The Cause of Housing Market Fluctuations in China

An Indirect Inference Perspective

Yue Gai

Supervisor: Prof. Patrick Minford

Dr Zhirong Ou

Economics Department

Cardiff University

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation contains fewer than 65,000 words including appendices, bibliography, footnotes, tables and equations and has fewer than 150 figures.

Yue Gai

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Abstract

This thesis addresses two main issues related to the housing market in China. It discovers: i) the key driving forces behind the movements of housing price and the evaluation of the model's capacity in fitting the data. ii) try to identify whether the Chinese housing market can be explained better by using a model with collateral constraint. The Dynamic Stochastic General Equilibrium (DSGE) model including the housing sector and capturing some important features of the Chinese economy is employed to explore the above questions. Moreover, an Indirect Inference method is used to explore these issues in an empirical way. Estimation results show that the estimated model using Indirect Inference method can explain the data behaviour well. The estimated model shows that the capital demand shock plays a significant major role in explaining the housing price dynamic. In terms of the second issue, the Indirect Inference testing results show that the model with collateral constraint cannot provide better performance in explaining the data.

Table of contents

List of figures

List of tables

Chapter 1

Introduction

1.1   Background and Motivation

Background

The housing market in China has experienced extraordinary development during recent decades. There was no housing market before 1980, with the Chinese government controlling housing investment and construction, treating houses as welfare goods before commencing reform. The state allocated housing to enterprises and institutions (also known as work units), with the work units providing apartments directly to their workers as welfare goods charging very low rent. According to Minetti and Peng (2012), 'welfare-oriented' public housing had some weaknesses. First, the state could not supply enough funding to take responsibility for housing maintenance or the increase in housing supply. Second, the low rent did not ensure good residential conditions. Gradual and persistent housing institution reforms started to be issued from 1980 onwards. In the very beginning, individuals could get state-owned houses at a lower price, roughly one-third of the cost of similar privately owned housing.

Full marketisation reform in the housing market started in 1998, promoting the privatisation of housing. The abolishment of the 'welfare-oriented' public housing provision and

adoption of a more radically 'market-oriented' housing provision accelerated the development of the housing market in China. Houses were treated as a commodity at prices determined by the market after market-oriented reform. This reform lead to the Chinese housing market boom. Figure 1.1 presents the official housing index obtained from the China Real Estate Index System (CREIS) [1] and shows that although full marketisation reform started in 1998, there was no significant increase until 2002. The Chinese housing market experienced substantial growth from 2002 until the recent global financial crisis in 2007. The housing price index jumped from 98 points at the very beginning to around 145 points in 2006 and around 190 points in 2010, an increase of 1.5 times in the former period and almost double in the latter period. Also, Liu and Ou (2017) highlight the dramatic increase (184%) in the price of commercial residential housing in China between 2002 and 2014.
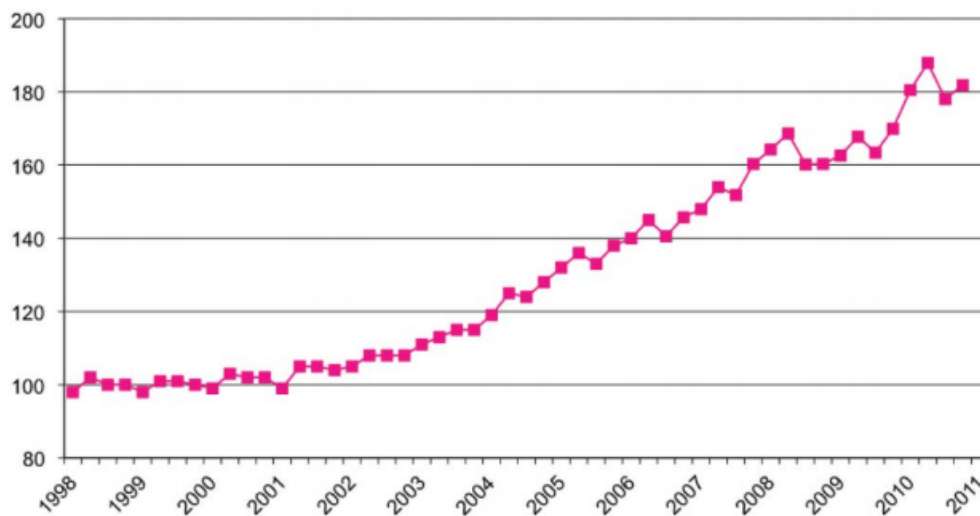
Fig. 1.1 The housing price index
Source: cited in Wu (2015)

The dramatic rise is not the only feature of Chinese housing prices, with volatility also a significant factor. Minetti and Peng (2012) use the log difference of seasonally adjusted real housing price to show the growth rate of housing price between 1998 and 2011. Figure 1.2

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[1]The National Statistics Bureau compile CREIS, which is based on a property sample from 70 cities.

shows the volatility of housing prices in China during that period, with the growth rate of housing prices changing frequently, ranging from approximately -7.5% to 10%.
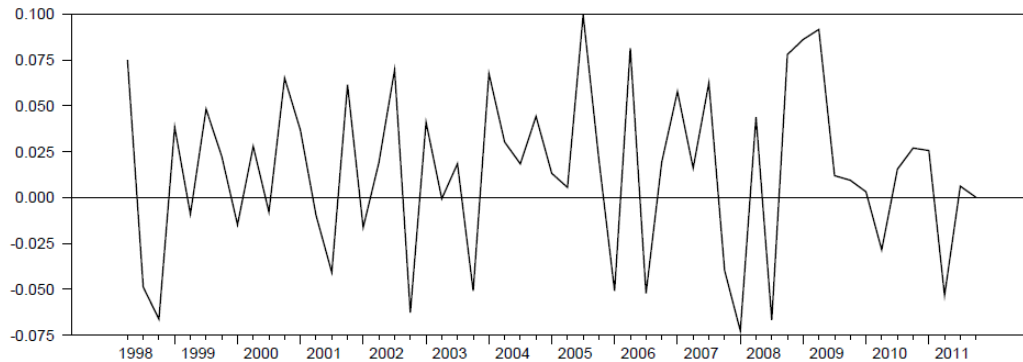
Fig. 1.2 The growth rate of housing price
Source: cited in Minetti and Peng (2012)

Motivation

Considerable attention is paid by not only academia but also society to the dynamic of housing prices, arousing wide concern and discussion. Many would agree that the development of the housing market has made an important contribution to the Chinese economy. Fluctuations in the Chinese housing market are also a concern, especially with the collapse of the US housing market in 2007 fresh in the memory. The following issues related to the housing market in China also focused my attention on undertaking research in this area.

Firstly, the large volatility in housing prices in China mentioned in the last section attracted me to understand what determines housing price dynamics in China? Accordingly, it is necessary to develop a theoretical framework that can maximally replicate housing market behaviour in China.

Secondly, there is growing interest in following Iacoviello type models that use housing as collateral to study the Chinese economy. However, whether housing collateral is important to the business cycle is an important question to investigate. I want to ascertain whether the model assumption (housing collateral) can fit the data in China. One reason for doubting

the reasonableness of the assumption concerns the propensity of consumption in China. The reason for introducing housing collateral in developed countries is practical, with housing often used as collateral for a large proportion of borrowing (Iacoviello (2005)). Compared to the high propensity to consume in developed countries, China has the highest saving rate in the world according to Kraay (2000). Household in China usually use their saving to consume, not borrowing, especially using housing as collateral. Baldacci et al. (2010) highlight this, showing that two components lead to a decline in the household consumption ratio, one being changes in the savings rate and the other the share of household income in GDP. Accordingly, Chapter 4 will test whether housing collateral is statistically important to the business cycle in China.

In summary, this thesis will examine two main issues: the key driving forces behind housing price movements and the evaluation of the benchmark model's capacity to fit the data; ii) to identify whether the Chinese housing market can be explained better by using a model with collateral constraint rather than the benchmark model.

1.2 Methodology and Findings

Methodology

A Dynamic Stochastic General Equilibrium (DSGE) model with Indirect Inference evaluation and estimation are employed to explore the above questions. In particular, some important features of the Chinese housing sector are considered in my model. Firstly, two sectors are allowed on the supply side of the economy with explicit modelling of the price and quantity of the housing sector to study the behaviour of the housing sector. Secondly, productivity shock in both housing and general sectors are assumed to be non-stationary. The reasons for including these features in the model will be carefully discussed in Chapter 3.

There are two contributions in this thesis. First, the New Keynesian dynamic stochastic general equilibrium (DSGE) model is set up by incorporating housing sector and some important features of the Chinese economy, providing a framework to describe the Chinese housing market in reasonable detail. Second, differing from previous literature, this research employs a different evaluation and estimation strategy - Indirect Inference method.

In order to check whether a theoretical framework can explain housing market behaviour in China, a powerful Indirect Inference testing procedure is employed to apply in the New Keynesian DSGE model with the housing sector. The Indirect Inference method evaluates the model's capacity to fit the data by providing a classical statistical inferential framework, as introduced by Minford et al. (2009) with Le et al. (2011) refining this method using Monte Carlo experiments. The evaluation aims to compare the simulated data generated by the model and the actual data through the auxiliary model . A cointegrated vector autoregressive with exogenous variables (VARX) has been chosen as the auxiliary model. The Wald statistic is employed as the criterion for evaluating the model, which compare the Wald statistic calculating using simulated data with using actual data.

The Indirect Inference estimation strategy is also used in this thesis. This estimation method is widely used in the estimation of structural models, such as by Smith (1993), Gregory and Smith (1991), Gourieroux et al. (1993) and Canova (2007). The idea behind the Indirect Inference estimation is to search for a set of parameters that are best able to satisfy the test criterion, with the details of Indirect Inference testing and estimation procedure introduced in Chapter 3.

Findings

The main empirical findings related to the above two research questions reveal: i) Indirect Inference testing results show that the data reject the model using the calibration values. However, the estimated model using Indirect Inference method can explain the data behaviour

well. I discover the housing market using the estimated model. Concerning the driving force behind fluctuations in the Chinese housing market, the variance and shock decomposition suggest that capital demand shock plays a significant major role in explaining housing prices. ii) Indirect Inference testing results show that the model with collateral constraint does not perform better at explaining the data. The benchmark model using the Wald statistic as a guide is the best model.

1.3   Thesis Structure

The remainder of this thesis is structured as follows. Chapter 2, following the above two motivations, summarises literature on the volatility of housing prices in term of theoretical and empirical works, and reviews structured DSGE models with collateral constraint and the transmission mechanism working behind it. Chapter 3 focuses on exploring the first research question concerning the key driving forces behind movements in the housing sector. In order to answer this question, a New Keynesian DSGE model incorporating the housing sector and some important features of the Chinese economy has been established as the benchmark model. This theoretical framework is then evaluated using Indirect Inference testing and estimated during the sample period by using Indirect Inference estimation. Standard analyses of housing price dynamics are also presented. Chapter 4 focuses on the second research question. One more feature, collateral constraint, is added to the benchmark model to identify whether the Chinese housing market can be explained better using a model with collateral constraint than the benchmark model. The Indirect Inference method is used to discriminate between these two models, with Monte Carlo experiments showing how powerful the test is. In addition, empirical analyses of the collateral model are displayed at the end of this chapter. Chapter 5 concludes all the findings of the different chapters.

Chapter 2

Literature Review

As mentioned in Chapter 1, there are two main research questions relating to the Chinese housing market I am going to answer in this thesis: i) The key driving forces behind the movements of housing price and the evaluation of the model's capacity in fitting the data. ii) try to identify whether the Chinese housing market can be explained better by using a model with collateral constraint compared to the benchmark model. Following these two motivations, this chapter surveys the literature on the housing market. More specifically, Section 2.1 summarises the literature on the volatility of housing price in terms of theoretical and empirical works. Section 2.2 reviews the structured DSGE models with collateral constraint and the transmission mechanism working behind it.

2.1   The Source of Housing price Dynamics

Empirical

In the existing empirical literature, the housing price fluctuation is affected by the economic fundamentals. The main fundamental explanatory factors are construction costs, disposal

income and population. There is no consensus among researchers regarding the source of housing price dynamics in the existing empirical literature.

Case and Shiller (1990) find various fundamental factors can explain the variation in housing prices, especially positively correlated with the change in construction costs, population growth and disposal income. The analogous results given by Clapp and Giaccotto (1994) show that population growth and employment have considerable forecasting ability to forecast the residential housing price variations. Capozza et al. (2002) use panel data to explore the driving force of real house price dynamics. The results of their research show that shocks such as growth rates,and construction costs affect house price differently. The high real income growth and high real construction costs lead to real house price continue to rise, which cause significant overshooting. However, population growth does not have explanatory power in explaining real house price dynamics. The results coincide with the findings given by Poterba et al. (1991). He attempts to explain why housing prices vary so dramatically in the US using the regression model. The empirical results suggest that household income and construction costs are the most important driving force leading house price dynamics.

Potepan (1996) include more social environmental variables into his research such as rent, land prices, household income, population, quality of public services, criminal rate, air pollution, inflation, mortgage, interest rates, property tax rate, construction costs, agricultural land prices and legal land use constraints. The results show that household disposable income and construction costs have stronger explanatory power on house price fluctuation.

Some fundamentals variables considerably influence housing price in the short-term, other variables have more explanatory power in the long-term. Quigley (2002) employ 41 U.S. metropolitan areas data over a fifteen-year period to study the average housing price variation influenced by economic fundamentals. The empirical findings show that some fundamentals variables such as unemployment rate, housing supply and construction permission cannot

give the powerful explanation in housing variation in the short run, but explain well in the long run.

Another explanation for the fluctuation of housing price is monetary policy. Jud and Winkler (2002) study the dynamics of real housing price appreciation in 130 metropolitan areas across the United States. Their study finds that not only population growth, real income changes can strongly affect real house price, but monetary policies also influence the variation in housing price in the long run. Ahearne et al. (2005) focus on the study of the influence of monetary policy on the housing price dynamics. The empirical results show that monetary policy plays a significant role in explaining the fluctuation of the house price. Similar results reported by Jacobsen and Naug (2005) show that interest rates, housing construction, unemployment rates and household income play an important role in explaining the house price dynamics in Norwegian.

For China, researchers also want to explore whether these factors have the same explanatory power on house price dynamics. They explore Chinese housing market influenced by the fundamental factors from both demand and supply sides. Many have the similar conclusion that the fluctuation of housing price in China is mainly a reflection of the market fundamentals.

Li and Chand (2013) study the contribution of market fundamentals to house prices in urban China using annual data from 29 provinces. Their findings show that the level of income, construction cost and user cost of capital are the primary determinants of house prices. It is quite interesting to find that the supply factors including construction costs, the user cost of capital play a significant role in explaining more developed provinces. Wang and Zhang (2014) evaluate the importance of fundamental changes in explaining the rising housing prices in China. The results suggest that the fundamental factors such as population, wage income and construction costs can account for a major proportion of the housing price rise. Similar results can be found in Chow and Niu (2015). They use annual data to show

that the fundamental economic factors in both demand and supply side can explain well in the variation in housing prices, with income determining demand and construction affecting supply. Deng et al. (2009) agree the conclusion that the fundamental factors such as income, housing supply and construction cost are the important determinant, but in their research, interest rate and population growth cannot explain the variation of housing price.

Monetary policy is also an explanation for the house price dynamics in China. Some researchers believe that the monetary policy plays a significant major role in explaining the real housing price in China rather than economic fundamentals. Xu and Chen (2012) employ quarterly data from 1998 to 2009 to study the impact of monetary policy variables on the fluctuation of house prices in China. Empirical results suggest that the volatility of housing prices is mainly driven by monetary policy, which an expansionary monetary policy increase the growth of housing price while restrictive monetary policy decreases the growth of housing price. The similar results can be found in Zhang et al. (2012), Yu (2010) and Guo and Li (2011). They believe that monetary factors such as bank loan rate, excess liquidity, money supply growth, mortgage rate and mortgage down payment requirement can explain the housing price dynamics well.

There is no consensus among researchers regarding the source of housing price dynamics in the existing empirical literature using a single regression model. Liu and Ou (2017) give the explanation why use single regression model may come across such an ambiguity. The first reason they summarised is using a single regression model may exit the omitted variable problem when the 'equilibrium conditions' are derived and put forward for estimation. Hence, it is easy to understand why some factor is shown to be significant in one model, but in other models not. It may be because the model has failed to consider other important factors that would reflect the facts.

The second issue when using this method is endogeneity problem, which forces econometricians either to assume these variables are exogenous such as Deng et al. (2009) just cited,

or using 'instruments' to avoid inconsistent estimation. Liu and Ou (2017) list two reasons showing that endogeneity problem does not go away even employing a more inclusive model, which is just inherent in any model version where equilibrium is estimated with a single equation. On the one hand, the economic interactions as reflected by the data would be artificially abandoned in the modelling process by imposing exogeneity. On the other, the partial equilibrium model omits the information about the rest of the world. The endogeneity arises due to little information about the 'true' instruments, which can overstate the standard error of the coefficients of these variables causing some variables to be shown insignificant even they are important.

These studies of the housing price dynamics using the various econometric models exist the above two issues that cannot solve to its root. Therefore, some researchers go one further to employ a dynamic econometric model (VAR or VECM). There are some advantages of using VAR and VECM model. On the one hand, VAR and VECM can circumvent the endogeneity problem through using lag for all explanatory variables. On the other hand, some factors such as gender, marriage and urbanisation are difficult to model in a structural model, but VAR and VECM can consider as one of the explanatory variables. (Liu and Ou (2017))

Vargas-Silva (2008) study the importance of monetary policy shock in explaining the housing market in the U.S. using VAR. The results show that monetary policy shock plays a significant role in explaining the house price dynamics. There is a negative relationship between housing price and contractionary monetary policy shock. Lastrapes et al. (2002) use a different identifying restriction to study the impact of money on the housing price. They have a similar conclusion that money supply shock contributes significantly to the variance in housing price. Gete (2009) use an SVAR to study the housing market in OECD countries. He finds that housing demand shock is the essential factor for house price dynamics.

In terms of the literature of housing price dynamics in China using VAR or VECM, Bian and Gete (2015) employ VAR identified with theory-consistent sign restrictions to study housing dynamics in China. They consider seven potential determining factors such as population increase, credit constraint, housing preference, savings rate, tax policy, change in land supply and productivity progress. Their results suggest that productivity, savings and policy stimulus play an important role in explaining the housing price dynamics in China, even if all shocks play relevant roles. Garriga et al. (2017) study the importance of the structural transformation and urbanisation process to the Chinese housing market. Their findings suggest that supply factors and productivity are the dominant drivers in housing price dynamics in China.

However, according to Liu and Ou (2017), there are some limitations that VAR or VECM cannot address. In terms of policy analyses, there is little information about the transmission mechanism that policymakers would be interested since these reduced form models cannot provide such information about how the housing price is determined. Although some researchers try to use theoretical restrictions on estimating to cover this issue, however, the implication is often sensitive to the imposed restrictions. Therefore, a micro-foundation structural model is chosen in this thesis to study the housing market dynamics in China, which can show the causalities among economic variables that established as a result of different agents' interactions with their optimal choice. Hence, it is necessary to set up a model that can capture the transmission mechanism and fit the data well.

Theoretical

A micro-founded dynamic stochastic general equilibrium (DSGE) model is widely used to study the dynamics of the housing market and the transmission mechanism working behind it. The increasing researchers have followed Iacoviello (2005) and Iacoviello and Neri (2010) to discover the housing market fluctuation, which use housing as collateral for loans to study

the housing sector and business cycles. In their extended model, the collateral constraint is faced by both firms and impatient households. Iacoviello and Neri (2010) construct a DSGE model including a rich housing sector to a framework to study the sources and consequences of fluctuations in the U.S. housing market using the Bayesian method. On the supply side of their model, they consider a multi-sector structure with different rates of technological progress to capture some important observations in the housing market. The other feature of their model is on the demand side. They introduce the collateral constraint by splitting households into two different types: patient (lenders) and impatient (borrowers). They treat the constraint as a channel to emphasise the spillovers effect, which the increase of housing price affect borrowing and consumption of constrained households. Their results show that housing demand shock and productivity shock in the housing sector are the main driving force of the volatility of housing prices. The contribution of monetary factors in housing price appears more important in the long term. In terms of consequences of fluctuations, their results show that the collateral constraint amplifies the effects on consumption given the increase of housing price.

