debt	0.783	0.91	t
hp	0.67	0.809	t
r	0.032	0.243	t
i	0.005	0	t
π	0	0.256	t
Test on first differences (5% p-value)			
h	0.005	0.005	i
hdi	0	0	i
debt	0.094	0	i
hp	0.021	0	i
r	0	0	i
i	0	0	i
π	0	0	i

[a] The null hypothesis is non-stationarity in both the ADF test and the PP test

[b] The different characteristics in the tests are: both time trend and intercept (t), or only intercept (i)

Figure B1: Cost-push shock (Transitory) - extended model

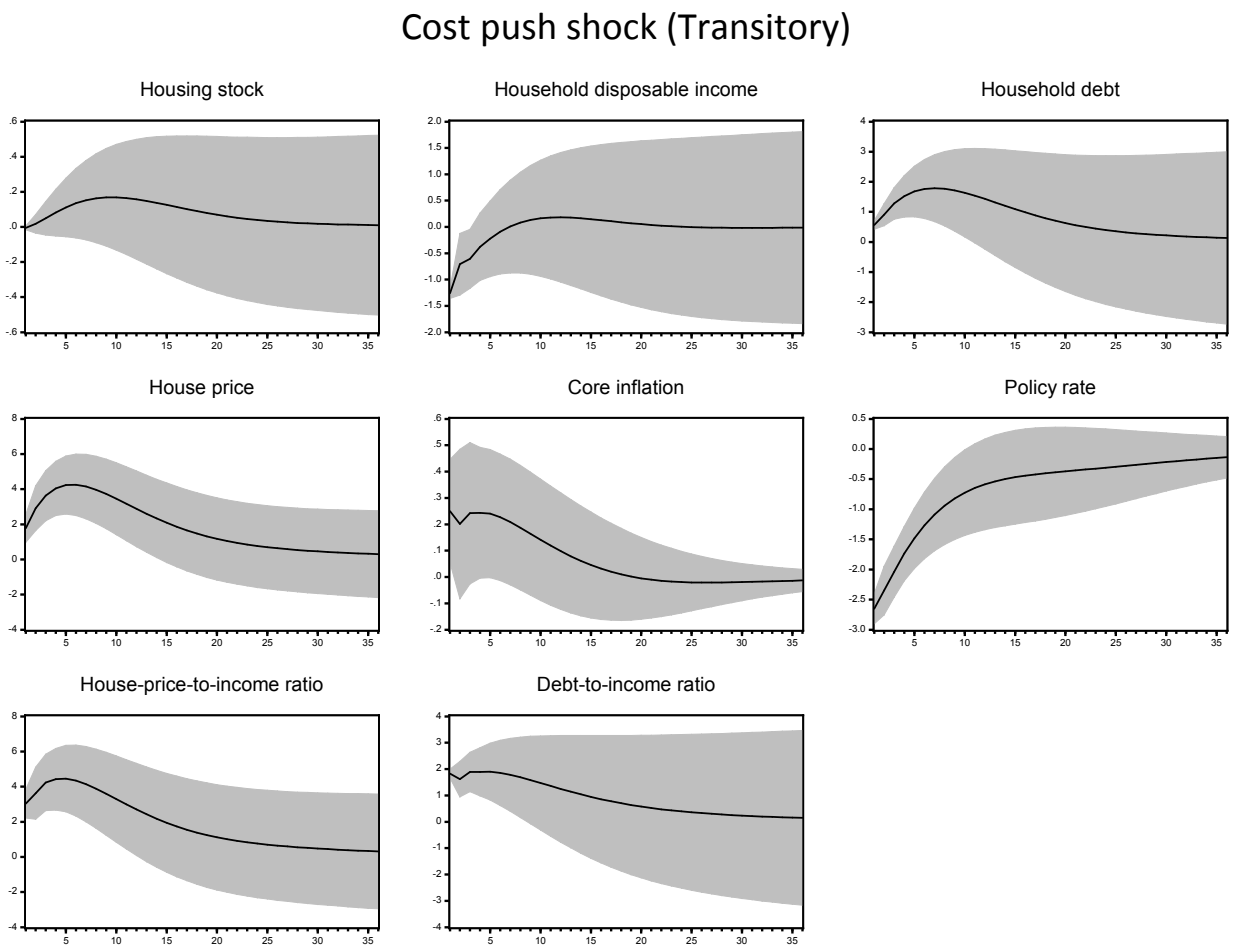


Figure B2: Housing supply shock (Permanent) - extended model

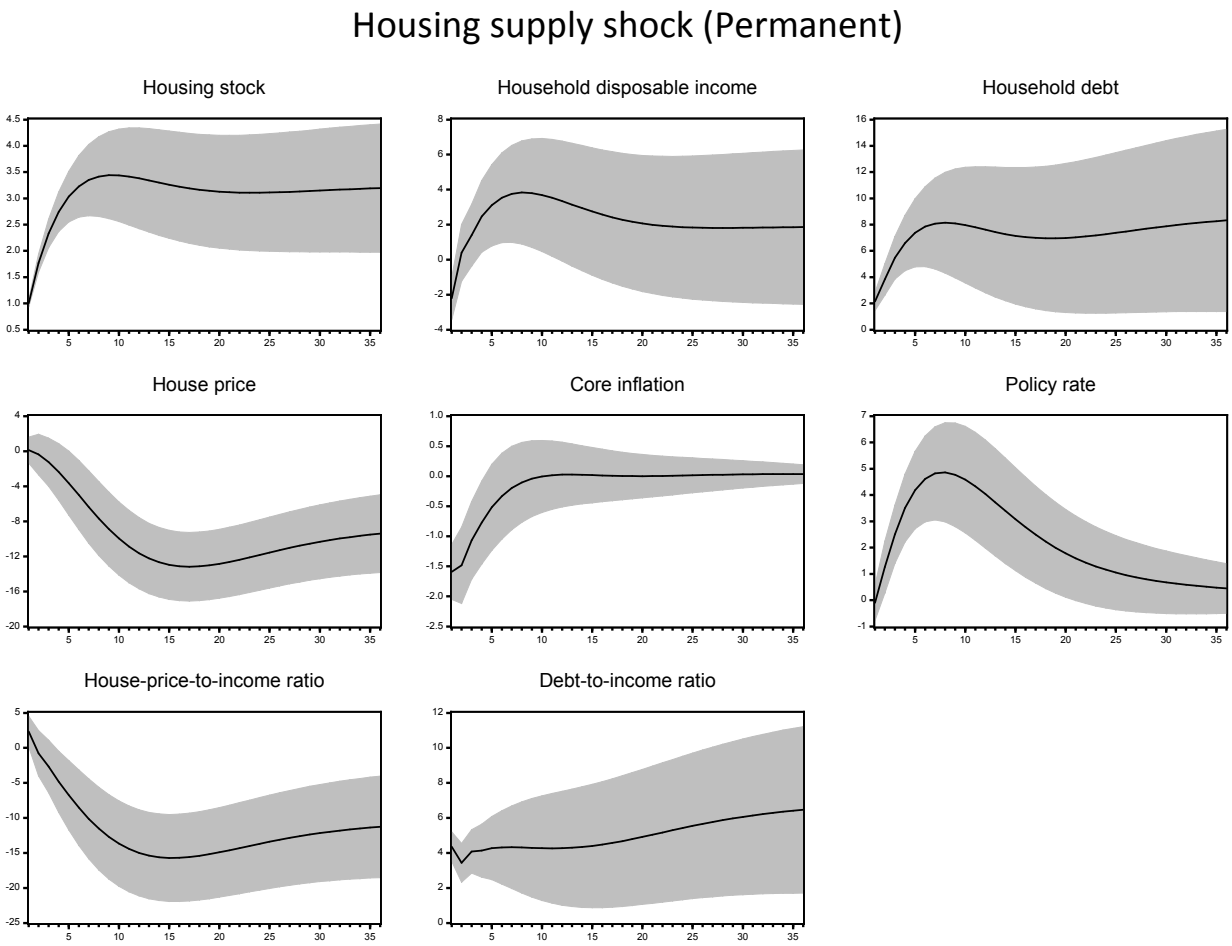


Figure B3: Household income shock (Permanent) - extended model