There is growing interest in Iacoviello-type model studying the driving forces of housing price dynamics in China. More factors are considered to enrich the model based on their analysis framework in the following literature. Minetti and Peng (2012) focus on the demand side and try to identify whether there is social psychology - the 'keeping up with the Zhangs' behaviour - that influence households' behaviour and thus drives the fluctuation of housing price. They include the factor of 'keeping up with the Zhangs' in the utility function and assume that there is a positive relationship between the household's utility and individual consumption in housing purchases. On the contrary, there is a negative relationship between the household's utility and society's average consumption in housing services. Their Bayesian estimation results show that there is 'keeping up with the Zhangs' and the presence of this social psychology play a significant major role in explaining the volatility of real housing

prices. Liu and Ou (2017) focus on the banking system to investigate the source of housing price dynamics, which allow for a 'shadow' bank affiliated to the 'normal' bank capturing Chinese economy. They find that housing demand shock is the main driving force for housing price fluctuation, which accounts for over 80%.

In terms of the DSGE framework, monetary policy variable is also an important explanation for the fluctuation of the house price. Researchers analyse different monetary policies to study how to stabilise the housing market in China. Ng (2015) use an estimated DSGE model with a Taylor rule to discover the sources and consequence of fluctuations in the Chinese housing market. In addition, they also discover what is housing demand shock in China. Their model is based on Iacoviello and Neri (2010)'s framework with sectoral heterogeneity on the supply side and collateral constraint considered on the demand side. Their estimated results show that housing demand shock is the main driving force in explaining the house price dynamics. Monetary policy also contributes significantly and appears more important in the 1990s. Ng (2015) employ a price rule - Taylor rule to study, while Wen and He (2015) adopt a quantity rule - McCallum rule to discover the key driving force of housing price fluctuations in China. Money supply and credit constraint are considered in their model to capture some features of the Chinese economy. Empirical results show that housing demand shock plays an important role in explaining the fluctuation of the house price. Money supply shock cannot explain housing price movements compared with housing demand shock. On the other hand, their policy suggestion shows that it is better to include the real housing price in monetary policymaking. The combination of real housing price and money supply rule can stabilise the Chinese economy. Zhou et al. (2013) consider in a similar vein. In order to study how to stabilise the expanding housing market, they summarised a series policies that the Chinese government issued into four different categories: land policy, monetary policy, property tax policy and affordable housing policy. The empirical results show that a policy

mix can keep the housing market stable, which the property tax policy control the demand side while the land policy adjusts the supply side.

In summary, most of the literature that using a micro-founded DSGE model employing Bayesian estimation have come to conclude that the housing demand shock plays an important role in explaining the fluctuation of housing price in China. Policy suggestion given by the above literature shows that some policy such as property tax and property purchasing limitations could affect housing demand directly so that to decrease the house price and keep the housing market stable.

2.2 Collateral Constraint

In the last section, I summarise the literature about the sources of fluctuations in the Chinese housing market. In this section, I am going to focus on the literature about collateral constraint in the structured DSGE model. We learn a lesson from some developed countries that a slump in housing prices might have a seriously negative effect on the wider macroeconomy. The reason is the housing property is usually used as a significant collateral. Therefore, the transmission mechanisms is set up through the collateral constraint and link the housing market and the real economy.

The model with collateral constraint

I introduce a channel that connects the housing market and the wider economy: the collateral constraint. There are different ways to introduce the collateral constraint into the structure model either on the firm side or the household side. In this thesis, I focus on the household side, which follows Iacoviello and Neri (2010) and includes the collateral constraints into the structured DSGE model.

The increasing interest in DSGE housing model literature have focused on the role of collateral constraint.The collateral constraint is first introduced to explain the financial crisis by Kiyotaki and Moore (1997). The line of this research introduces how collateral constraint interact with aggregate economic activity over the business cycle. More specifically, they endogenise the collateral constraint that limits the borrowing capacity. There are two types of agents in their framework: patient agent and impatient agent. The patient agents are called gatherers in their paper, which is a saver. The impatient one are called farmers in their paper, which can be thought as entrepreneurs or firms that wish to borrow from the patient agent to finance their investment projects. The difference between the patient agent and impatient agent is that they have a different rate of time preference. The collateral constraint is faced only by the impatient agent.[1] Therefore, loans will only be made when the impatient household use some other form of capital (such as land, buildings and machinery) as collateral. The borrowers' credit limit and an investment decision are affected by the value of the collateral asset and the tightness of the credit market. That implies if the value of durable assets decreases for any reason, the borrowing capacity of the impatient household also decreases. In such an economy, A significant transmission mechanism is generated through the dynamic interaction between credit constraint and asset prices, which the effects of exogenous shocks persist, amplify and spread out.

The transmission mechanism of collateral constraint in Kiyotaki and Moore (1997) shows that how a small scale, temporary shocks to productivity or income distribution can give rise to large changes in production and asset prices and also their effects spillover to the rest of the economy. The key point in their paper is the collateralisable asset plays two different roles in their model: i) they are a factor of production. ii) they serve as collateral for loans. Suppose that there is a negative productivity shock, which reduces the land price. The decrease in land price reduces the net worth of the impatient agents because land is the collateralisable asset.

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[1]The collateral constraint in Kiyotaki and Moore (1997) is: $R_t b_t \leq q_{t+1} k_t$, where R_t is the nominal interest rate, b_t is the amount of borrowing, q_{t+1} is the durable asset price in the next period,k_t is the durable asset.

The constrained agents are forced to reduce their investment, which also affects them in the next period. The credit cycle works like this: less revenue they earn (due to less investment), less net worth they gain. Again they reduce investment because of credit constraints. That implies the temporary shock in period t has a significant impact on the behaviour of the constrained agents not only in period t but also in following periods. There are two factors affect the amplification of the shock: the credit limit and the price of the collateralisable asset. Therefore, a significant transmission mechanism is generated through the dynamic interaction between credit limits and asset prices, which amplify the shocks and spillover to the economy.

Extension of the model with collateral constraint

Following Kiyotaki and Moore (1997)'s work, Iacoviello (2005) extend his work by including two features. First, instead of using land as the collateral, he uses housing stock owned by the entrepreneurs as the collateral to borrow. Second, he uses nominal debts like Christiano et al. (2010). He studies a monetary business cycle model with endogenous collateral constraints and nominal debt. The estimation results show that the collateral effects significantly improve the efficiency of the economy to a positive demand shock. In particular, Iacoviello and Neri (2010) consider the collateral constraint in the housing market. They construct a dynamic stochastic general equilibrium model with collateral constraints estimated using Bayesian methods to study the source and consequence in the US housing market.

There are two important features of housing captured by the DSGE model of the housing market they developed. The first is sectoral heterogeneity on the supply side. The second is the collateral constraint on the demand side. On the supply side of the economy, Iacoviello and Neri (2010) allow for multiple sectors with different rates of technological progress. The non-housing sector employs labour and capital to produces consumption, business investment and intermediate goods. The housing sector using capital, labour land and intermediate goods

to produce new houses. In their model, following most of the DSGE literature, nominal wage rigidity is presented in both the non-housing and housing model and price rigidity is only allowed in the non-housing sector. The reason for developing the multi-sector structure is based on the observation of the housing market. The post-world-war-II U.S. data show that the relative price of housing has a long-run upward trend. The probable reason is heterogeneous trend technological progress between the housing and other sectors of the economy.

The second feature of their model is the collateral constraint on the demand side. Iacoviello and Neri (2010) introduce this constraint on the demand side by splitting households into two different types: patient household (lenders) and impatient household (borrowers). Similar in Kiyotaki and Moore (1997), the difference between patient and impatient household is they have a different rate of time preferences. Patient households buy consumption goods and housing goods and also supply labour. They lend funds to both firms and impatient household. Impatient households also buy consumption and housing goods and supply labour. The difference is they need to borrow money from the patient household to finance their down payment due to their high impatience. Hence, the change in housing price affects the behaviour of the impatient household.

The collateral constraint is one of the important feature in Iacoviello and Neri (2010)'s work. The transmission mechanism of collateral constraint in Iacoviello type model work as following. When there is a positive demand shock, the demand for housing rise, housing price also increases. The rise in asset prices increases the borrowing capacity of the debtors. That implies they can borrow more due to the high asset prices, allowing them to spend and invest more. The change in investment will cause the output to fluctuate, which in turn influences the current asset price. Therefore, a significant transmission channel is generated through the dynamic interaction between the credit constraint and asset prices.

Based on their analysis framework, more types of shocks and frictions are introduced to study the housing market. Ng (2015) employ Iacoviello type model to study the sources and consequences of the fluctuations in the Chinese housing market. In terms of the nature of shocks driving housing price dynamic, they find that housing demand shock explains the majority of the fluctuations in housing price. In terms of spillover effect work through the collateral constraint, there is not a unique way to quantify the effect, which depends on the nature of shocks. Housing demand shock has a larger contribution to the spillover effect compared to the technology shock. However, the technology shock plays a negligible role in the spillover effect. Liu and Ou (2017) use a DSGE model with a collateral constraint considering shadow bank to study the Chinese housing market. Apart from investigating the main driving force of housing market fluctuation, they also study the housing market spillovers effect in China. They find that there is a weak spillover effect from the housing market to the wide economy. He et al. (2017) employ a Bayesian DSGE model with collateral constraints to investigate the interaction between the housing market and the business cycle. They find that the collateral constraint plays a significant role in explaining the fluctuate of the business cycle in China, which amplifies the impact of various economic shocks.

Chapter 3

Benchmark Model

3.1 Introduction

Based on the background of the housing market in China discussed in Chapter 1, we know that the Chinese housing market has experienced extraordinary growth during the past decades. In the very beginning, the individuals could get the state-owned houses at a meagre price which is only one-third of the cost of housing. The full marketisation reform started in July 1998 in the following stages. The housing market in China has experienced the first round of market boom since that. Liu and Ou (2017) mentioned in their paper, there is a considerable increase (184%) of commercial residential housing price in China over the period between 2002 and 2014. Besides, according to Minetti and Peng (2012), the Chinese housing prices are volatile. They show that the growth rate of housing prices approximately ranged from -7.5% to 10% and the growth rate changes frequently. Therefore, these factors raise my interest to think about what is the main driving force behind housing price fluctuations in China. This is also one of the research questions I listed in Chapter 1, which I am going to answer in this chapter.

As Reviewed in Chapter 2, the Chinese housing market has been attracting the increasing economists to study although it does not exist for a long time. A dynamic stochastic

general equilibrium (DSGE) model constructed by Iacoviello and Neri (2010) estimated using Bayesian methods is widely used to identify the main driving force of housing price fluctuation in China and study the transmission mechanism working behind it. Ng (2015) use an estimated DSGE model with a Taylor rule (price rules) to discover the sources and consequence of fluctuations in the Chinese housing market. They find that not only housing preference shock, monetary policy shock also contribute significantly to the volatility of housing prices in China. While in the same year, Wen and He (2015) adopt another policy rule, McCallum rule (quantity rules), to check whether it can stabilise the housing market. They show that housing demand shock is the main driving force in housing price dynamics, and a real house price-augmented money supply rule is a better monetary policy for China's economic stabilisation. Minetti and Peng (2012) using a DSGE model to analyse China's housing market in a different way. They focus on the demand side and try to identify whether there is a social psychology force that affects households' behaviour in the housing market and thus drives the housing price dynamic. The results show that the social psychology "keeping up with the Zhangs" plays an important role in explaining housing price dynamic. Liu and Ou (2017) employ a DSGE model to investigate the driving force of housing price dynamics in China. In order to capture the situation in China, they model the featured operating of the ordinary and 'shadow' banks in China. They have the similar findings that the housing demand shock is the essential factor of the housing price fluctuation. In summary, most of the literature that using a micro-founded structural DSGE model employing Bayesian methods have come to conclude that the housing demand shock plays an important role in explaining the fluctuation of housing price in China.

It should be noticed that none of the previous DSGE literature about Chinese housing market evaluates the model's capacity in fitting the data. It is quite important to evaluate how best the empirical performance of DSGE models is. Therefore, this gap is going to be filled in this chapter. A powerful testing procedure (Indirect Inference) is employed to

apply in the New Keynesian dynamic stochastic general equilibrium (DSGE) model with the housing sector in China and check whether this theory can explain China's housing market. The Indirect Inference evaluation is proposed initially in Minford et al. (2009) and refines by Le et al. (2011) who evaluate this method using Monte Carlo experiments. This testing aims to compare the simulated data with the actual data through the auxiliary model. An auxiliary model that is entirely independent of the theoretical one is used in this approach to generate a description of data against the performance of the theory. A cointegrated vector autoregressive with exogenous variables (VARX) is chosen as the auxiliary model. The Wald statistic is employed as the criterion for evaluating the model, which compare the Wald statistic calculating using simulated data and using actual data. For Indirect Inference estimation, a set of parameters that are best able to satisfy the test criterion are found when carried out the testing. In the empirical procedures, Indirect Inference is used to test the model on some initial parameter values that mainly based on previous literature. If the structured model with calibrated value cannot pass the test, Indirect Inference estimation is used to improve the overall performance of modelling fitting, which is based on Indirect Inference testing. It allows the parameters to move flexibly to the values that maximise the criterion of replicating the data behaviour. The detail of Indirect Inference testing and estimation procedure are going to be introduced in Section 3.3.

This chapter is organised as follows: In Section 3.2, I first highlight some features of the model in this chapter and then display the model setting. The principles and procedures of the indirect inference method for evaluating and estimation are explained in Section 3.3. Section 3.4 displays data description and also shows the calibration of the structure model. Empirical results are discussed in Section 3.5. Firstly, I present the estimation and testing results and then check the properties of the model like impulse response functions, shock and variance decomposition. Section 3.6 is the conclusion part.

3.2 Model

3.2.1 Key Features in the Model

As mentioned in Chapter 1, there are two main research questions relating to the Chinese housing market I am going to answer: i) the key driving forces behind the movements of housing price and the evaluation of the model's capacity in fitting the data. ii) try to identify whether the Chinese housing market can be explained better by using a model with collateral constraint compared to the benchmark model. A Dynamic Stochastic General Equilibrium (DSGE) model with Indirect Inference evaluation and estimation are employed to explore the above questions. This chapter focus on the first issue that what is the sources of fluctuations in the Chinese housing market. There are some important features of the Chinese housing sector considered in my research. First of all, two sectors are allowed on the supply side of the economy with explicit modelling of the price and quantity of the housing sector to study the behaviour of the housing sector. Secondly, the productivity shock in both housing and general sector are assumed to be the non-stationary shock.

In terms of the first feature, early literature on using a micro-foundation based DSGE modelling approach studying the housing sector usually construct a multi-sector structure which includes housing and non-housing products in a Real Business Cycle (RBC) model such as Campbell and Ludvigson (1998), Davis and Heathcote (2005) and Baxter (1996). They allow homogeneity among different sector enjoying the same competitive attribute - perfect competition. However, in the Real Business Cycle (RBC) model, money is typically said to be neutral in both the long run and short run. Some monetary transmission mechanism cannot work in this scenario. As we know from some previous literature, monetary policy variables play a significant role in explaining the real housing price. I also want to check how monetary policy works in the structure model. In Iacoviello and Neri (2010)'s work, price rigidity is introduced in the general sector and keep the housing price flexible. There

are several reasons why housing might have the flexible price. According to Barsky et al. (2003), housing production is very sensitive to a monetary contraction, while the production of general goods not. More specifically, the value of new houses decreases by almost 10% compared to CPI when there is a monetary contraction. They also show that compared to the inflation persistence of CPI, there do not exhibit any inflation persistence of new houses. As in Barsky et al. (2007), a high value on the housing allows a bargaining space on the price of housing goods. I follow their idea to construct the firm side with two sectors but simplify their setting, which assumes factor market in both sectors operates perfectly competitive.

In terms of the second feature of the model, other than most previous literature, the productivity shocks in both housing sector and general sector are assumed to be non-stationary. The reason for setting non-stationary productivity shock is practical and substantial: practical because, empirically, after the financial crisis, the output cannot go back to the previous level. Le et al. (2014) use Figure 3.1 to show this stylized fact in China, which shows the level of output cannot reach its previous level after the crisis. The non-stationary shocks could shed light on the large deviations from steady time trends that economies experience no matter booms or crises; Substantial because, non-stationary is the feature of macroeconomic data. On the other hand, a model using nonstationary data could explain the large deviations from steady state, which those models using stationary data do not. The business cycle model focus on studying the dynamics and choice of macroeconomic policy on stabilising the fluctuations, which try to abstract from the uncertainty surrounding the economy's long-term future and eliminate the trends from the data so as to make it stationary. Hodrick-Prescott (HP) and Band Pass (BP) filters are the most common techniques that used in trend-removal. However, HP and BP filters are a mathematical tool used in the business cycle to decompose the raw data into cyclical and trend component, which are not based on theories. Hence, the precision of the driving process that leads to trend behaviour cannot be identified using these techniques. In addition, according to Cogley and Nason (1995) and Murray (2003), they

study the spurious dynamic causing from HP and BP filters to non-stationary data and show that these filters cannot distinguish between difference-stationary and trend-stationary. The business cycle dynamics can be generated using the HP filter even if they are not present in the original data. Therefore, instead of using filtered data, the non-stationary data are used to evaluate and estimate the model.

In addition, according to Le et al. (2014), they develop a model of the Chinese economy using a DSGE framework with a banking sector based on non-stationarity to shed light on the banking crisis in China. The model with non-stationary productivity shock can successfully explain China's economy well. Therefore, I follow Le et al. (2014) to propose a DSGE model with non-stationary productivity shock to study the Chinese housing market in my research.
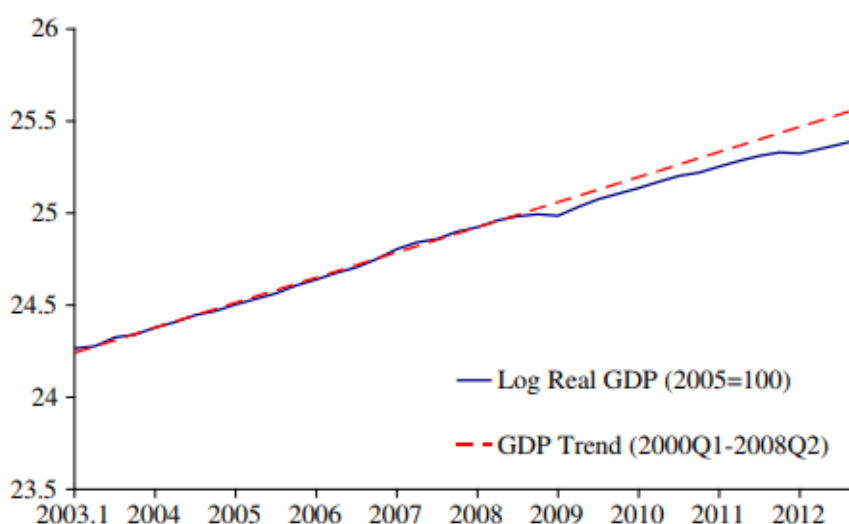
Fig. 3.1 China real GDP per capita and pre-crisis trend
Source: cited in Le et al. (2014)

3.2.2 The Model Setting

The households on the demand side of the economy try to maximise their lifetime utility by choosing general consumption goods as well as bond, supplying labour and accumulating housing in each period. There are two goods sectors on the supply side: housing goods sector and general goods sector. Housing sector produces new housings, and general sector produces general consumption goods. Assuming labour and capital markets in both sectors operate perfectly competitive and factors flow freely across two sectors. Price rigidity is allowed in the general sector and flexible price presents in the housing sector. Taylor rule is used as monetary policy by the central bank. A various of shocks are introduced in the economy, which will be specified in the model.

Households

There is a continuum of measure one of households. The household's decisions consist of maximising lifetime utility subject to a period by period budget constraint. Assuming a constant relative risk aversion utility function (CRRA), the representative households' lifetime utility can be written as

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \varepsilon_t^p \left[\frac{C_t^{1-\sigma_c}}{1-\sigma_c} + \varepsilon_t^h \frac{H_t^{1-\sigma_h}}{1-\sigma_h} - \varepsilon_t^l \frac{N_t^{1+\eta}}{1+\eta} \right] \tag{3.1}$$

where E_0 is the expectation formed at period 0, $\beta \in (0,1)$ is the discount factor. The households obtain utility from general consumption goods C_t, houses H_t and disutility from labour supply N_t. The parameters σ_c, σ_h are the inverse of intertemporal elasticity of substitution of consumption and housing, while η denotes the inverse of the elasticity of labour supply with respect to real wage. It measures the substitution effect of a change in the wage rate on labour supply.

Three shocks are introduced in the utility function: $\varepsilon_t^p, \varepsilon_t^h$ and ε_t^l. The terms ε_t^p and ε_t^l capture the shocks to intertemporal preferences and to labour supply. The shock ε_t^h is what the previous literature called housing preference shock or housing demand shock. According to Iacoviello and Neri (2010), the housing demand shock can be some social, institutional or income changes and so on, which might shift households preferences on purchase housing relative to other consumption goods. According to the literature, all these three shocks are assumed followed an AR(1) process:

$$\ln \varepsilon_t^p = \rho_p \ln \varepsilon_{t-1}^p + v_{p,t} \tag{3.2}$$

$$\ln \varepsilon_t^h = \rho_h \ln \varepsilon_{t-1}^h + v_{h,t} \tag{3.3}$$

$$\ln \varepsilon_t^l = \rho_l \ln \varepsilon_{t-1}^l + v_{l,t} \tag{3.4}$$

where $v_{p,t}$, $v_{h,t}$ and $v_{l,t}$ are independently and identically distributed i.i.d. processes with variances σ_p^2, σ_h^2 and σ_l^2.

The households' period by period budget constraint in real terms is given by:

$$C_t + p_{h,t}[H_t - (1 - \delta_h)H_{t-1}] + B_t = w_t N_t + (1 + r_{t-1})B_{t-1} + \Pi_t \tag{3.5}$$

From equation (3.5), it should be noticed that the households can use his wealth in each period to buy consumption goods, bond and also to accumulate houses. Note that the housing price is the relative price. All of these outflows of funds of the households is shown on the left-hand side of equation (3.5). The households' wealth on the right-hand side consists of real wages w_t earned from supplying labour N_t, the interest rate gain of bond holdings from the previous period $(1 + r_{t-1})B_{t-1}$ and also the real profits Π_t from firms. Then, the aim of the households is trying to maximise the utility function (3.1), subject to the budget constraint

(3.5) by choosing C_t, N_t, B_t and H_t via the Lagrangian. Given the first order conditions, there comes:

$$\varepsilon_t^p C_t^{-\sigma_c} = \lambda_t \tag{3.6}$$

$$\varepsilon_t^l \varepsilon_t^p N_t^{\eta} = \lambda_t w_t \tag{3.7}$$

$$\lambda_t = \beta E_t \lambda_{t+1}(1 + r_t) \tag{3.8}$$

$$\lambda_t p_{h,t} = \varepsilon_t^p \varepsilon_t^h H_t^{-\sigma_h} + \beta E_t \lambda_{t+1}(1 - \delta_h) p_{h,t+1} \tag{3.9}$$

For all the above equations, the marginal utility loss of choosing relevant allocations is shown on the left-hand side. Compared to that, the right-hand side expresses the marginal utility gain. Combining equation (3.6) and equation (3.8), we could get the well-known Euler equation. It is a dynamic optimality condition showing a dynamic optimality decision for consumption in the present and the future. The optimal intra-temporal substitution between labour and consumption is shown when combining equation (3.7) and equation (3.6). The difference between this paper and the classical New Keynesian model is I have one more equation to represent housing demand, which can be found in equation (3.9). In the housing demand equation, we can see that the marginal utility gain of increasing in housing services is equal to the marginal utility loss of decreasing in consumption. There are two parts consisting of marginal utility gain of increasing housing housing services. One is housing services in the current period. The other is the expected value of housing.

Firms

On the supply side, as mentioned earlier, there are two sectors: general sector as well as the housing sector. The general sector and housing sector produce consumption goods and new houses using capital ($K_{c,t}$, $K_{h,t}$) and labour ($N_{c,t}$, $N_{h,t}$). Sticky prices is introduced in the general sector by assuming monopolistic competition through Calvo-style contracts and flexible housing price is allowed in the housing sector, which two sectors use different technologies ($A_{c,t}$, $A_{h,t}$). As mentioned in Section 3.2.1, there are two reasons why housing might have flexible prices. First, housing is relatively expensive, which have a bargaining space on the price of housing. Second, housing production is very sensitive to a monetary contraction. In the following, I first display some common features in both housing sector and general sector and then discuss the behaviour of each sector respectively.

The Representative Firm

The general sector and housing sector both hire labour ($N_{c,t}$, $N_{h,t}$) and buy capital ($K_{c,t}$, $K_{h,t}$) to produce consumption goods ($Y_{c,t}$) and new houses ($Y_{h,t}$). The technology in different sectors available to economy is described by a constant-return to scale production function [1]:

$$Y_{i,t} = A_{i,t} K_{i,t-1}^{\alpha} N_{i,t}^{1-\alpha} \quad i = c, h \tag{3.10}$$

where $0 \leq \alpha \leq 1$ is output elasticities of capital. It measures the responsiveness of output to the change of capital. $Y_{i,t}$ is consumption goods when $i = c$ and is housing goods when

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[1] I do not include the factor land on the supply side of the housing sector in my research. The reason is I focus on the cyclical fluctuations in the Chinese housing market and abstract from the long-run housing price dynamics that may be related to long-run income and population growth. Land expansion is a proportion of the population growth. According to Deng et al. (2008), they use the empirical study to show that the population growth in China is one of the key variables in the urban land expansion. And also, Deng et al. (2009) reject the role that population growth is an important determinant factor in explaining the fluctuation of housing price in China. In addition, the housing price consists of land price and house value. The land price rise in proportion with population, which is not concerned in my research. I focus on the later one housing value that is the fluctuation of the housing price.

$i = h$. $K_{i,t-1}$ and $N_{i,t}$ represent capital and labour in the different sectors. $A_{c,t}$ measures productivity in the non-housing sector and $A_{h,t}$ captures the technology in the housing sector. As mentioned earlier, the productivity shock in both sectors are assumed to be non-stationary, which follow a stochastic trend. Therefore, the stochastic process of productivity shock can be written as:

$$\Delta lnA_{c,t} = \rho_{c,t}\Delta lnA_{c,t-1} + v_{c,t} \tag{3.11}$$

$$\Delta lnA_{h,t} = \rho_{h,t}\Delta lnA_{h,t-1} + v_{h,t} \tag{3.12}$$

This specification implies that shocks, $v_{i,t}$, will have permanent effects on the level of $A_{i,t}$. The firm invest capital following the linear capital accumulation identity.

$$K_{i,t} = I_{i,t} + (1 - \delta_k)K_{i,t-1} \quad i = c, h \tag{3.13}$$

where δ_k is the depreciation rate and $I_{i,t}$ is the gross investment in the different sector.

Housing Sector

Firms in the housing market operate the perfectly competitive product, which hire labours and buy capitals to produce new houses. Empirical studies show that the capital stock does not change very much from period to period. Economists usually rationalise this by assuming that there are some forms of "adjustment costs" that prevent firms from changing their capital stock too quickly. Hence, the "capital adjustment costs" is introduced in the firm side so that to avoid the investment excessively volatility. Assuming there is a convex adjustment cost to capital facing by the representative firm. I use the quadratic form for tractability.

$$\Phi(.) = \frac{\kappa}{2}(K_{h,t+1} - K_{h,t})^2 \tag{3.14}$$

The function $\Phi(.)$ represents capital adjustment costs, which is assumed to satisfy $\Phi(0) = \Phi'(0) = 0$ and $\Phi''(0) > 0$. κ captures a multiplicative constant, which affects adjustment costs. The firms discount future profit flows by stochastic discount factor. The stochastic discount factor was defined as:

$$M_t = \beta^t \frac{E_0 u'(C_t)}{u'(C_0)} \tag{3.15}$$

The reason why the stochastic discount factor written like this is because this is how households value future dividends. An additional units of utility $u'(C_t)$ is generated at time t because of one unit of dividend returned to the household, which using β to discount back to the present period 0. Therefore, the firm maximise the present discounted value of profit,

$$V_h = E_0 \sum_{t=0}^{\infty} M_t [Y_{h,t} p_{h,t} - I_{h,t} - (w_t + \varepsilon_t^{nh}) N_{h,t} - \frac{\kappa}{2} (\Delta K_{h,t})^2] \tag{3.16}$$

subject to the constraints law of motion of the capital stock (3.13) and production function (3.10) by choosing capital $K_{h,t}$ and labour $N_{h,t}$

Imposing the constraints in each period, the firm's problem can be re-written as:

$$\max_{K_{h,t}, N_{h,t}} V_h = E_0 \sum_{t=0}^{\infty} M_t [(A_{h,t} K_{h,t-1}^{\alpha} N_{h,t}^{1-\alpha}) p_{h,t} - (w_t + \varepsilon_t^{nh}) N_{h,t}$$
$$- (1 + \varepsilon_t^{kh}) K_{h,t} + (1 - \delta_k) K_{h,t-1} - \frac{\kappa}{2} (\Delta K_{h,t})^2] \tag{3.17}$$

where the terms ε_t^{nh} and ε_t^{kh} are the labour demand shock and capital demand shock in the housing sector, which capture other imposts or regulation on firms' use of capital and labour respectively. Over the last two decades, China has maintained a rapid economic growth rate and experienced housing institution reforms. These have significantly affected capital demand of housing industries and are plausible sources of capital demand shock. The firms in the housing sector optimally choose capital and labour to maximise their profits. The

demand for labour and capital are represented below:

$$(1 - \alpha) \frac{Y_{h,t}}{N_{h,t}} p_{h,t} = (w_t + \varepsilon_t^{nh})$$ (3.18)

Equation (3.18) shows the labour demand of firms in the housing sector, which sets the marginal product of labour equal to labour price- the real unit cost of labour to the firm w_t and the stochastic shock term ε_t^{nh}.

$$(1 + r_t)[1 + \kappa(K_{h,t} - K_{h,t-1}) + \varepsilon_t^{kh}] = \frac{\alpha Y_{h,t}}{K_{h,t}} p_{h,t} + (1 - \delta_k) + \kappa(K_{h,t+1} - K_{h,t})$$ (3.19)

Equation (3.19) represents the capital demand of firms in the housing sector. ε_t^{kh} is the stochastic shock to capital demand. From the above equation, we can see that firms can either invest $1 + \kappa(K_{h,t} - K_{h,t-1}) + \varepsilon_t^{kh}$ amounts of bonds in period t, which yields a gross return of $(1 + r_t)[1 + \kappa(K_{h,t} - K_{h,t-1})]$ in period $t + 1$ or to get the additional unit of capital (marginal product of capital) yields $A_t F_K(K_t, N_t)$ units of output next periods. Also, an extra unit of capital reduces tomorrow's adjustment costs by $\kappa(K_{h,t+1} - K_{h,t})$

General Sector

Production in the general sector is split into two stages, where the final goods stage operate perfect competition and the intermediate goods stage is monopolistic competition. For the final goods stage, the general final goods are produced by applying a constant elasticity (CES) bundler of intermediate goods. The downward sloping demand curve for intermediate goods producers is obtained through the profit maximisation in the final goods sector operating competitively. For the intermediates goods stage, the intermediate goods are produced using the Cobb-Douglas production function. The large number of intermediates producers behave as monopolistically competitive and have pricing power. The difference between the general

sector and the housing sector is the intermediate producers in the general sector optimises along three dimensions, not only capital and labour but also price of intermediate goods. The intermediate goods firms in the general sector can exploit their market power.

The Final Goods

There are one final goods firm and a continuum of intermediate goods firms (of unit indexed by $k \in [0,1])$. The final goods firms behave as perfectly competitive and produce the final goods at the time $t, Y_{c,t}$, which aggregates the continuum of intermediate goods in period t, $Y_{c,t}(k)$ according to the CES production function.

$$Y_{c,t} = \left[\int_0^1 Y_{c,t}(k)^{\frac{\psi-1}{\psi}} dk \right]^{\frac{\psi}{\psi-1}} \tag{3.20}$$

where there is an assumption: $\psi > 1$; ψ is the elasticity of substitution among the different intermediate goods. The integral is raised to the power $\psi/(\psi-1)$ to make the production function display constant returns to scale.

Final good firms face the problem of profit maximising.

$$\max_{Y_{c,t}(k)} P_{c,t} Y_{c,t} - \int_0^1 P_{c,t}(k) Y_{c,t}(k) dk \tag{3.21}$$

substitute out $Y_{c,t}$ using equation (3.20). The profits will end up with zero since the firm behaves as perfectly competitive, which total revenue that the final goods price times the amount of final goods minus total cost that the price of all intermediate goods times quantity.

$$\max_{Y_{c,t}(k)} P_{c,t} \left[\int_0^1 Y_{c,t}(k)^{\frac{\psi-1}{\psi}} dk \right]^{\frac{\psi}{\psi-1}} - \int_0^1 P_{c,t}(k) Y_{c,t}(k) dk \tag{3.22}$$

The first order conditions with respect to $Y_{c,t}(k)$:

$$P_{c,t} \left[\int_0^1 Y_{c,t}(k)^{\frac{\psi-1}{\psi}} dk \right]^{\frac{1}{\psi-1}} Y_{c,t}(k)^{-\frac{1}{\psi}} = P_{c,t}(k) \tag{3.23}$$

this results in the demand function for intermediate goods k

$$Y_{c,t}(k) = Y_{c,t} \left(\frac{P_{c,t}(k)}{P_{c,t}} \right)^{-\psi} \tag{3.24}$$

this demand function represents that the demand for intermediate goods depends negatively on its relative price and positively on total production. Substitute out $Y_{c,t}(k)$ using equation (3.24) into (3.20) comes:

$$Y_{c,t} = \left[\int_0^1 \left[Y_{c,t} \left(\frac{P_{c,t}(k)}{P_{c,t}} \right)^{-\psi} \right]^{\frac{\psi-1}{\psi}} dk \right]^{\frac{\psi}{\psi-1}} = Y_{c,t} \left[\int_0^1 \left(\frac{P_{c,t}(k)}{P_{c,t}} \right)^{1-\psi} \right]^{\frac{\psi}{\psi-1}} \tag{3.25}$$

rewrite equation (3.25) gives,

$$\frac{1}{P_{c,t}} = \left[\int_0^1 \left(\frac{1}{P_{c,t}(k)} \right)^{\psi-1} dk \right]^{\frac{1}{\psi-1}} \tag{3.26}$$

and this results the aggregate price level,

$$P_{c,t} = \left[\int_0^1 P_{c,t}(k)^{1-\psi} dk \right]^{\frac{1}{1-\psi}} \tag{3.27}$$

The Intermediate Goods Firms

The intermediate goods firms behave as monopolistically competitive, and the Cobb-Douglas production function is used to produce intermediate goods. They optimise along three dimensions, not only capital and labour like in the housing sector but also price. The intermediate goods firms set price following a Calvo rule (Calvo (1983)). That is in each period, a fraction $1 - \omega$ of firms are randomly selected to reset their price for period t, $P_t^\star(k)$.

The rest fraction ω of firms are not able to choose their prices optimally. They keep their price as same as the last updating.

The intermediate goods firms in the general sector share the similar optimal behaviour of choosing capital and labour like in the housing sector. The optimal choice of labour and capital in the general sector are presented below [2]:

$$(1 - \alpha)\frac{Y_{c,t}}{N_{c,t}} = (w_t + \varepsilon_t^{nc}) \tag{3.28}$$

Equation (3.28) shows the labour demand of firms in the general sector. The marginal product of labour equal to its price w_t, which is the real wage that is common to all firms in both sectors. ε_t^{nc} is the labour demand shock in the general sector.

$$(1 + r_t)[1 + \kappa(K_{c,t} - K_{c,t-1}) + \varepsilon_t^{kc}] = \frac{\alpha Y_{c,t}}{K_{c,t}} + (1 - \delta_k) + \kappa(K_{c,t+1} - K_{c,t}) \tag{3.29}$$

Equation (3.29) represents the capital demand in the general sector. It shares the same interpretation in the housing sector. The left-hand side of equation (3.29) gives the intermediate firms behaviour of investing bonds in period t with the gross return of $(1 + r_t)[1 + \kappa(K_{c,t} - K_{c,t-1})]$ in period $t+1$. The right-hand side shows the return of getting the additional unit of physical capital. Therefore, it is equivalent to invest bond or capital. ε_t^{kc} is capital demand shock in the general sector.

The labour demand and capital demand in the general sector are obtained by maximising the discounted present value of profits. However, the choice of optimal price is not part of today's maximisation problem. The reason is the optimal price that chosen in period $t+n$ is independent of the price chosen today, which depends on the realisation of the economy from period t to period $t+n$ and information available in period $t+n$. There are often two steps to

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[2]The detailed derivation can be found in Housing sector

obtain the optimal price. First, minimise the costs to get marginal cost and then maximise the market value of intermediate goods firms subject to the demand for their output by the final goods firm following a Calvo contract (Calvo (1983)).

The firms in the general sector face the cost minimisation problem.

$$\min_{K_{c,t}(k),N_{c,t}(k)} \left[r_t K_{c,t}(k) + w_t N_{c,t}(k) \right] \tag{3.30}$$

subject to the production function, equation (3.10). obtain the marginal cost

$$mc_t = \frac{1}{\alpha^\alpha (1-\alpha)^{1-\alpha}} A_t^{-1} r_t^\alpha w_t^{1-\alpha} \tag{3.31}$$

Price rigidity is introduced in the general sector and follow Calvo (1983) contract. That implies the firms cannot change their prices freely each period. In particular, in each period a fraction ω of firms are not able to change its price and has to stick to the price chosen in the previous period. The rest firms $(1-\omega)$ can adjust their prices at time t. A firm is given the ability to change its price at time t. It adjusts their prices to maximise the expected discounted value of profits, since it will, in expectation, be stuck with this price for more than just the current period. In this case, the firm discount factor contains two parts, not only have the usual stochastic discount factor but also include the probability that firm cannot change their price. Hence, the firms will discount profits s periods into the future by:

$$\beta^s \frac{u'(C_{t+s})}{u'(C_t)} \omega^s \tag{3.32}$$

where $\beta^s \frac{u'(C_{t+s})}{u'(C_t)}$ is the usual stochastic discount factor and ω^s is the probability that firm will be stuck with a price for s periods. If ω is small, then the firms get to update their prices frequently and thus will heavily discount future profit flows when making current pricing decisions. On the other hand, if ω is large, it is very likely that a firm will be "stuck" with

whatever price it chooses today for a long time and thus be relatively more concerned about the future when making its current pricing decisions.

The intermediate goods firms choose the optimal price in case of the possibility of being stuck with a price. The firms try to maximise the profit :

$$\max_{P_{c,t}(k)} E_t \sum_{s=0}^{\infty} (\omega\beta)^s \frac{u'(C_{t+s})}{u'(C_t)} \left(\frac{P_{c,t}(k)}{P_{c,t+s}} Y_{c,t+s}(k) - mc_{t+s}Y_{c,t+s}(k) \right) \qquad (3.33)$$

substitute out $Y_{c,t+s}(k)$ using equation (3.24) gives:

$$\max_{P_{c,t}(k)} E_t \sum_{s=0}^{\infty} (\omega\beta)^s \frac{u'(C_{t+s})}{u'(C_t)} \left(\frac{P_{c,t}(k)}{P_{c,t+s}} \left(\frac{P_{c,t}(k)}{P_{c,t+s}} \right)^{-\psi} Y_{c,t+s} - mc_{t+s} \left(\frac{P_{c,t}(k)}{P_{c,t+s}} \right)^{-\psi} Y_{c,t+s} \right)$$
$$(3.34)$$

Equation (3.34) shows the problem that intermediate goods firm faced to maximise the real profits discounted by the stochastic discount factor and the probability of being able to change the price. The optimal behaviour of choosing price is:

$$E_t \sum_{s=0}^{\infty} (\omega\beta)^s \Lambda_{t,t+s}((1-\psi)P_{c,t}(k)^{-\psi}P_{c,t+s}^{-(1-\psi)}Y_{t+s} + \psi P_{c,t}(k)^{-\psi-1}mc_{t+s}P_{c,t+s}^{-(1-\psi)}Y_{c,t+s}) = 0$$
$$(3.35)$$

where $\Lambda = \frac{u'(C_{t+s})}{u'(C_t)}$, to make it simply:

$$E_t \sum_{s=0}^{\infty} (\omega\beta)^s \Lambda_{t,t+s}((\psi-1)P_{c,t}(k)^{-\psi}P_{c,t+s}^{-(1-\psi)}Y_{c,t+s})$$
$$= E_t \sum_{s=0}^{\infty} (\omega\beta)^s \Lambda_{t,t+s}(\psi P_{c,t}(k)^{-\psi-1}mc_{t+s}P_{c,t+s}^{-(1-\psi)}Y_{c,t+s}) \qquad (3.36)$$

Here come the optimal price $P_t^{\star}$ that replaced $P_{c,t}(k)$ set by intermediate goods firms:

$$P_t^{\star} = \frac{\psi}{\psi - 1} \frac{E_t \sum_{s=0}^{\infty} (\omega \beta)^s \Lambda_{t,t+s} (mc_{t+s} P_{c,t+s}^{-(1-\psi)} Y_{c,t+s})}{E_t \sum_{s=0}^{\infty} (\omega \beta)^s \Lambda_{t,t+s} (P_{c,t+s}^{-(1-\psi)} Y_{c,t+s})} \tag{3.37}$$

Each firm updating their price will follow the same optimal pricing behaviour, which is shown in equation (3.37) since each firm face the same marginal cost and take aggregate variables as given. This optimal price setting equation will be used to derive the equation for price dynamics of the model.