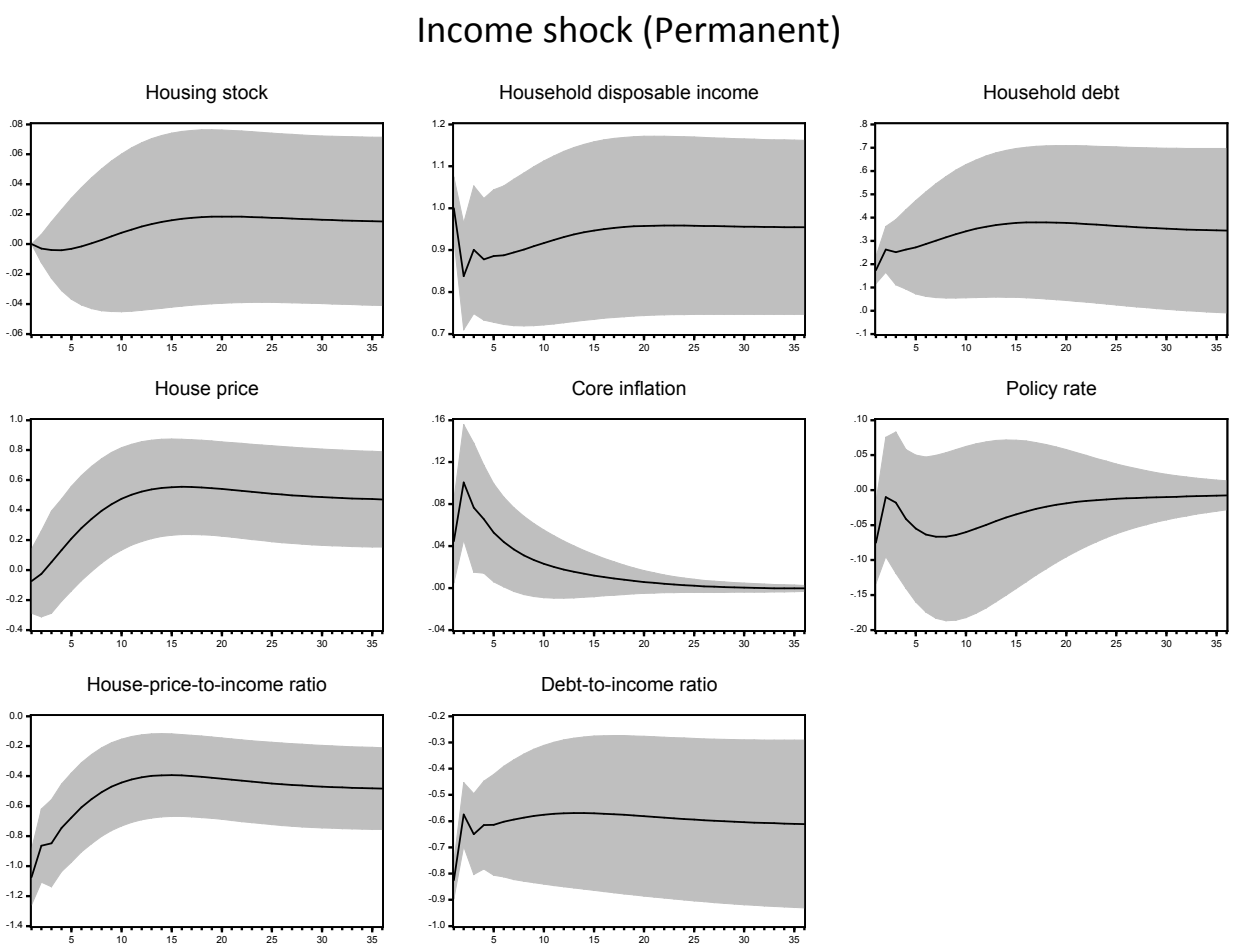


Figure B4: Credit condition shock (Permanent) - extended model

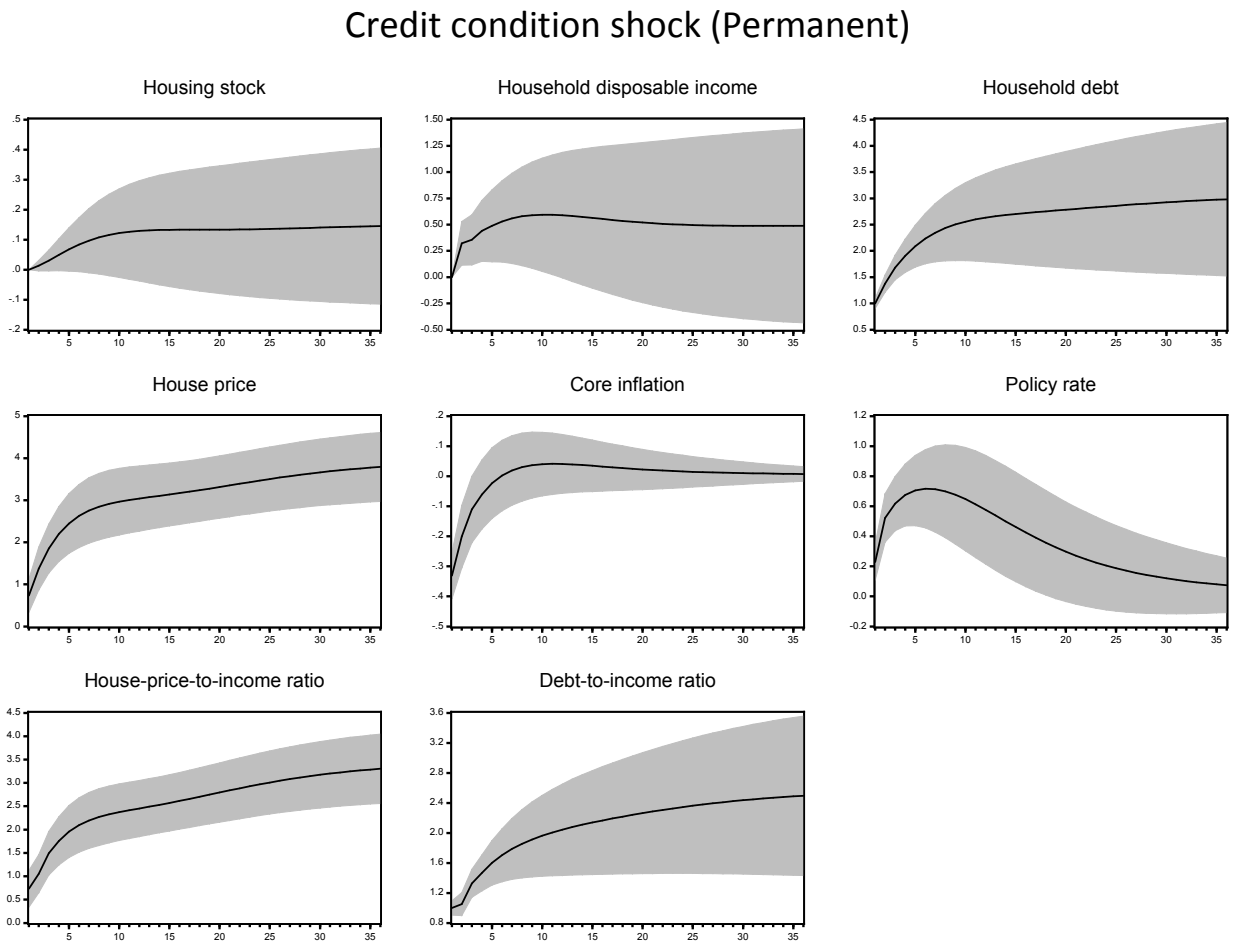
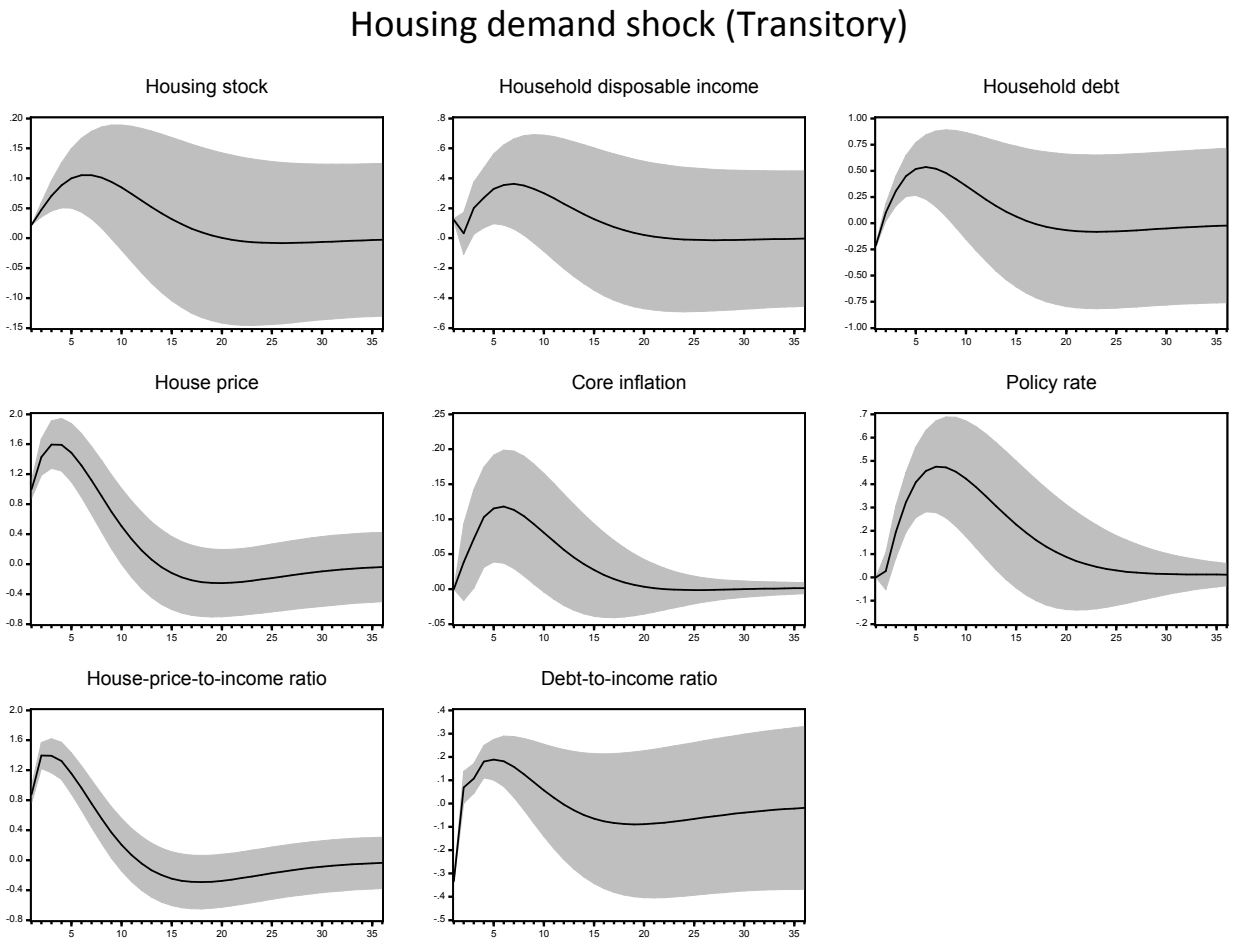