As mentioned, there are $1 - \omega$ of firms optimal reset their price for period t, $P_t^{\star}(k)$ and ω fraction of the firms cannot adjust their price following the assumption that keeps their price as same as in the previous period. Recall the pricing rule of final goods firms (3.27) and split it into two part: the optimal pricing part and the previous price part. This gives the updating price level expression:

$$P_{c,t} = (1 - \omega) P_t^{\star} + \omega P_{c,t-1} \tag{3.38}$$

log-linearisation of optimal price equation (3.37) and updating price level (3.38), Combining them gives the standard forward-looking *New Keynesian Phillips curve*:

$$\tilde{\pi}_{c,t} = \beta E_t \tilde{\pi}_{c,t+1} + \frac{(1 - \omega)(1 - \omega \beta)}{\omega} \tilde{mc}_t \tag{3.39}$$

Monetary Policy

Monetary policy is determined by a version of a Taylor rule, which is the central bank reacts to the inflation. In my research, the central bank reacts to the inflation of consumption goods and total GDP.

$$\tilde{i}_t = \bar{i} + \theta_{\pi}(\tilde{\pi}_{c,t} - \pi^{\star}) + \theta_{GDP}(\tilde{GDP}_t - \tilde{GDP}_t^{\star}) + \tilde{\varepsilon}_t^m \tag{3.40}$$

where following Iacoviello and Neri (2010), GDP consists of the value of consumption goods and the value of housing. That is $GDP_t = Y_{c,t} + \bar{p}_{h,t} Y_{h,t}$. where $\bar{p}_{h,t}$ is the steady state real

housing prices. In consonance with the definition, GDP growth will not be affected when changing the housing price in the short run. In equation (3.59), $\tilde{i}_t$ is the target short-term nominal interest rate. $\tilde{\pi}_{c,t}$ is the rate of inflation as measured by the GDP deflator, $\pi^{\star}$ is the desired rate of inflation, $\bar{i}$ is the assumed equilibrium real interest rate, $\tilde{GDP}_t$ is the logarithm of real GDP, $\tilde{GDP}_t^{\star}$ is a function of productivity in both general and housing sectors.

Market Equilibrium and Identities

The equilibrium of this economy are shown in this section, which solves the different agents' maximisation problems given the exogenous stochastic processes and initial state variables. The housing market clears:

$$Y_{h,t} = H_t - (1 - \delta_h)H_{t-1} \tag{3.41}$$

The general market clears:

$$Y_{c,t} = C_t + (I_{c,t} + I_{h,t}) + G_t \tag{3.42}$$

The Defination of GDP

$$GDP_t = Y_{c,t} + \bar{p}_{h,t}Y_{h,t} \tag{3.43}$$

Total Labour Demand:

$$N_t = N_{c,t} + N_{h,t} \tag{3.44}$$

Total Capital Demand:

$$K_t = K_{c,t} + K_{h,t} \tag{3.45}$$

Fisher Identity:

$$r_t = i_t - E_t \pi_{c,t+1} \tag{3.46}$$

3.2.3   The Linearised Housing Model

The log-linearised housing model is presented in this section. It is convenient for the empirical analysis when the models described above are linearised. Log-linearisation is a technique that can convert a non-linear equation into a linear equation, which non-linear model cannot be solved in a closed form. Moreover, it is quite useful to study economic data using the logarithm term. I take nature logarithms for the variables in the model. The~above represents the logarithmic variables.

Household

The *consumption equation* is given by:

$$\tilde{c}_t = E_t \tilde{c}_{t+1} - \frac{1}{\sigma_c} r_t + \frac{1}{\sigma_c}(\tilde{\varepsilon}_t^p - E_t \tilde{\varepsilon}_{t+1}^p) \tag{3.47}$$

This equation is a traditional forward-looking consumption equation. From this equation, it can be seen that consumption depends positively on expected future consumption and negatively on real interest rate.

The *housing demand equation* is given by:

$$\tilde{h}_t = \frac{1-A}{A\sigma_h} E_t \tilde{p}_{h,t+1} - \frac{1}{A\sigma_h} \tilde{p}_{h,t} + \frac{\sigma_c}{A\sigma_h} \tilde{c}_t - \frac{(1-A)\sigma_c}{A\sigma_h} E_t \tilde{c}_{t+1} - \frac{1-A}{A\sigma_h}(\tilde{\varepsilon}_t^p - E_t \tilde{\varepsilon}_{t+1}^p) + \frac{1}{\sigma_h} \tilde{\varepsilon}_t^h \tag{3.48}$$

where $A = 1 - \beta(1 - \delta_h)$. From the housing demand equation, it is known that the housing demand depends on the current and the future relative price of housing and the current and expected future consumption. It is obviously seen from the equation that no matter the current and future relative price or consumption, all of them depend on the intertemporal elasticity of substitution of the housing.

The *total labour supply* is given by:

$$\tilde{w}_t = \eta \tilde{n}_t + \sigma_c \tilde{c}_t + \tilde{\varepsilon}_t^l \tag{3.49}$$

Equation (3.49) is labour supply function. The total labour supply is given by the household. From this equation, we can see that the real wage depends positively on the labour supply and real consumption.

Housing Sector

The *labour demand equation* is shown as:

$$\tilde{n}_{h,t} = \tilde{y}_{h,t} - \tilde{w}_t + \tilde{p}_{h,t} + \tilde{\varepsilon}_t^{nh} \tag{3.50}$$

Equation (3.50) is labour demand equation in the housing sector. From this equation, it can be seen that labour demand in housing sector have a positive relationship with housing price and housing supply. On the contrary, it depends negatively on the real wage.

The *capital demand equation* is shown as:

$$\tilde{k}_{h,t} = k_{11}\tilde{k}_{h,t-1} + k_{12}E_t\tilde{k}_{h,t+1} + k_{13}\tilde{y}_{h,t} - k_{14}\tilde{r}_t + k_{15}\tilde{p}_{h,t} + \tilde{\varepsilon}_t^{kh} \tag{3.51}$$

Equation (3.51) is the capital demand equation in the housing sector. The coefficients in front of each variable are calibrated value followed by Meenagh et al. (2010). As we can see that the expected and past capital, housing output, housing price as well as real interest rate all affect the capital demand in the housing sector. There is negative effect on real interest rate and positive effect on other variables.

The *housing supply* is shown as:

$$\tilde{y}_{h,t} = \alpha\tilde{k}_{h,t} + (1 - \alpha)\tilde{n}_{h,t} + \tilde{\varepsilon}_t^{ph} \tag{3.52}$$

Equation (3.52) is housing supply function. The housing goods are supplied according to a constant returns to scale production function. The firms use capital and labour to produces housing goods.

The ***housing market clearing condition*** can be written as:

$$\tilde{y}_{h,t} = \frac{H}{Y_h}\tilde{h}_t - (1 - \delta_h)\frac{H}{Y_h}\tilde{h}_{t-1} \tag{3.53}$$

Equation (3.53) is the housing market clearing condition. The total housing supply is equal to the total housing demand, where $\frac{H}{Y_h}$ is the proportion of housing demand in the total supply of housing.

General Sector

The ***labour demand equation*** is shown as:

$$\tilde{n}_{c,t} = \tilde{y}_{c,t} - \tilde{w}_t + \tilde{\varepsilon}_t^{nc} \tag{3.54}$$

Equation (3.54) is labour demand equation in the general sector. Similar to the labour demand in the housing sector, the labour demand in the general sector have positive effect on general output and negative effect on real wage.

The ***capital demand equation*** is shown as:

$$\tilde{k}_{c,t} = k_{11}\tilde{k}_{c,t-1} + k_{12}E_t\tilde{k}_{c,t+1} + k_{13}\tilde{y}_{c,t} - k_{14}\tilde{r}_t + \tilde{\varepsilon}_t^{kc} \tag{3.55}$$

Equation (3.55) is capital demand equation in the general sector. Similar to the capital demand in the housing sector, the capital demand in the general sector depends negatively on the real interest rate and positively on other variables. I follow Meenagh et al. (2010) to calibrate these parameters.

The ***price setting equation*** is given by:

$$\tilde{\pi}_{c,t} = \beta E_t\tilde{\pi}_{c,t+1} + \frac{(1 - \omega)(1 - \omega\beta)}{\omega}\tilde{mc}_t \tag{3.56}$$

The corresponding ***marginal cost*** is given by:

$$\tilde{mc}_t = (1-\alpha)\tilde{w}_t + \alpha\tilde{r}_t - \tilde{\varepsilon}_t^{pn} \tag{3.57}$$

Equation (3.56) is the standard purely forward-looking New Keynesian Phillips curve. The above two equations (3.56) and (3.57) show that the current inflation depends on expected future inflation and the current cost, which the marginal cost is a function of real interest rate, the real wage and the productivity.

The ***general goods market clearing condition*** can be written as:

$$\tilde{y}_{c,t} = c_0\tilde{c}_t + k_0\tilde{k}_t - k_0(1-\delta_k)\tilde{k}_{t-1} + \tilde{\varepsilon}_t^g \tag{3.58}$$

Equation (3.58) is the general goods market equilibrium condition, where c_0 is the steady-state consumption-output ratio, k_0 is the steady state capital-output ratio. There are two kinds of goods produced in the general goods sector: general consumption goods and capital goods. Therefore, the supply of capital goods can be found in this equation. The general consumption goods can be consumed by the household and the capital goods can be invested by firms themselves in both sectors.

Central Bank

The ***Taylor rule*** can be expressed as:

$$\tilde{i}_t = \bar{i} + \theta_\pi(\tilde{\pi}_{c,t} - \pi^\star) + \theta_{GDP}(G\tilde{D}P_t - G\tilde{D}P_t^\star) + \tilde{\varepsilon}_t^m \tag{3.59}$$

The simply Taylor's rule is set to achieve both its short-run goal for stabilising the economy and its long-run goal for inflation. Coefficients θ_π and θ_{GDP} are assumed to be positively and chosen by the monetary authority. $\tilde{\varepsilon}_t^m$ can be interpreted as monetary policy shock, which deviates from the steady state due to a change in the policy. A positive $\tilde{\varepsilon}_t^m$ can be interpreted

as a contractionary monetary policy shock. On the contrary, a negative $\tilde{\varepsilon}_t^m$ represents an expansionary monetary policy shock.

It should be noticed that the model is loglinearised around a steady state growth path driven by the growth of the shocks, including the drift term in non stationary productivity. On the other hand, the level of potential GDP varies with the stochastic trend in productivity. Therefore, the model is loglinearising around potential GDP which is following the deterministic trend and stochastic trend.

Equations (3.47) to (3.59) and some identities equations ((3.43) to (3.46)) determine seventeen endogenous variables in the model. There are eleven exogenous shock variables in the model driving the stochastic behaviour of the system of linear rational expectations equations.

3.3 The Method of Indirect Inference

3.3.1 Introduction of Indirect Inference

There are two contributions in this chapter. First, the dynamic stochastic general equilibrium model is set up incorporating housing sector and some important features of the Chinese economy. This provides a framework to describe the Chinese housing market in a reasonable detail. Second, the evaluation and estimation strategy followed Indirect Inference method using unfiltered non-stationary data are employed in this chapter. The benchmark model has already discussed in the last section. Therefore, in this section, I focus on introducing the Indirect Inference method. To be specific, Indirect Inference evaluation and estimation are going to be introduced in the following. I will emphasise the feature of the unfiltered non-stationary data in the next section.

Indirect Inference method evaluates the model's capacity in fitting the data, which introduced by Minford et al. (2009) and Le et al. (2011) refine this method using Monte

Carlo experiments. Bayesian also can evaluate the model by creating a likelihood ratio, but the problem is it can only compare the model with the benchmark model and cannot evaluate the model against the real data. However, Indirect Inference can provide a classical statistical inferential framework for testing, which provides a statistical criterion and tells how close the model is to the actual data. In addition, Le et al. (2016) use Monte Carlo experiments to compare the power of the Indirect Inference test with the power of the likelihood ratio test [3]. The results show that the power of the Likelihood Ratio test is much lower than the Indirect Inference test especially in the small sample. The idea of Indirect Inference evaluation is that the auxiliary model completely independent of the theoretical model is used to compare the performance estimated on the real data and simulated data. The auxiliary model in my research is VARX since the unfiltered data are used in evaluation and estimation. According to Meenagh et al. (2012b), a Vector Error Correction (VECM) model or Vector Auto Regression with the Exogenous variable model (VARX) can be used as an auxiliary model if the shocks are non-stationary. Wald test is employed as the criterion when evaluating the model, which compare the Wald statistic calculated using simulated data with the Wald statistic calculated using actual data. If the model can pass the test, that implies the simulated data generated by the model are similar to those generated using the actual data. It shows that the model can explain the economy properly. For this reason, the behaviour of simulated data is not significantly different from the behaviour of actual data. If the model fails the test, Indirect Inference estimation is used to search for a set of coefficients that could improve the performance of the model.

In terms of indirect inference estimation, which has been widely used in the estimation of structural models (eg.Smith (1993), Gregory and Smith (1991) Gourieroux et al. (1993)(Gregory and Smith, 1991); Gourieroux and Monfort (1996) and Canova (2007))[4]. Indirect Inference estimation is based on the Indirect Inference testing, which repeats the

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[3]They use both stationary and non-stationary data to do the comparison.

[4]Recent literature using this method include Minford and Ou (2010), Liu and Minford (2014) and Le et al. (2014)

testing procedure to find out the global minima of the Wald statistic. The basic idea of Indirect Inference is trying to search for a set of coefficients that are best able to satisfy the test criterion. Simulated Annealing algorithm is employed to execute the idea of finding the minimum Wald statistics.

In summary, the reason why use Indirect Inference evaluation and estimation in my research is one can test the model unconditionally against the data and can find a certain set of structural parameters to ensure it to fit the data as closely as possible. On the other hand, according to Le et al. (2015) the low sample bias feature is another advantage of the Indirect Inference for small samples. Consider the Chinese housing market does not last for a long time, the data is limited. Therefore, it is valid and efficient for using indirect inference method.

3.3.2 Indirect Inference Testing

Indirect Inference is a simulation-based method for estimating the parameters of economic models. Therefore, it is better to know the testing principle and procedure before estimation. Testing uses the auxiliary model to compare the actual data with the simulated data generated from the model. Vector Auto Regression with the Exogenous variable model (VARX) is employed as an auxiliary model following Meenagh et al. (2012b). The detail of the auxiliary model will be discussed in the following section. The Wald statistic is used as the criterion when testing the model, which is the differences between the coefficients from simulated and actual data. The VAR coefficients β^{α} can get from the actual data and the N sets of VAR coefficients $\beta^i (i = 1 : N)$ can be obtained from the simulated data, from which we perform the relevant calculation. The Wald statistic is calculated as following:

$$W = (\beta^{\alpha} - \bar{\beta})' \Omega^{-1} (\beta^{\alpha} - \bar{\beta}) \tag{3.60}$$

where $\bar{\beta} = E(\beta^i) = \frac{1}{N}\sum_{i=1}^{N}\beta^i$ and $\Omega = cov(\beta^i - \bar{\beta}) = \frac{1}{N}\sum_{i=1}^{N}(\beta^i - \bar{\beta})(\beta^i - \bar{\beta})'$

It is interesting to find whether the Wald statistic calculated using actual data lie in the range of Wald statistic get from the N sets of simulated data. If in that range the model can pass the test, which means the macroeconomic model is the data generating mechanism.

There are three steps to perform the testing procedure, which originally proposed in Minford et al. (2009) and Le et al. (2011) refined using Monte Carlo experiments, and also Le et al. (2016) apply this testing procedure using non-stationary data. A brief testing procedure is presented in the following.

Step1: Calculate shock processes

The residual and innovation of economic model condition on the data and parameters are calculated first. If the model equation has no future expectations, the structural errors can be simply back out from the observed data and parameters of the model. If there are expectations in the model equations, the rational expectation terms can be calculated using the robust instrumental variables methods of McCallum (1976) and Wickens (1982). The lagged endogenous data are used as instruments and hence the auxiliary VAR model are used as the instrumental variables regression. The errors are treated as autoregressive processes and use OLS to estimate the autoregressive coefficients and innovations.

Step 2: Simulated data by bootstrapping

Step two is simulating the data. The innovation can be obtained from step one, and the simulated data can be obtained by bootstrapping these innovations. Bootstrap by time vector is used to preserve any simultaneity between them and solve the resulting model using Dynare. This process needs to be repeated so that I can get the N bootstrapped simulations [5], drawing each sample independently.

Step 3: Compute the Wald statistic

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[5]I bootstrap 1000 times in my research.

I use both actual data and the N samples of simulated data obtained from the last step to estimate the auxiliary model, which can obtain the coefficients of the auxiliary model from both actual and simulated data. Then, I use Equation (3.60) to calculate the Wald statistic. According to Le et al. (2011), there are two different types of Wald statistic: the 'Full Wald' and the 'Directed Wald'. In the Full Wald, all the endogenous variables from the DSGE model need to be considered in the auxiliary model. It should be noticed that the more variables and lags are included in the auxiliary model, the higher the chance that the model will be rejected. Adding more endogenous variables to the auxiliary model will raise the power of the test, which provides a more stringent test. Therefore, the Directed Wald statistic is used to focus on some aspects of the model's performance, which consider some key endogenous variables in the auxiliary model.

In order to make the model to fit the data at the 95% confidence level, Wald statistic for the actual data should be less than the 95th percentile of the Wald statistics from the simulated data. In order to make it easier to understand whether the model has been rejected by the data, the transformed Wald is introduced. The criteria of rejection is that when the Wald statistic was equal to the 95th percentile from the simulated data, which the transformed Wald is 1.645 using Formula 3.61. Then compare the transformed Wald of the actual data with the criteria (Transformed Wald of 1.645). If the transformed Wald of the actual data is greater than 1.645, then the model reject by the actual data. If it is less than the criteria, that means the structure model can replicate the behaviour of the data.

$$T = 1.648\left(\frac{\sqrt{2w^{\alpha}} - \sqrt{2k-1}}{\sqrt{2w^{0.95}} - \sqrt{2k-1}}\right) \qquad (3.61)$$

where w^{α} is the Wald statistic on the actual data and $w^{0.95}$ is the Wald statistic for the 95th percentile of the simulated data.

The above steps show how to test a given model with particular parameter values. These steps can be also shown graphically. I follow Minford and Ou (2010) to illustrate testing procedure using the diagram (Figure 3.2) below. Panel A of Figure 3.2 summarises the main features of Indirect Inference testing I described above. The mountain-shape diagram in Panel B, replicated from Meenagh et al. (2009), shows that how 'reality' is compared to the model's predictions using the Wald test when two parameters are considered. In panel B, the mountain represents the corresponding joint distribution generated from model simulations and the real data estimation can be either spot. If point A is the real data based estimates, the theoretical model falls the test because what the model predicts is too far away from what reality suggests. In contrast, if the real data based estimates 'on the mountain',that means the reality is captured by the joint distribution of the chosen features implied by the model. The Wald statistic I introduce above formally evaluates these distances.

Panel A:

Model(s) to be tested
↓   (Bootstrap simulations)

Actual data   Simulated data
↓   ↓
VAR representation   VAR representation
↓   ↓
The VAR inference (the 'reality')   *vs.*   Distribution(s) of the VAR inference

Wald statistic

Panel B:
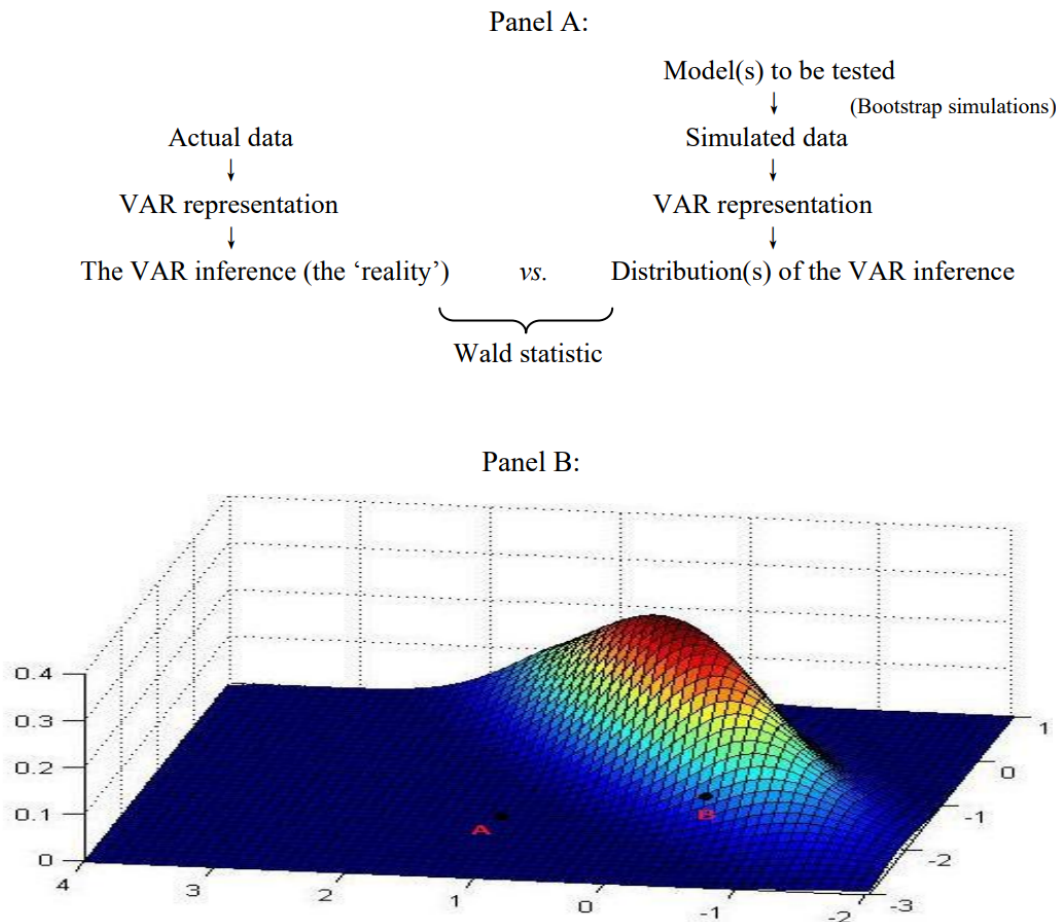
Fig. 3.2 The Principle of testing using indirect inference
Source: Minford and Ou (2010)

The above have already shown how a given model with particular parameter values is tested specifically and expressed the principle using the graph. These parameter values can get from calibration. However, if the calibrated value is inaccurate, the model would be probability rejected since the power of the test is high. Therefore, it is necessary to search for a set of coefficients that can explain the behaviour of data. This is where I introduce Indirect Inference Estimation. The idea of this estimation is that searching for the numerical parameter values to minimise the Wald statistic and test the model on these values. The

model itself is rejected if it is rejected on these values. The detail of Indirect Inference estimation is going to be introduced in the next section.

3.3.3   Indirect Inference Estimation

The evaluation method using Indirect Inference is to check whether the chosen parameter set could have generated the actual data. As discussed in the above section, the model would be probability rejected if the calibrated value is inaccurate. Another set of parameters could pass. If no set of parameters can be found to pass the test, then the model itself is rejected. Maybe the model has already unrejected since it has already gotten closer to the data with alternative parameters. Indirect estimation is used to find the parameters that can minimise the overall Wald statistic and maximise the chances of the model will not be rejected. The process of Indirect Inference estimation is simply shown as the following: First, the coefficients are taken as an input to minimise the object function, then do the testing procedure as mentioned above. At last, the output is the Wald statistic.

Following Le and Meenagh (2013), a simulated annealing algorithm is chosen as the minimising algorithm to perform the Indirect Inference estimation, which is a way to imply the Indirect Inference into practice. Simulated annealing is the physical process of heating to minimising the system energy by lowering the temperature to decrease defects. It is the same logic to search for a minimum in a more general system when applying to Indirect Inference. The algorithm is used when finding the minimum Wald statistics implied by the real and simulated data. A new state is randomly generated at each iteration of the simulated annealing algorithm and then decides whether to moving the system to a new state or just staying in the current state. The distance between new state and the current state is based on a probability distribution with a scale proportion to the temperature. This leads the system to move to the states of lower Wald statistic. At last, this iteration will stop when the objective function is minimised.

The advantage of simulated annealing compare to other methods is the algorithm avoids become trapped in the local minima and can find globally for more possible solutions. It repeats the testing procedure to search for the global minima of the Wald statistic. A smaller Wald statistic compared with any point preceding it in the previous is found at a new point in the parameter space. The algorithm chooses this current point as a starter to search for the minimum proceeds. In the following searching procedure, it is normal for the algorithm to move to points with larger Wald statistic. At last, after a certain number of best points are found, the search is once again widened by increasing the acceptance probability. There are different setting for Simulated Annealing. In my research, the bounds are set to be within 40% of the initial calibrated parameters and the maximum number of iterations is set to be 1000.

3.3.4   The Choice of the Auxiliary Model

As mentioned in Section 3.2.1, the technology shock in both housing and general sector are non-stationary shock and the data used in the evaluation and estimation are unfiltered data. According to Le et al. (2016), if the data are non-stationary, in order to do the evaluation, an auxiliary model with stationary errors need to be created. Therefore, VAR with the exogenous variable is used as the auxiliary model when data are non-stationary. Meenagh et al. (2009) also mentioned that the VAR model is an approximation of the reduced form of the DSGE model.

The structural DSGE model after log-linearisation usually can be written as a function:

$$A(L)y_t = B(L)E_t y_{t+1} + C(L)x_t + D(L)e_t \tag{3.62}$$

where y_t is a vector of endogenous variables, $E_t y_{t+1}$ is a vector of expected future endogenous variables, x_t is an exogenous variable which is assumed to be driven by

$$\Delta x_t = \alpha(L)\Delta x_{t-1} + d + b(L)z_{t-1} + c(L)\varepsilon_t \tag{3.63}$$

The exogenous variables x_t including stationary and non-stationary shocks like productivity shocks. e_t and ε_t are both i.i.d and the means are zero. x_t is non-stationary, y_t is linearly dependent on x_t. Therefore, y_t is also non-stationary. L is the lag operator $Y_{t-s} = L^s Y_t$ and $A(L)$, B(L) etc is a matrix polynomial functions in the lag operator of order h that have roots of the determinantal polynomial lies outside the complex unit circle.

The general solution of y_t can be written as

$$y_t = G(L)y_{t-1} + H(L)x_t + f + M(L)e_t + N(L)\varepsilon_t \tag{3.64}$$

where f is a vector of constants and polynomial functions in the lag operator have roots outside of the unit circle. Since y_t and x_t are both non-stationary, the solution of the model has p cointegrated relations given by:

$$y_t = [I - G(1)]^{-1}[H(1)x_t + f] = \Pi x_t + g \tag{3.65}$$

The matrix Π is a $p * p$ matrix, which has rank $0 \le r < p$, where r is the number of linearly independent cointegrating vectors. $y_t - [\Pi x_t + g] = \eta_t$, where η_t is the error correction term. y_t is a function of deviation from the equilibrium in the short run. In the long run, the solution to the model is given by:

$$\bar{y}_t = \Pi \bar{x}_t + g \tag{3.66}$$

$$\bar{x}_t = [1 - \alpha(1)]^{-1}[dt + c(1)\xi] \tag{3.67}$$

$$\xi_t = \sum_{s=0}^{t-1} \varepsilon_{t-s} \tag{3.68}$$

where $\bar{y}_t$ and $\bar{x}_t$ are the long run solution to y_t and x_t respectively. It can be seen that the long run solution of $\bar{x}_t$ can be decomposed into two components: a deterministic trend $\bar{x}_t^d = [1 - \alpha(1)]^{-1}dt$ and a stochastic trend $\bar{x}_t^s = [1 - \alpha(1)]^{-1}c(1)\xi_t$. There are two components in the endogenous variables: this trend and a VARMA in deviations from it. Meenagh et al. (2012a) formulate this as a cointegrated VECM with a mixed moving average error term, w_t.

$$\begin{aligned} \Delta y_t &= -[I - G(1)](y_{t-1} - \Pi x_{t-1}) + P(L)\Delta y_{t-1} + Q(L)\Delta x_t + f + M(L)e_t + N(L)\varepsilon_t \\ &= -[I - G(1)](y_{t-1} - \Pi x_{t-1}) + P(L)\Delta y_{t-1} + Q(L)\Delta x_t + f + w_t \end{aligned} \tag{3.69}$$

$$w_t = M(L)e_t + N(L)\varepsilon_t \tag{3.70}$$

This suggests that the VECM can be approximated by the VARX:

$$\Delta y_t = -K(y_{t-1} - \Pi x_{t-1}) + R(L)\Delta y_{t-1} + S(L)\Delta x_t + g + \zeta_t \tag{3.71}$$

where ζ_t is an i.i.d with zero mean, since

$$\bar{x}_t = \bar{x}_{t-1} + [1 - \alpha(1)]^{-1}[d + \varepsilon_t] \tag{3.72}$$

$$\bar{y}_t = \Pi\bar{x}_t + g \tag{3.73}$$

The VECM can be also rewritten as:

$$\Delta y_t = K[(y_{t-1} - \bar{y}_{t-1}) - \Pi(x_{t-1} - \bar{x}_{t-1})] + R(L)\Delta y_{t-1} + S(L)\Delta x_t + h + \zeta_t \qquad (3.74)$$

According to Le et al. (2016), either equations (3.71) or (3.74) can be used as the auxiliary model. The equation (3.71) can be rewritten as following:

$$y_t = [I - K]y_{t-1} + K\Pi x_{t-1} + n + t + q_t \qquad (3.75)$$

where the errors q_t now consist of the lagged difference regressors and the deterministic time trend in $\bar{x}_t$ which affect both endogenous and exogenous variables. The equation (3.74) is used throughout my research followed Le et al. (2016), which distinguishes between the effect of the trend component and the temporary deviation of x_t from the trend. The advantage is that it is possible to estimate the parameters of equation (3.74) using classical OLS methods. It also proved by Meenagh et al. (2012a) that this procedure is extremely accurate using Monte Carlo experiments.

3.4 Data and Calibration

3.4.1 Description of Data

Chinese quarterly data over the period 2000Q1 - 2014Q4 are used to do the evaluation and estimation. A full data description can be found in the Appendix A. In order to match the variables in the log-linear model, I first convert all the nominal variables to the real term per capita. Then, I take nature logarithms of the unfiltered observable. Figure 3.3 shows the real term per capita time series data.

data.png data.png data.png data.png
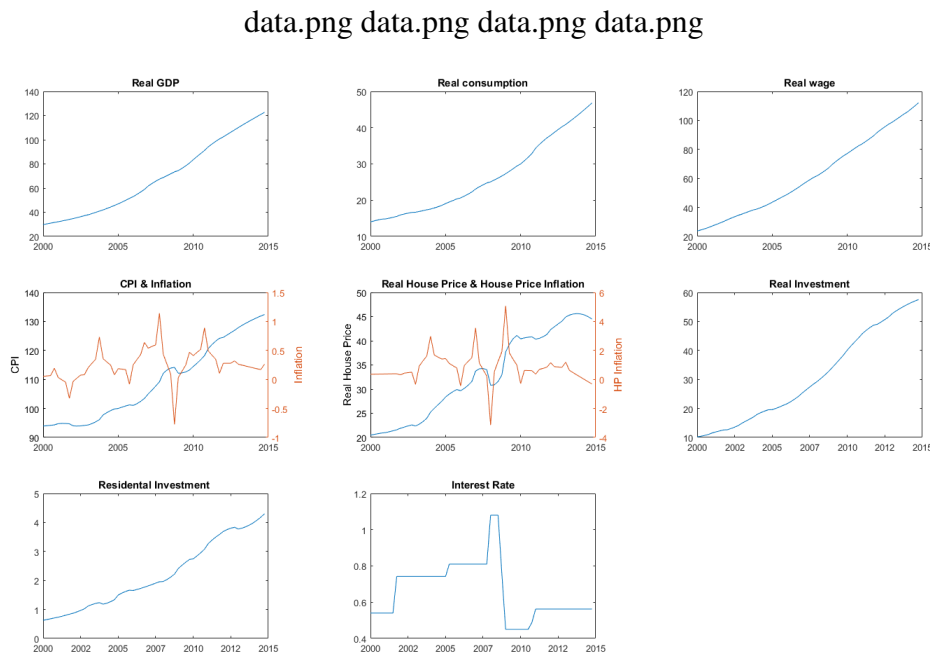
Fig. 3.3 Chinese macroeconomic data: 2001Q1 to 2014Q4

It can be seen from the Figure 3.3, the Chinese real housing price has been increasing dramatically since the end of 2002 and is sustained for several years until the recent global financial crisis. It should be noted that there is a significant drop after 2007. The housing price rises immediately and reaches its peak in 2009. It also can be seen that the growth rate become less immoderate after 2009.

3.4.2 The Advantage of Non-stationary data

As mentioned earlier, one of the important contribution made in this research is that the unfiltered data are used in the evaluation and estimation. The business cycle model focus on studying the dynamics and the choice of macroeconomic policy on stabilising the fluctuations, which try to abstract from the long run uncertainty economic surrounding. Most researchers use some technique such as the Band Pass (BP) and the Hodrick-Prescott (HP) filters to abstract the uncertainty trend. However, there is a criticism of both the HP filter and BP filter. According to Harvey and Jaeger (1993), the HP filter can lead to spurious cyclical behaviour. Moreover, Cogley and Nason (1995) and Murray (2003) study the spurious dynamic causing from HP and BP filters to non-stationary data and show that these filters cannot distinguish between difference-stationary and trend-stationary. The HP and BP filters are a mathematical tool used in the business cycle, which are not based on theories. Hence, the precision of the driving process that leads to trend behaviour cannot be identified using these techniques. Some researchers maybe consider linear detrend to make the time series stationary. However, the problem of this method is some data cannot be stationary even if they have already linear detrended. According to Canova (1998), the linear detrend maybe not accurate when the data have a stochastic trend since it cannot isolate fluctuations. On the other hand, the non-stationary data used in the model could shed light on the economy in a significant way where the stationary data do not. Meenagh et al. (2012b) take the recent Great Recession as an example to express this idea.[6] Le et al. (2014) also find this stylised fact in China.

In summary, the advantage of using non-stationary data would be twofold: On the one hand, the filters cannot provide an appropriate and precise decomposition into a non-stationary time series. The business cycle dynamics can be generated using the filters even if they are not present in the original data. On the other, I am interested in the stochastic trend, which arises from the unit root processes of the technology shocks. I want to keep

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[6]There is a severe decrease in the OECD after the crisis. However, the trend level of GDP still cannot reach its previous level.

the non-stationarity and do not remove it since the non-stationary data could explain some dynamic properties of the model that stationary data could not.

3.4.3 Calibration

In this section, the calibrated values in my research are introduced before evaluating and estimating. The parameter values are partitioned into two groups. The first group of parameters conduct the dynamics of the model, which can be found in Table 3.1. These parameter values are calibrated according to the previous literature and the observations in some empirical analyses. For example, the coefficients of the Taylor rule and the quarterly depreciation rate of housing and capital. The second group of the parameters are the steady state of the model, which is shown in Table 3.2. These kinds of parameter values used in this chapter are obtained from the data. For example, the consumption output ratio or residential investment ratio. I am going to test the model with these calibration values in the following. If the model cannot pass the test, the Indirect Inference estimation will carry out to reestimate these parameters. In the estimation, I fix these parameters $(\beta, \delta_k, \delta_h)$ because the accounting information is used to identify them.

On the households side, β is set to be 0.985, using Chinese quarterly data. This is in line with the standard in the most DSGE housing literature, which implies a steady state annual real interest rate of around 4 percent[7].

σ_i denotes the coefficient of relative risk aversion of households. The elasticity of intertemporal substitution is given by $1/\sigma_i$, which measures the responsiveness of the growth rate of consumption to the real interest rate. The range of σ_i, according to Gandelman and Hernández-Murillo (2015) , is between 0 and 3. I calibrate coefficient of relative risk aversion for consumption (σ_c) at 2 in the general sector according to Walsh (2003) and 1 (σ_h) in the housing sector in accordance with Iacoviello (2005), implying the elasticity of intertemporal

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[7]Using steady state $\bar{R} = \frac{1}{\beta}$ to get β

substitution of 0.5 in the general sector and 1 in the housing sector. In general, a low value of σ_i (high intertemporal elasticity) means that consumption growth is very sensitive to changes in the real interest rate. I calibrate σ_h is lower than σ_c since substitution of housing goods is relatively more sensitive compared to the substitution of general consumption goods when changing in the real interest rate.

η is the inverse of elasticity of labour supply, that is $\eta = 1/\xi$, where ξ is the Frisch elasticity of labour supply. The Frisch elasticity of labour supply measures the elasticity of labour supply with respect to wages, which captures the substitution effect of a change in the wage on labour supply. I follow Iacoviello and Neri (2010) to set the inverse of elasticity of labour supply at 0.5, which implies the elasticity of labour supply at 2. The lower inverse of elasticity of labour supply makes the labour supply elastic.

On the firm side, I follow Liu and Ou (2017) to set quarterly depreciation rate of housing and capital (δ_h and δ_k) equaling to 0.015 and 0.03 respectively. It implies an annual depreciation rate of around 6% in housing and 12% in general capital.

Following Liu and Ou (2017)'s study, the capital-output elasticity α in the Cobb-Douglas production function is set to 0.3, which is consistent with previous literature. I calibrate price rigidity ω at 0.84, which in line with Zhang (2009) who employ Chinese quarterly data to estimate the New Keynesian Phillips curve using GMM. The higher ω implies the longer durations between price changes. The capital demand coefficients in both sectors getting from Meenagh et al. (2010) are 0.51, 0.47, 0.02, 025, 0.5 respectively.

In terms of the monetary policy rule, The standard value of θ_π=1.5 and θ_{GDP}=0.125 are chosen in line with Taylor (1993). The coefficient of interest rate response to inflation (θ_π) is set greater than one, which satisfies the Taylor principle. I follow Smets and Wouters (2003) to set the persistence parameters for different shocks of the exogenous processes, which most of them are chosen to be 0.85.

Table 3.1 Calibrated Coefficients - Benchmark Model

Defination	Parameter	Calibration
Households:		
Elasticity of substitution of normal goods consumption	σ_c	2
Elasticity of substitution of housing goods consumption	σ_h	1
Inverse of elasticity of labour	η	0.5
Household's discount factor	β	0.985
Firms:		
Price rigidity	ω	0.84
Output elasticity of capital	α	0.3
Quarterly depreciation rate of housing	δ_h	0.015
Quarterly depreciation rate of capital	δ_k	0.03
Capital demand coefficients	k_{11}, k_{12}	0.51, 0.47
Capital demand coefficients	k_{13}, k_{14}	0.02, 0.25
Capital demand coefficients	k_{15}	0.5
Monetary Policy:		
Taylor Rule response to inflation	θ_π	1.5
Taylor Rule response to output	θ_{GDP}	0.125

Table 3.2 Steady state ratios- Benchmark Model

Defination	Parameter	Data
Consumption Ratio	C/Y	0.38
Investment Ratio	I/Y	0.45
Capital Ratio in General sector	K_c/K	0.78
Capital Ratio in Housing sector	K_h/K	0.22
Labour Ratio in General sector	N_c/N	0.79
Labour Ratio in Housing sector	N_h/N	0.21
Residential Investment ratio	Y_h/GDP	0.03

3.5 Empirical Results

3.5.1 Estimation

Model fit

The evaluation and estimation strategy have already been introduced in Section 3.3. Calibration value of the parameters will be used in the testing, choosing VARX as an auxiliary model as mentioned in Section 3.3.4. The choice of variables in the auxiliary model was straightforward. The total output is essential to include in the auxiliary model. No matter what kind of macro model is, it should at least be able to explain the behaviour of output. One of the main contributions of this thesis is to evaluate whether the DSGE model with the housing sector would be able to capture the features of the housing market in China. Hence, the housing variables need to be considered in the auxiliary model. Housing price is chosen as the second variable in the auxiliary model since it is the most concern housing variable. The third variable is the interest rate. The reason I choose it in the auxiliary model is the change in interest rate would affect the housing market that I concerned. Therefore,

the three variables used in the auxiliary model are: GDP, housing price and interest rate. If the model does not pass the test, the calibrated value can be predefined as starting value to implement Indirect Inference estimation. Hence, in this section, I am going to discuss the Indirect Inference empirical results. Table 3.3 shows the model coefficients of calibration and estimation together with the testing results that presented in the form of transformed Wald and P value.