Figure B5: Housing demand shock (Transitory) - extended model



Appendix C

Appendix Chapter 4

Table C1: Variable definition and data source

Variable	Source	Description
Credit growth	BIS	The year-to-year growth rate of Credit to Private non-financial sector from all sectors at market value - US dollar - Adjusted for breaks
Credit-to-GDP gap	BIS	Calculated by applying the modified BN filter to the credit-to-GDP ratio, which is the Credit to Private non-financial sector from all sectors at market value - Percentage of GDP - Adjusted for breaks
Real GDP growth	OECD	Year-to-year growth
Inflation	OECD	Calculated from OECD CPI index
Short rate	OECD	three month Interbank rate
Long rate	OECD	mostly 10-year government bonds
Term spread	OECD	Calculated as the gap between the long rate and the short rate
Current account in percentage of GDP	OECD	
Real effective exchange rate	OECD	Index 2015=100
Equity price growth	OECD	Year-to-year growth, calculated from OECD share price index, 2010=100
Real house price growth	OECD	Year-to-year growth, calculated from OECD real house price index
House-price-to-income ratio	OECD	
House-price-to-rental ratio	OECD	
House-price-to-income gap	OECD	Calculated by applying the modified BN filter to the house-price-to-income ratio
House-price-to-rental gap	OECD	Calculated by applying the modified BN filter to the house-price-to-rental ratio