In terms of evaluation, the testing results show in the bottom of Table 3.3, which represents that the structural model with the calibrated parameters cannot explain the data behaviour. More specifically, the Transformed Wald statistic for variables GDP, housing price and the interest rate is 7.41 that greater than the critical value 1.645. Also, the P-value is 0 when the model employs calibration value, which shows that the model is severely rejected. This indicates that the structural model does not perform well in generating the observed data using calibrated parameters. The reason might be either the unreasonable values for some parameters or the failure of the structural model. Therefore, it is necessary to search for the numerical parameter values that minimise the Wald statistic and then test the model on these values. This is why Indirect Inference estimation is employed. The bottom of the last column in Table 3.3 shows the transformed Wald statistic of the estimated coefficients. The results show that the estimated model using Indirect Inference method can fit the data well according to the transformed Wald 1.02 comparing with the critical transformed Wald of 1.645. The p-value of 0.11 also verifies the finding.

In terms of estimated results, the last column in Table 3.3 provides the best fit of coefficients values. It should be noticed that all coefficients are allowed to change except quarterly household's discount factor (β), the depreciation rate of capital and housing (δ_k, δ_h) since other information are used to identify them.

All of these coefficients have moved within the 40% interval of the initial calibration value. On the household side, the estimated elasticity of substitution of normal goods

consumption (σ_c) has jumped to 2.65. The higher value of σ_c implies the lower intertemporal in general sector, which means the consumption is relatively insensitive to the change in the real interest rate compared with the calibration value. In the housing sector, the elasticity of substitution of housing goods consumption (σ_h) decreases to 0.73 , implying that the housing consumption growth is much more sensitive to changes in the real interest rate than that in calibration. These estimated elasticity coefficients are in line with the assumption, which the consumption is very insensitive in the general sector and sensitive in the housing sector to the change in the real interest rate in China. The estimated coefficient of the inverse elasticity of labour supply (η) is 0.41 lower than its calibrated value of 0.5, which implies the elasticity of labour supply is around 2.5. This makes the labour supply more elastic comparing with the calibration value, which implies that the workers in China are more willing to smooth working hours when the wage rate change.

On the firm side, the price stickiness ω adjusts to 0.52 after estimation, lower than the calibration value. That implies the data suggest a lower degree of nominal rigidity in China, which shows short durations (around two quarters) between price changes. This estimation result is similar to the finding in Liu and Ou (2017) who provide the estimated price rigidity ω=0.41. The value of the share of capital in production is significantly higher than what was initially thought, a value of 0.66 is much closer to Zhang (2009) in their work. For the capital demand coefficients, the coefficients k_{11} is lower than the starting value of 0.51, which implies lower adjustment cost. The higher value of estimated k_{12} in the housing sector implies that a lower discount rate of capital. The estimated coefficients in the capital demand equation satisfy that the sum of k_{11}, k_{12} and k_{13} is equal to 1.

For Taylor rule, monetary policy is estimated to be more responsive to inflation and output fluctuation. More specifically, the inflation response θ_π increase from 1.5 to 1.88, which satisfies the Taylor principle. That implies when interest rate change one unit, the reaction of inflation will be greater than one-for-one.

Table 3.3 Model Coefficients: 2000Q1-2014Q4

Defination	Parameter	Calibration	Estimation
Households:			
Elasticity of substitution of consumption	σ_c	2	2.65
Elasticity of substitution of consumption	σ_h	1	0.73
Inverse of elasticity of labour	η	0.5	0.41
Household's discount factor	β	0.985	0.985
Firms:			
Price rigidity	ω	0.84	0.52
Output elasticity of capital	α	0.3	0.66
Quarterly depreciation rate of housing	δ_h	0.015	0.015
Quarterly depreciation rate of capital	δ_k	0.03	0.03
Capital demand coefficients	k_{11}, k_{12}	0.51, 0.47	0.30, 0.69
Capital demand coefficients	k_{13}, k_{14}	0.02, 0.25	0.01, 0.37
Capital demand coefficients	k_{15}	0.5	0.86
Monetary Policy:			
Taylor Rule response to inflation	θ_π	1.5	1.88
Taylor Rule response to output	θ_{GDP}	0.125	0.25
Trans-Wald (GDP, HP, R)		**7.41**	**1.02**
P-value		**0.00**	**0.11**

Error Properties on Non-stationary Data

Unfiltered data are used when doing the evaluation and estimation. The testing and estimation results show that the structural model that integrates the housing sector can perform well in generating the observed data. Hence, in this part, the error properties on non-stationary data are analysed. I follow Le et al. (2014) idea to analyse the error properties. To do this, the shocks are backed out of the model using unfiltered data and fit to each an AR time-series process over the period. There are two different types of stationarity test for each calculated shock process. That is Augmented Dickey-Fuller (ADF) test and the Kwiatkowski Phillips Schmidt Shin (KPSS) test. The ADF test tests the null hypothesis of the unit root against the stationarity. On the contrary, the KPSS test evaluates the null hypothesis that the shock is stationary against the alternative hypothesis that the shock follows a unit root process. Table 3.4 reports the stationarity of each shock and Table 3.5 presents the AR parameters.

It should be noted that the null hypothesis of a unit root cannot be rejected at 5% level for productivity shock in both housing and general sector under the ADF test. Also, the KPSS test verifies this finding that all the shocks fail to reject the stationary apart from the productivity shock in both sectors. That means the productivity shocks in both sectors contains a stochastic trend, which cannot be the deterministic trend stationary. Hence, the productivity shocks in both sectors are specified in first differences. This provides evidence to support modelling productivity shock as the non-stationary shock.

For some shocks like government spending shock, preference shock, labour demand shock in housing sector and capital demand shock in both sectors cannot be rejected the null hypothesis of a unit root at 5% significant level using the ADF test, but the KPSS testing results show that it cannot reject the null of stationarity at 10% significant level. Hence, these shocks are treated as either stationary or trend stationary due to the theoretical grounds in line with the setup in Le et al. (2014).

For labour supply shock, housing demand shock, monetary policy shock and labour demand in general sector no matter the P-value from the ADF test or the statistics from the KPSS test all imply that these shocks processes are stationary. In the previous literature, some works using different specification for the exogenous processes. For example, Smets and Wouters (2007) employ an ARMA mark-up shock to help to fit the model well and also a higher-order autoregressive process used as the government spending shock in Del Negro and Schorfheide (2009). In my research, apart from the productivity shocks in different sectors, the other exogenous shocks processes follow AR(1) dynamics or AR(1) dynamics with a deterministic trend. The AR coefficients are determined by the estimation process, which also can be found in Table 3.5. Most of the exogenous process are highly persistence.
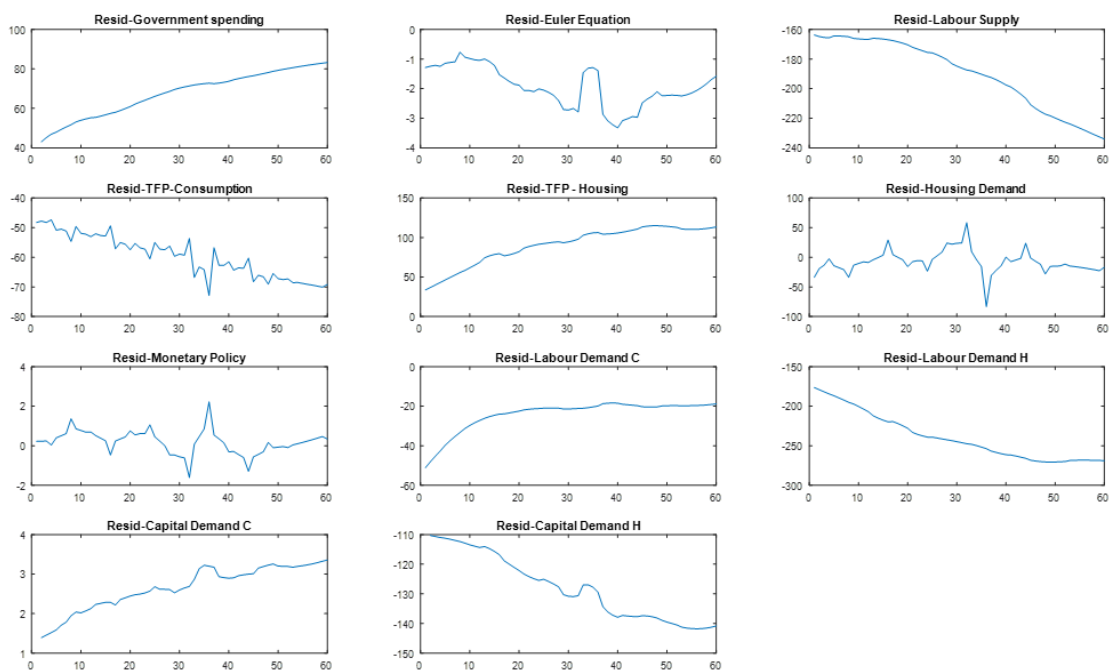
Fig. 3.4 Structure Shocks

Table 3.4 Stationarity of Residual

Shocks	ADF p-value	KPSS Statistic	Conclusion
Government spending	0.4593	0.238410	Trend Stationary
Preference	0.1980	0.195231	Trend Stationary
Labour supply	0.0497**	0.180101	Trend Stationary
TFP – General sector	0.9993	0.955905***	Nonstationary
TFP – Housing sector	0.7184	0.885958***	Nonstationary
Housing Demand	0.0246**	0.120453	Stationary
Monetary policy	0.0327**	0.061916	Stationary
Labour demand - General	0.0451**	0.213222	Trend Stationary
Labour demand - Housing	0.1381	0.236403	Trend Stationary
Capital demand - General	0.1401	0.209563	Trend Stationary
Capital demand - Housing	0.1801	0.179087	Trend Stationary

Notes:
1. p-value with ** rejects the unit root process at 5%
2. KPSS with ** (***) rejects stationarity at 5% (1%)

Table 3.5 Estimated Shocks Coefficient

Shocks	Estimated Coefficient
Government spending	0.9292
Preference	0.8805
Labour supply	0.9569
TFP – General sector	-0.6054
TFP – Housing sector	0.6399
Housing Demand	0.5938
Monetary policy	0.6378
Labour demand - General	0.8914
Labour demand - Housing	0.9997
Capital demand - General	0.8692
Capital demand - Housing	0.9301

3.5.2   Properties of the Model

In Section 3.5.1, I have already discussed that the structural model with the estimated parameters does perform well in generating the observed data. Therefore, in this section, the estimated model is used to address one of the research questions that raised at the beginning of this chapter. That is what determines the housing prices in China. In the following, the variance decomposition of the main variables, shock decomposition of housing price and impulse response functions of different shocks are employed to analyse the housing price fluctuation in China.

Variance Decomposition

Variance decomposition of forecast errors investigates how much of the forecast error variance of each of the variables can be explained by exogenous shocks to the other variables. Table 3.6 reports the variance decomposition of forecast errors of total output, inflation, consumption, housing price and the interest rate at different horizons using estimated coefficients.

In terms of housing price, in the short run (1 year), the dominant driving force of housing price fluctuations is capital demand shock in the housing sector, which explain 65.59% of the variance in housing price. The housing demand shock also contributes to the volatility of housing price, which accounts for 18%. By contrast, monetary policy shock only accounts for 9.90% in the short run. In the long run (10 years), the influence of capital demand shock and housing demand shock decrease, which the former explains 51.65% while the latter explains only 10.32%. By contrast, the influence of technology shock in the general sector on housing price increase, which accounts for 21.26%

As mentioned previously, the capital demand shock in housing sector captures the regulation on firms' use of capital. That implies the change in regulation on supply side related to capital usage affects the housing price dramatically. Chinese housing market experiences substantial reforms starting in 1998, the full marketisation reform promoted the privatisation of housing. A series of regulation changes on the supply side are plausible sources of capital demand shock. Houses were treated as welfare before reform, which the Chinese government control the housing construction. There is no housing market at that time. However, after reform, houses were treated as a commodity at prices determined by the market, which can be purchased or rented. In order to boost housing market development, a series of reforms were established on the supply side when housing has been commodified, which develop some new regime of capital accumulation such as expanding production capacity and attracting foreign investment in economic development. This reform witnessed the Chinese housing market boom and the Chinese housing industry have become a pillar industry in the Chinese

economy. According to Wu (2015), he believed that capital accumulation is a causative factor in the growth of the housing market. The change in capital accumulation is linked with related regulation changes[8]. These regulations on the supply side played a key role in housing development.

For the real consumption, the variance decomposition shows that intertemporal preference shock and technology shock in the general sector play a significant major role. The volatility of real consumption is mainly driven by intertemporal preference shock. The shock explains 47.74% of the variance in real consumption in the short run (1-year forecast horizons) and explains 13.49% in the long run (10-year forecast horizons). Technology shock in the general sector also contributes significantly and explains 22.06% of the variance in real consumption in the short run. However, in the long run, technology shock in the general sector becomes more important and explains 68%. The reason why the preference shocks play an important role in explaining the real consumption in the short run due to the inter-temporal Euler equation, which directly affects the real consumption. We know from the model that the productivity technology shock is the non-stationary shock, which implies it has a permanent effect on output, consumption, capital and investment. Therefore, this explains why productivity shock contributes significantly to explaining real consumption in the long run.

The following variables in Table 3.6 GDP, inflation, and interest rate are non-housing variables. The demand shock (housing preference) in the housing market plays a role in driving the cyclical fluctuations, which account for over 10% of most variables in the short run. The supply shock (housing technology), however, plays a minor role in driving the cyclical fluctuations, which accounts for less than 5% of most variables. However, The contribution of productivity shock in the general sector to the fluctuations in non-housing variables is more important especially for the most non-housing variable. Technology shock explains 37.87% of the variances in GDP in short tun and about 67.66% in the long run.

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[8]Regulation change such as economic decentralisation, fiscal reform etc.

Table 3.6 Variance Decomposition of aggregate variables- Benchmark Model

Variable	Gover. Spend.	Intert. Pref.	Lab. Supply	Tech. in General	Tech. in House	House Demand	Monet. Policy	Lab. D. General	Lab. D. House	Capit. D. General	Capit. D. House
1 Year:											
GDP	0.07	0.84	1.19	37.87	1.58	22.18	27.07	0.04	0.84	1.01	7.31
Inflation	15.40	23.40	13.90	0.61	0.51	16.00	21.13	0.37	7.49	0.09	1.10
Consumption	0.70	47.74	1.03	22.06	3.36	3.97	8.89	0.02	0.40	1.63	10.20
Housing Prices	0.20	0.27	0.08	1.80	0.70	18.80	9.90	0.00	0.13	2.53	65.59
Interest rate	3.82	1.56	0.19	13.66	1.03	55.19	9.66	0.00	0.04	1.26	13.59
5 Year:											
GDP	0.37	0.64	0.83	60.56	2.05	13.35	16.14	0.02	0.76	0.63	4.62
Inflation	19.36	15.85	16.25	2.69	0.83	10.75	13.78	0.27	13.33	0.29	6.61
Consumption	2.47	28.44	3.80	37.72	3.71	5.08	8.04	0.05	0.25	0.94	9.50
Housing Prices	1.04	0.69	0.49	6.02	1.80	14.08	8.77	0.01	2.78	1.59	62.73
Interest rate	3.25	2.46	1.04	35.38	1.44	35.58	6.90	0.01	0.68	1.03	12.32
10 Year:											
GDP	0.36	0.52	0.66	67.66	2.63	10.53	12.73	0.02	0.72	0.50	3.67
Inflation	14.19	11.09	12.94	20.15	2.22	7.51	9.62	0.19	15.89	0.29	5.92
Consumption	1.41	13.49	2.61	68.56	2.31	2.44	3.84	0.03	0.17	0.45	4.70
Housing Prices	0.78	0.56	0.38	21.26	2.36	10.32	6.43	0.01	5.09	1.17	51.65
Interest rate	3.35	2.61	1.56	31.82	1.39	36.60	7.11	0.02	1.72	1.07	12.77

Historical Decompositions

The historical decomposition measures the contribution of each shock to the volatility of variables over a certain sample period. Figure 3.5 decompose the real housing price over the shocks during 2000Q1 to 2013Q4. There are some common features when decomposing the real housing price comparing with those of the forecast error variance decompositions.

In order to make the figure clear, I classify these 11 shocks (government spending shock, preference shock, housing demand shock, labour supply shock, productivity shock in both housing and general sectors, capital demand as well as labour demand in both sectors and monetary policy shock) into 6 categories. The preference shock and labour supply shock belong to private shocks. The public shocks contain labour demand shock in different sectors and capital demand shock in the general sector and housing sector. The policy shocks consist of monetary policy shock and government spending shock. The total factor productivity (TFP) include the technology shock in two sectors. The housing demand shock does not classify into private shocks category as I want to observe how this shock influence the real housing price.

From Figure 3.5, I find that the fluctuation of housing price is mainly driven by the technology shock, public shocks as well as housing demand shock, which in line with the finding in the variance decomposition. As can be seen in Figure 3.5, the housing price experienced a sharp increase at the middle of 2005 and public shock made a major contribution to the surge in the real housing price. An explanation of this sharp increase is the abolishment of welfare housing provision and adoption of a more radically market-oriented approach to housing provision at the beginning of 2005. Housing commodification accelerates the development of housing industries, that implies more capital are needed. The injection of capital has to lead to a new housing market cycle, which in line with Wu (2015). It also supports the finding in variance decomposition that capital demand shock is the main driving force of the fluctuation of real housing price. A series of housing tightening

policies were issued to slow down the housing price increase at starting from 2006. These policies affect the sharp increase in the real housing price but the housing market did not experience a sharp downturn before the global financial crisis. Hence, households needed to think carefully about housing purchase. However, the housing boom was hit hardest in late 2007. The outflow of capital caused by the boom of the stock market in 2007. Households engaged in the stock market. Hence, the demand of housing decrease. In the following, the housing market also hit by the global economic crisis in 2008. One of the approaches that the central government attempt to stimulate economic growth after the crisis is using housing industries as a booster. The stimulation package includes investment in the housing market, a reduction in interest rates and enhancing capital liquidity. Some new regimes of capital accumulation such as expanding production capacity and attracting foreign investment were launched to encourage the housing market. According to Wu (2015), the minimum capital requirement for commodity housing projects was reduced from 30% to 20%. This is shown clearly from the graph, in which the rapid rebound following the temporary slowdown. After 2010, the housing price started to fall down. A series of property purchases restrictions and low productivity, I believe, is the main culprit.
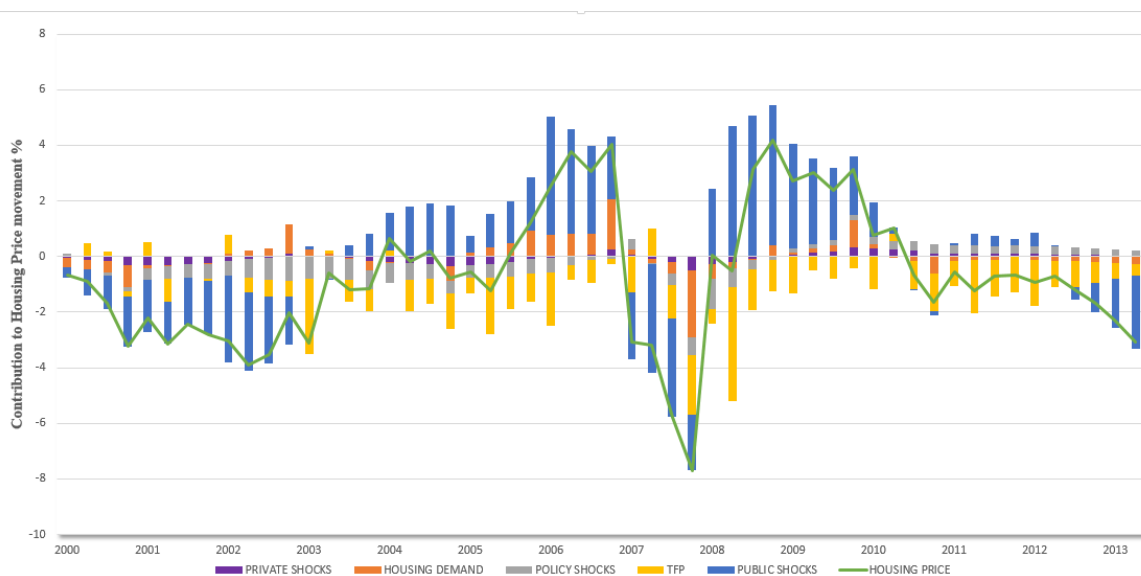

Fig. 3.5 Shock Decomposition - Real Housing Price

Impulse Response Functions

Impulse response functions obtained from the estimated model are shown in this section. There are three main shocks I concern about: housing demand shock, monetary policy shock and technology shock in the general sector. In order to study the reaction to these shocks in different sectors, in the first row I report the response of main model variables in the general sector and the response of main model variables in the housing sector are shown in the second row. The third row shows the total GDP and interest rate. The other shocks can be found in Appendix B

The effects of housing demand shock

Figure 3.6 shows how these key macro variables behave in different sectors when there is a positive housing demand shock (15.5 standard error). It is assumed that the shocks ε_t^h following the exogenous process $\ln \varepsilon_t^h = \rho_h \ln \varepsilon_{t-1}^h + v_{h,t}$. I focus on the housing sector first. A positive housing demand shock leads to a significant increase in housing demand, which lead to the increments in housing price. Supply of housing also rises to meet the high demand for housing. The housing boom not only affect the housing sector, but the general sector is also been affected. The housing boom leads to the expansion of output in the general sector and inflation, which slightly increase compared to those in the housing sector. And a subsequent increase in interest rate. The impulse responses of selected variables to housing demand shock are in line with the main findings in many previous literature.

   As mentioned in the model part, housing demand shock can be think as the change of preferences on housing due to social, institutional or income changes. The housing institution reforms can be explained as the important institutional changes. The private housing market was established after a series of reforms. A series of reforms were launched, and the welfare-oriented housing provision was abolished. These lead to the increments in housing demand. In order to meet the extra demand, the supply of housing raised. Overall, the housing
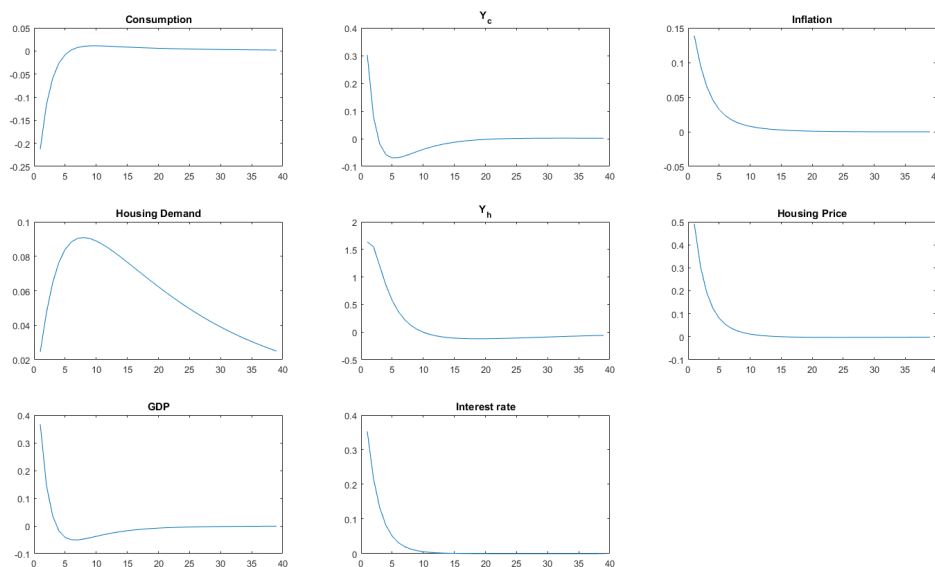
Fig. 3.6 Impulse responses to Housing Demand Shock

reform stimulate the whole economic growth, which is a significant fundamental economic change. On the other hand, China has experienced economic transformation involving fast productivity progress. According to Bian and Gete (2015), the higher income the household obtain benefit from higher productivity, the higher demand for housing they desire.

The effects of the monetary policy shock

Figure 3.7 plots impulse responses to the monetary policy shock (0.45 standard error) to the economy. A positive shock to the monetary policy decrease all the variables in different sectors. The standard interest rate channel of monetary policy transmission show that such monetary contraction discourages the investment and consumption so that decrease the total output. The decrease of consumption shifts the pressure through changes in inflation, which lower the inflation as well as housing price. That means a tightening of monetary policy can have a drop in housing price. This maybe due to the Taylor Rule in the model affect the consumption through Euler equation. This leads to influence the demand of housing,
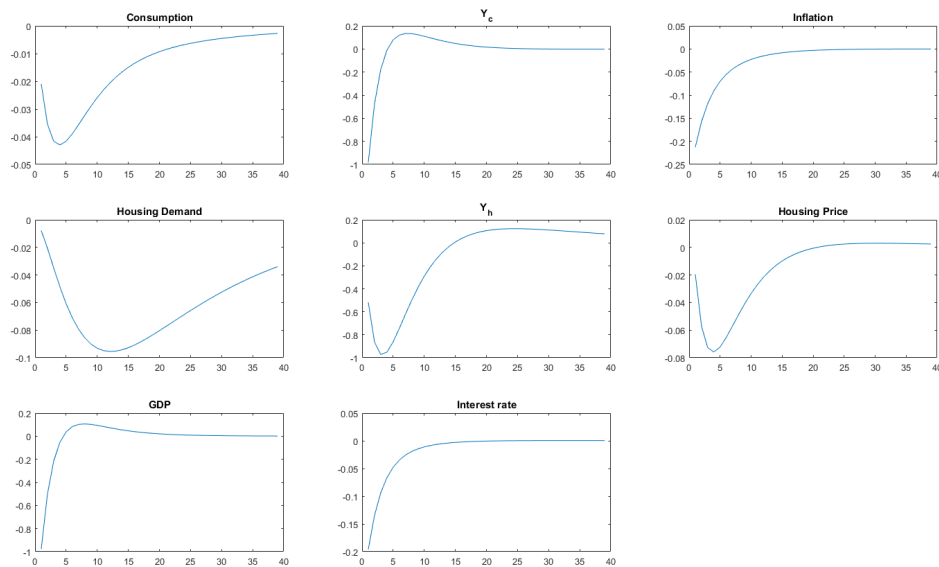
Fig. 3.7 Impulse responses to Monetary Policy Shock

which triggers the housing price. These results are consistent with the main finding of many previous literature. A tightening of monetary policy shock decreases all components of real aggregate demand and real housing prices.

The effects of technology shocks in the general sector

Figure 3.8 plots the impulse responses of model variables to a 3.20 standard error total factor productivity shock. It should be noticed that the productivity shock in both sectors follow a unit root process. This non-stationary process has the permanent effect on some macroeconomic variables such as total output, output in different sectors, real consumption, housing demand and the stock of physical capital. These variables become more persistent afterwards lasting over 40 quarters. In response to a positive productivity shock in the general sector, the supply of output in the general sector goes up due to superior technology. The increase in supplying lead to the decrease in inflation. The interest rate decrease as a results of falling inflation. In the housing sector, we can see that the increase of housing
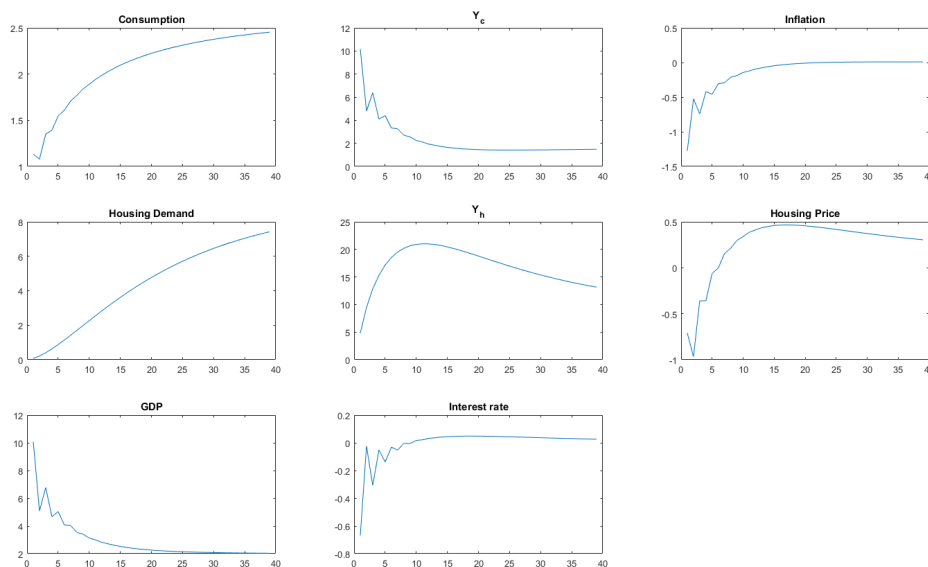
Fig. 3.8 Impulse responses to Technology shocks in general sector

supply decrease the housing price at the very beginning. As the demand for housing increase

significantly after period 5, the housing price pushes up at the same period.

3.6   Conclusion

The aim of this chapter is focusing on answering the first research question: What is the

driving force in the fluctuations of housing price. The estimated DSGE model with explicit

modelling of the price and quantity of the housing sector and non-stationary productivity

shock is used to study housing market fluctuations in China. Indirect Inference method

is employed to find a right model to explain the data behaviour in the Chinese housing

market. The testing results show that the model using the calibration value is rejected by the

data. Hence, the Indirect Inference method is used to estimate the model over the period

2000-2014, which find out a set of coefficients that can past the test. The model can fit the

data well when a variety of endogenous variables are added to the auxiliary model, explaining

the output, housing price and interest rate that I concerned about. Once find the right model

that can perform well in explaining the data, I discover the housing market using this model. In terms of the driving force of fluctuations in the Chinese housing market, the variance and shock decomposition suggest that the capital demand shock plays a significant major role in explaining the housing price. That maybe because the housing market reform stimulates the Chinese housing industry, which develops some new regime of capital accumulation. These regulation change on the supply side played a key role in housing development.

Chapter 4

Model with Collateral Constraint

4.1 Introduction

In the last chapter, I have established a benchmark model with a rich set of shocks to explain the behaviours and the sources of fluctuations in the Chinese housing market using Indirect Inference method. The testing results show that the estimated benchmark model can fit the Chinese data well on the one hand, and that encompasses most of the views on the sources and propagation mechanism of business cycles on the other hand. The increasing interest in the DSGE housing model literature have focused on the collateral constraint on the households' side, which treats as a channel that connects the housing market to the wider economy. Previous studies emphasise the role play as the housing collateral in the households' optimal decision. They add the channel by splitting the households into two types: patient (lenders) and impatient (borrowers). The impatient households in the economy face a binding collateral constraint when participating in loan and mortgage market. Therefore, the collateral constraint is a channel to amplify the collateral effect on households borrowing to the whole economy.

One important work is that Iacoviello and Neri (2010) present a Bayesian estimated DSGE model to study the housing market and business cycle, which emphasise the spillovers

effect from the housing market to the wider economy by adding the collateral constraint on the households' side. There are different ways to quantify housing market spillovers. The Iacoviello type model focus on one aspect of spillovers, that is, the relationship between housing wealth and non-housing consumption. Inspired by Kiyotaki and Moore (1997), these Iacoviello type model feature a collateral constraint on the households side. That implies the borrowing capacity of impatient households is limited by a fraction of the expected present value of total assets such as houses, lands and capitals. In their model, the borrowing constraint can be thought as a channel to connect the housing market and the rest of the economy, allowing for 'spillover' from one sector to the other through that channel.

Iacoviello (2005) constructs a DSGE model including collateral constraints tied to real estate values for the impatient households. In the extended model, both firms and impatient households face the credit constraint. The model is used to explain both the business cycle facts and the interaction between asset prices and economic activity. Then, Iacoviello and Neri (2010) extend the work of Iacoviello (2005) and present a Bayesian estimated DSGE model. They show that collateral effects on households borrowing amplify the response of non-housing consumption to given changes in fundamentals, thus alter the propagation mechanism.

The transmission mechanism of collateral constraint in Iacoviello type model work as following. When there is a positive demand shock, the demand for housing rise, housing price also increases. The rise in asset prices increases the borrowing capacity of the debtors. That implies they can borrow more due to the high asset prices, allowing them to spend and invest more. The change in investment will cause the output to fluctuate, which in turn influences the current asset price. Therefore, a significant transmission channel is generated through the dynamic interaction between the credit constraint and asset prices.

Based on their analysis framework, more types of shocks and frictions are introduced to study the housing market. Ng (2015) employ Iacoviello type model to study the sources

and consequences of the fluctuations in the Chinese housing market. In terms of the nature of shocks driving housing price dynamic, they find that housing demand shock explains the majority of the fluctuations in housing price. In terms of spillover effect work through the collateral constraint, there is not a unique way to quantify the effect, which depends on the nature of shocks. Housing demand shock has a larger contribution to the spillover effect compared to the technology shock. However, the technology shock plays a negligible role in the spillover effect. Liu and Ou (2017) also use a DSGE model with a collateral constraint to study the Chinese housing market. Apart from investigating the main driving force of housing market fluctuation, they also study the housing market spillovers effect in China. They find that there is a weak spillover effect from the housing market to the wide economy. He et al. (2017) employ a Bayesian DSGE model with collateral constraints to investigate the interaction between the housing market and the business cycle. They find that the collateral constraint plays a significant role in explaining the fluctuate of the business cycle in China, which amplifies the impact of various economic shocks.

While these studies have highlighted the collateral constraint on households borrowing, to date there has been no evaluation of the general equilibrium model with collateral constraint. This is the perspective adopted here. Indirect Inference evaluation is used to check whether the DSGE housing model with a collateral constraint on the household side can explain the Chinese housing market well. From the modelling point of view, my starting point is the benchmark model that introduced in Chapter 3, which a DSGE model include the explicit modelling of the price and quantity of the housing sector with non-stationary productivity shock. In order to examine whether the model with collateral constraint can explain the Chinese housing market well, I include another feature into the benchmark model. That is collateral constraints tied to the housing values for impatient households, as in Iacoviello and Neri (2010). This chapter tries to identify whether the Chinese housing market can be

explained better using a model with collateral constraint compared to the benchmark model through Indirect Inference evaluation.

This chapter is structured as follows: the model with a collateral constraint is presented in Section 4.2, and the collateral channel is also analysed. The estimation part is outlined in Section 4.3, which introduce the data used in this chapter and the baseline calibration as well as the estimation results. In this section, I will explore whether the model can perform well if it introduces the collateral constraint. The standard analyses are shown in Section 4.4 that including historical and variance decomposition and impulse response functions to different shocks. Finally, I conclude the housing model with collateral constraint in Section 4.5.

4.2 Model

Impatient households are introduced to feature the collateral constraint. Therefore, there is one more household on the demand side. Five types of agent exist in the economy: patient households, impatient households, housing sector, general sector and central bank. The key feature that distinguishes between patient and impatient households is the discount rate. Impatient households discount future utilities more heavily than the patient ones due to the heterogeneous preference. In each period, patient households consume, accumulate housing and supply funds to impatient households. Impatient households work, consume, purchase housing through borrowing from patient households. The firms in both sectors behave as before, and I keep them as same as in the benchmark model.

Impatient Households

There is a continuum of measure 1 of impatient households. The representative impatient households derive utility from consumption, housing purchase and disutility from supplying labour. The representative impatient households expected discounted lifetime utility is given

by

$$U_{It} = E_0 \sum_{t=0}^{\infty} \beta^{It} \varepsilon_t^p \left[\frac{C_{It}^{1-\sigma_c}}{1-\sigma_c} + \varepsilon_t^h \frac{H_{It}^{1-\sigma_h}}{1-\sigma_h} - \varepsilon_t^l \frac{N_t^{1+\eta}}{1+\eta} \right] \tag{4.1}$$

where E_0 is the expectation formed at period 0, β^{It} is the subjective discount factor, the impatient households obtain utility from consumption goods C_{It}, new housing H_{It} and get disutility from labour supply N_t. The parameters σ_c, σ_h are the inverse of intertemporal elasticity of substitution of consumption and housing, while η denotes the inverse of the elasticity of work time with respect to real wage.There are three shocks in the utility function like in Chapter 2. They are ε_t^p, ε_t^h and ε_t^l respectively. ε_t^p and ε_t^l are shown here to express intertemporal preferences shock and labour supply shock. The term ε_t^h captures shock to housing demand [1]. The impatient households' budget constraint is

$$C_{It} + p_{h,t}(H_{It} - (1-\delta_h)H_{I,t-1}) + (1+r_{t-1})B_{I,t-1} = w_t N_t + B_{It} \tag{4.2}$$

From equation (4.2), it can be seen that the wealth of impatient households consists of two parts, which is shown on the right-hand side. One of the incomes comes from supplying labour $w_t N_t$. The other comes from borrowing from patient households B_{It}. The left-hand side displays the outflow of funds. The impatient households use his wealth in each period for buying consumption goods C_{It}, new housing H_{It} with relative price $p_{h,t}$ and payback last period's debt with r_{t-1}.

Collateral constraint

Private borrowing is subject to an endogenous limit as in Iacoviello and Neri (2010). Impatient households borrow from patient households to finance their consumption and housing purchases. The borrowers face the borrow constraint: the value they can borrow is limited by

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[1]The detail of housing demand shock can be found in Chapter 2

a fraction of the expected present value of their housing asset. That is,

$$B_{It} \leq mE_t\left(\frac{p_{h,t+1}H_{It}}{1+r_t}\right) \tag{4.3}$$

where m is the loan to value ratio for impatient households. It should be noticed that the change in the expected relative price of housing affects the ability of borrowing directly. This collateral constraint can be treated as a channel to evaluate the transmission of monetary policy shocks in the model. For simplicity, there is an assumption that has to hold when finding the optimal behaviour of impatient households: the collateral constraint (4.3) is always satisfied with equality. That means parameters are calibrated in a way to make it bind. Therefore, in the steady state, the impatient households' borrowing constraint is always binding.

Impatient households' Problem

The impatient households' problem is choosing C_{It}, N_t, B_{It} and H_{It} to maximise their lifetime utility (4.1) subject to (4.2) and (4.3). The Lagrangian:

$$\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^{It} \left\{ \varepsilon_t^p \left(\frac{C_{It}^{1-\sigma_c}}{1-\sigma_c} + \varepsilon_t^h \frac{H_{It}^{1-\sigma_h}}{1-\sigma_h} - \varepsilon_t^l \frac{N_t^{1+\eta}}{1+\eta} \right) \right.$$
$$-\lambda_{It}[C_{It} + p_{h,t}(H_{It} - (1-\delta_h)H_{I,t-1}) + (1+r_{t-1})B_{I,t-1} - w_tN_t - B_{It}] \tag{4.4}$$
$$\left. -\lambda_{It}'[B_{It} - mE_t\left(\frac{p_{h,t+1}H_{It}}{1+r_t}\right)]\right\}$$

The first order conditions:

$$C_{It}: \qquad C_{It}^{-\sigma_c}\varepsilon_t^p = \lambda_{It} \tag{4.5}$$

$$N_t: \qquad \varepsilon_t^p\varepsilon_t^l N_t^{\eta} = w_t\lambda_{It} \tag{4.6}$$

$$B_{It}: \qquad \beta^{It} E_t \lambda_{I,t+1}(1+r_t) = \lambda_{It} - \lambda'_{It} \qquad (4.7)$$

$$H_{It}: \qquad \lambda_{It} p_{h,t} = \varepsilon_t^p \varepsilon_t^h H_{It}^{-\sigma_h} + \beta^I E_t (\lambda_{I,t+1} p_{h,t+1}(1-\delta_h)) + \lambda'_{It} m \frac{E_t p_{h,t+1}}{1+r_t} \qquad (4.8)$$

The marginal utility losses of choosing relevant allocation are shown on the left-hand sides of the above equations. On the contrary, marginal utility gains of choosing relevant allocations are represented on the right-hand sides of the above equations. It should be noticed that both the Euler equation (4.7) and the housing demand equation (4.8) are different from the standard form due to the presence of λ'_{It}, which is the Lagrange multiplier on the borrowing constraint. The multiplier λ'_{It} represents utility increase that would come from borrowing, consuming in (4.7) or investing in (4.8).

Equation (4.5) links the borrower's marginal utility of consumption to the Lagrangian multiplier. Equation (4.6) is a standard labour supply equation which represents the substitution between labour supply and consumption. Equation (4.7) is impatient households' borrowing. The left-hand side of equation (4.7) is the marginal utility loss, which is the expected value of debt repayment of one unit of borrowing $\beta^{It} E_t \lambda_{t+1}(1+r_t)$. The right-hand side shows the marginal utility gain, which is the utility gain comes from one unit of additional consumption λ_{It}, get rid of the loss of value due to the borrowing constraint, λ'_{It}. A standard Euler condition is presented when $\lambda'_{It} = 0$ for all t in equation (4.7). Equation (4.8) represents an intertemporal condition on housing demand, which requires the marginal utility of current general goods consumption equal to the marginal gain of housing services. The marginal utility gain of housing services shown on the right-hand sides of equation (4.8) consists of three components: first, the direct utility from an additional unit of housing. The second component is the expected utility coming from the possibility of expanding future

consumption relying on the realised resale value of the housing purchased in the previous period. The third component is the marginal utility gain from the value of housing as the collateral asset. Further imply:

$$\frac{N_t^{\eta}}{C_t^{-\sigma_c}}\varepsilon_t^l = w_t \tag{4.9}$$

$$\frac{H_{It}^{-\sigma_h}}{C_{It}^{-\sigma_c}}\varepsilon_t^h + \beta^I(1-\delta_h)E_t(p_{h,t+1}\frac{C_{I,t+1}^{-\sigma_c}}{C_{It}^{-\sigma_c}}\frac{\varepsilon_{t+1}^p}{\varepsilon_t^p}) + (1-\beta^I(1+r_t))E_t(\frac{C_{I,t+1}^{-\sigma_c}}{C_{It}^{-\sigma_c}}\frac{\varepsilon_{t+1}^p}{\varepsilon_t^p}))m\frac{E_tp_{h,t+1}}{1+r_t} = p_{h,t} \tag{4.10}$$

In order to understand the behaviour of impatient households of housing purchases, I combine the binding borrowing constraint (4.3) with the budget constraint (4.2) and obtain:

$$(p_{h,t} - \frac{m}{1+r_t}E_tp_{h,t+1})H_{It} = w_tN_t + p_{h,t}(1-\delta_h)H_{I,t-1} - C_{I,t} - (1+r_{t-1})B_{I,t-1} \tag{4.11}$$

From equation (4.11), the term $mE_tp_{h,t+1}/(1+r_t)$ represents the amount of funds that the impatient households can borrow from the patient households. The term $p_{h,t} - mE_tp_{h,t+1}/(1+r_t)$ is the instalment payment required to purchase one unit of housing. The net worth of the impatient households in period t can be found on the right-hand side of equation (4.11). The total worth consists of the labour income from supplying labour to the firms plus the value of housing accumulated in the previous periods. The net worth of the impatient households is that the total worth gets rid of the net of consumption and debt repayment. In the long equilibrium, the impatient households use all their net worth to finance the instalment payment that required to purchase H_{It} units of housing.

Patient Households

The representative patient households derive utility from consumption and housing. In this category of consumers, I follow Monacelli (2009) assuming that the typical patient households are the owner of the monopolistic firms in each sector. The patient households try to maximise lifetime utility:

$$U_{pt} = E_0 \sum_{t=0}^{\infty} \beta^{pt} \varepsilon_t^p \left[\frac{C_{pt}^{1-\sigma_c}}{1-\sigma_c} + \varepsilon_t^h \frac{H_{pt}^{1-\sigma_h}}{1-\sigma_h} \right] \tag{4.12}$$

where the variables in (4.12) share the similar interpretations in equation (4.1). The key feature that distinguishes the patient and impatient households' behaviour is the discount factor. In equilibrium, the patient households lend to the impatient households with borrowing constraint binding in the steady state. I assume that patient households are more patient than impatient households, implying

$$\beta^{pt} \geq \beta^{It} \tag{4.13}$$

The patient's sequence of budget constraints reads:

$$C_{pt} + p_{h,t}(H_{pt} - (1-\delta_h)H_{p,t-1}) + S_t = (1+r_{t-1})S_{t-1} + \pi \tag{4.14}$$

The right-hand side of equation (4.14) represents the total wealth of patient households, which consists of gross returns from lending and the profits from the holding of monopolistic competitive firms. The left-hand side of equation (4.14) is the outflow of funds of the patient households, which contain consumption, housing purchase and lending. Following Monacelli (2009), there are two reasons to disregard the labour supply choice by the patients' households. First, for simplicity, I disregard for labour supply of patient households making the level of output independent of the relative labour share of the two households. Second, the patient households are more patient than impatient households, which prefer to hold their

wealth obtain from lending funds and from owning firms in different sectors. Hence, they will end up owning all assets and choose to work very little in the steady state.

Patient households' Problem

The patient households try to maximise a lifetime utility function (4.12) subject to the budget constraint (4.14) through Lagrangian:

$$\mathscr{L} = E_0 \sum_{t=0}^{\infty} \beta^{pt} \left\{ \varepsilon_t^p \left(\frac{C_{pt}^{1-\sigma_c}}{1-\sigma_c} + \varepsilon_t^h \frac{H_t^{1-\sigma_h}}{1-\sigma_h} \right) - \lambda_{pt} [C_{pt} + p_{h,t}(H_{pt} - (1-\delta_h)H_{p,t-1}) + S_t - (1+r_{t-1})S_{t-1} - \pi] \right\}$$

$$(4.15)$$

The first order conditions:

$$C_{pt}: \qquad C_{pt}^{-\sigma_c} \varepsilon_t^p = \lambda_{pt} \qquad\qquad (4.16)$$

$$S_t: \qquad \lambda_{pt} = \beta^{pt} E_t \lambda_{p,t+1}(1+r_t) \qquad\qquad (4.17)$$

$$H_{pt}: \qquad \lambda_{pt} p_{h,t} = \varepsilon_t^p \varepsilon_t^h H_{pt}^{-\sigma_h} + \beta^p E_t (\lambda_{p,t+1} p_{h,t+1}(1-\delta_h)) \qquad\qquad (4.18)$$

Again, in the above equations, the marginal utility losses of choosing relevant allocations is shown on the left-hand sides; the marginal utility gains of choosing relevant allocations is presented on the right-hand sides. For housing demand of patient households (4.18), the marginal utility gain only depends on two components compared to the housing demand of impatient households. That is the direct utility gain of an additional unit of housing and the expected utility coming from the future consumption. Further imply:

$$C_{pt}^{-\sigma_c} \varepsilon_t^p = \beta^p E_t C_{p,t+1}^{-\sigma_c} \varepsilon_{t+1}^p (1+r_t) \qquad\qquad (4.19)$$

$$\varepsilon_t^h H_{pt}^{-\sigma_h} = C_{pt}^{-\sigma_c} p_{h,t} - \beta^p E_t(C_{p,t+1}^{-\sigma_c} p_{h,t+1}(1-\delta_h)\frac{\varepsilon_{t+1}^p}{\varepsilon_t^p}) \qquad (4.20)$$

4.3   Estimation

4.3.1   Data

The collateral constraint is introduced in the benchmark model by splitting the households into two types (patient households and impatient households). Therefore, five more variables involved in this model. They are consumption of patient households (C_{pt}), consumption of impatient households (C_{It}), housing demand of patient households (H_{pt}), housing demand of impatient households (H_{It}) and impatient households borrowing (B_{It}). The rest variables are the same as that used in Chapter 3, which sample period covers from 2001Q1 to 2014Q4. The detail of data description are outlined in the Appendix A. It should be noticed that the unfiltered data also used in this chapter to do the evaluation and estimation.

4.3.2   Calibration

Calibrated parameter values are introduced in this section, which are divided into two groups like in Chapter 3. The parameter values in the first group govern the dynamics of the model, which are calibrated according to previous literature and the observations in some empirical analyses. If the model using these calibrated values cannot pass the test, I would reestimate these parameters using Indirect Inference estimation. The calibration values in this group keep as same as those in Chapter 3 except for β^p, β^I, m. These three more parameters are introduced since the collateral constraint is employed in this chapter. The second group of the parameters are the steady state of the model, which are obtained from the data same in those in Chapter 3.

In this chapter, I split out the households into two types (patient households and impatient households) and introduce the collateral constraint between these two households. The key feature that distinguishes between patient and impatient households is they have the different discount factor. The discount factor of impatient households is less than the discount factor of

patient households, which implies the patient households are more patient than the impatient households. Hence, these two parameters are calibrated to evaluate and estimate. They are the discount factor of patient households β^P, the discount factor of impatient households β^I. Because of lending between two different households, one more parameter is introduced. That is loan-to-value ratio m.

In terms of the discount factor, I calibrate β^P at 0.985 and β^I at 0.97 in line with Iacoviello and Neri (2010) to guarantees that the borrowing constraint is binding for the impatient households in equilibrium. The binding constraint captures the financial accelerator effect, which allows the interaction between the housing sector and the rest of the economy.

m is the loan-to-value ratio, which captures the amount of loan that impatient households can get with a given market value of the house. The maximum loan-to-value ratio in China is 0.8. However, the average loan-to-value ratio is much lower than that, around 0.3 to 0.4[2]. According to Liu and Ou (2017), the observed debt-to-GDP ratios of households is around 23%. Hence, I calibrate the loan-to-value ratio at 0.3, which captures the features of the Chinese economy.

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[2]The data are from Housing Finance Network.

Table 4.1 Calibrated Coefficients - Model with Collateral Constraint

Defination	Parameter	Calibration
Households:		
Elasticity of substitution of normal goods consumption	σ_c	2
Elasticity of substitution of housing goods consumption	σ_h	1
Inverse of elasticity of labour	η	0.5
Patient households' discount factor	β^p	0.985
Impatient households' discount factor	β^I	0.97
Loan-to-value ratio	m	0.3
Firms:		
Price rigidity	ω	0.84
Output elasticity of capital	α	0.3
Quarterly depreciation rate of housing	δ_h	0.015
Quarterly depreciation rate of capital	δ_k	0.03
Capital demand coefficients	k_{11}, k_{12}	0.51, 0.47
Capital demand coefficients	k_{13}, k_{14}	0.02, 0.25
Capital demand coefficients	k_{15}	0.5
Monetary Policy:		
Taylor Rule response to inflation	θ_π	1.5
Taylor Rule response to output	θ_{GDP}	0.125

4.3.3   Empirical Results

In this section, I am going to discuss the Indirect Inference empirical results. The VARX auxiliary model is still used in the evaluation and estimation in this chapter. The choice of the auxiliary model is in line with the model in Chapter 3, which include total output, housing price and nominal interest rate in the auxiliary model. I do the evaluation first. If the model does not pass the test, the calibrated value can be predefined as starting value to implement Indirect Inference estimation. It should be noticed that all the coefficients are allowed to change when doing the estimation except for quarterly discount rate of patient and impatient households (β^p, β^I), quarterly depreciation rate of capital and housing (δ_k, δ_h) and the loan-to-value ratio (m) because they are identified through accounting information or other government policy. The simulated annealing algorithm is used when applying Indirect Inference estimation to discover the best fit set of coefficients. Table 4.2 presents the empirical results for the model with collateral constraint. The calibration values are also shown here for comparison.

I compare the estimated values with the calibrated values. The results show that all of these estimated values have moved some way from the initial calibration values. On the households side, for the estimated elasticity of substitution of consumption and housing, σ_c is estimated to be 3.30 and σ_h has increased to 2.55, both estimated values are larger than the initial values. The higher value of σ_i means that the consumption growth is less sensitive to changes in the real interest rate. From the estimated results, the estimated σ_h is still lower than the estimated σ_c, which implies that the substitution of housing goods is still relatively more sensitive compared to the substitution of general consumption goods when changing in the real interest rate. The estimated inverse of elasticity of labour supply η is significantly larger than the starting value, which implies that labour supply inelastic. However, this high inverse of elasticity of labour supply is much closer to other research reported by Zhang (2009) who employed the DSGE model to study Chinese monetary policy.

On the firm side, for nominal rigidities parameters, the price stickiness ω is estimated to be 0.33, much lower than the calibration value. The parameter ω measure the degree of nominal rigidity. The estimated result shows that only around 33% of all firms cannot adjust their price while the remaining 67% can adjust. This implies that the Chinese economy may not be that sticky, which is similar to the empirical results in Liu and Ou (2017).

The value of the share of capital in production adjusts slightly, which only increase to 0.31. For capital demand coefficients, the coefficient k_{11} is lower than the starting value. This implies that lower adjustment cost. The higher value of estimated k_{12} implies that lower discount rate of capital. The coefficients k_{13} remains the same as the starting value. The long-run relationship among coefficients in the capital demand equation is also approximately satisfied, which is that $k_{11} + k_{12} + k_{13} = 1$.

Overall, monetary policy is estimated to be less responsive to inflation and more responsive to output fluctuation. More specifically, the responsiveness of interest rates to inflation θ_π increase from 1.5 to 1.2. On the contrary, the responsiveness of output increase to 0.42 compared with the calibrated value.

This chapter aims to investigate the case when there is a collateral constraint. I want to explore whether the model can perform well if it introduces the collateral constraint. To this end, I compare the testing results generated from the benchmark model, where there is no lending, with those with collateral constraint. Table 4.3 represents the comparison of the testing results based on Indirect Inference estimation of the two models. The results show that both models can pass on the weaker test, but the model with the collateral constraint is obviously inferior to the benchmark model according to the Wald statistic. The benchmark model is more probable.

In order to check both models performance with the stronger test, I add one more endogenous variable to the existing auxiliary model. The test becomes more stringent and powerful when I extend the features of the structural model that the auxiliary model seeks

to match. The second row of Table 4.3 shows the testing results when I raise the power of the test. The results display that the only benchmark model can pass the stronger test at 3% significance level, while the collateral model does not pass. That implies the benchmark model is the best model using the Wald statistic as a guide.

Different model with different coefficients may give different analysing results. Therefore, it should be cautious when choosing the model. The benchmark model is better to be chosen when do not focus on the lending since it has the better Wald statistic. If lending is the important part when analysing the economy, the model with collateral constraint should be considered. In the following, I am going to do the standard analysis such as impulse response functions, variance and historical decomposition for the model with collateral constraint.

Table 4.2 Estimated Coefficients - Model with Collateral Constraint

Defination	Parameter	Calibration	Estimation
Households:			
Elasticity of substitution of consumption	σ_c	2	3.30
Elasticity of substitution of housing	σ_h	1	2.55
Inverse of elasticity of labour	η	0.5	6.96
Patient households' discount factor	β^P	0.985	0.985
Impatient households' discount factor	β^I	0.97	0.97
Loan-to-value ratio	m	0.3	0.3
Firms:			
Price rigidity	ω	0.84	0.33
Output elasticity of capital	α	0.3	0.31
Quarterly depreciation rate of housing	δ_h	0.015	0.015
Quarterly depreciation rate of capital	δ_k	0.03	0.03
Capital demand coefficients	k_{11}, k_{12}	0.51, 0.47	0.46, 0.53
Capital demand coefficients	k_{13}, k_{14}	0.02, 0.25	0.02, 0.14
Capital demand coefficients	k_{15}	0.5	1.33
Monetary Policy:			
Taylor Rule response to inflation	θ_π	1.5	1.2
Taylor Rule response to output	θ_{GDP}	0.125	0.42
Trans-Wald (GDP, HP, R)		**22.67**	**1.49**
P-value		**0.00**	**0.06**

Table 4.3 Comparison of the Testing Results Based on II estimation

Auxiliary Model-VARX(1)	Benchmark Model	Collateral Model
GDP, HP, R	1.02	1.49
	(0.11)	(0.06)
GDP, HP, R, C	1.92	3,46
	(0.03)	(0.00)

4.3.4   Indirect Inference Power Test

In the last section, the Indirect Inference testing is employed to evaluate the estimated structural model. We would like to know how powerful the Indirect Inference test is. Therefore, in this section, I am going to check the evaluation of the power of Indirect Inference. In order to evaluate the power of Indirect Inference test on both benchmark model and model with collateral constraint, I follow Le et al. (2012) and Le et al. (2016) to conduct Monte Carlo power statistical test against parameter misspecification. Following their research, they assume the models they used is the true model and the estimated residuals are also treated as the true residual. Then they use the result of the Monte Carlo experiment to establish their degree of accuracy.[3] They use the Monte Carlo experiment to show that how often the test rejects at the chosen nominal rejection rate. Their results show that the confidence level is 5.7% when the true rejection rate at a nominal 5%. Therefore, this experiment is fairly accurate. I employ their experiment results and treat estimated benchmark model as well as the constraint model as the true model, using the true rejection rate at a nominal 5% with a three variables VARX(1). Now I am interested in how the frequency of rejection of the false model when both true models deviate increasingly from the original.

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[3]10000 Monte Carlo experiments are set up to obtain the 10000 sample of data. In each sample, the innovations were bootstrapped to find the Wald distribution.

The false models are created by moving the parameters away from their true values (estimated value) by x % in both directions for alternate values.

Table 4.4 displays the rejection rates at a nominal 5% given the parameter falseness from 0.5% to 7%. [4] We can see clearly from the table that when the falsity of parameters increases, the probability of rejecting the false model increase. This implies the power is considerably high given a significant falseness. More specifically, the benchmark model is 100% rejected when the falsity of parameters increases to 7%. Comparing with the benchmark model, the model with collateral constraint seems more sensitive to the increase in the degree of falseness. The rejection rate has already increased to 100 when the degree of falseness equal to 3. It is interesting to find that the model with collateral constraint has more power compared with the benchmark model. It might be because the collateral model has more restrictions, so a small change in the parameter will create the more significant overall worse match.

Table 4.4 Monte Carlo Power test- 3 variables VARX(1)

Parameter Falseness	TRUE	0.5%	1%	1.5%	3%	3.5%	5%	7%
Benchmark Model	5	7.2	9.6	13.4	41.1	63	85.6	100
Model with collateral constraint	5	20.5	57.4	88.7	100	100	100	100

The testing results in the last section show that the benchmark model passed at 3% significance level while the model with collateral constraint did not pass when a 4-variable VARX(1) was used. I want to check how robust the benchmark model is with respect to misspecification and I also want to gauge to what extent the collateral model was misspecified. Hence, this attracts me to do the Monte Carlo experiment again, but this time, the rejection rates at a nominal 3% with a 4-variable VAR. Table 4.5 displays that how the rejection rates vary when one more endogenous variable is included in the auxiliary models. It is interesting

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[4]The rejection rate is obtained using true data from the true model and false model, which calculate how many false model would be rejected by the true data from the true model with 95% confidence.

to find that increasing one more endogenous variable raise the power of Indirect Inference test as well. In this case, the benchmark model is already 100% when the falsity of parameters just increase to 5%. Comparing with the benchmark model, the collateral model rejects 99% of the time when the parameter falseness only raises to 3.5%. The more features that the auxiliary model tries to match, the higher the probability that model is rejected by the data, which is in line with the argument.

Table 4.5 Monte Carlo Power test- 4 variables VARX(1)

Parameter Falseness	TRUE	0.5%	1%	1.5%	3%	3.5%	5%	7%
Benchmark Model	3	3.7	4.9	6.6	42	82.2	100	100
Model with collateral constraint	3	6.1	7.1	8.4	65.8	99	100	100

4.3.5 Error Properties on Non-Stationary Data

In the last section, I discuss the estimation and testing results of the model with collateral constraint. Before doing the standard analysis such as IRFs, variance and historical decomposition, I follow Le et al. (2014) to analyse the error properties. These shocks are backed out of the model using the non-stationary data (Figure 4.1) and fit to each an AR time series process over the period. Table 4.6 shows the stationarity of each shock and also the estimated AR parameters. I employ two different types of stationarity test for each calculated shock process: Augmented Dickey- Fuller (ADF) test and Kwiatkowski Phillips Schmidt Shin (KPSS) test.

The ADF test tests the null hypothesis that the shock follows a unit root process, against the alternative hypothesis that the shock is stationary. The ADF testing results show in the second column of Table 4.6, we can see from the table that the labour supply shock, housing demand shock, capital and labour demand shock in general sector as well as the monetary policy shock reject the unit root process at 10%, 5% and 1% significant level

respectively. The p-value of the rest shocks, except for productivity shock in different sectors, show the borderline non-rejection at 10% significance. However, the p-value of productivity shock in both sectors approximately equals to 1, which implies a strong non-rejection of the null hypothesis. According to DeJong et al. (1992), the very low power when errors are autoregressively correlated is one of the problems of the ADF test. That implies the testing does not perform well when errors are autoregression. Therefore, the KPSS stationary test is employed to re-evaluate the structural error.

In terms of the KPSS test, on the contrary, tests the null hypothesis that the shock is stationary against the alternative hypothesis that the shock follows a unit root process. The KPSS testing results represent on the third column of Table 4.6. The results show that all the shocks fail to reject the stationary except for the productivity shock in both sectors. It should be noticed that no matter an ADF test or KPSS test, the stationarity test show that productivity shock in different sectors contains a stochastic trend. This interesting finding support modelling productivity shock as the non-stationary shock.

The last column of Table 4.6 shows the estimated AR coefficients of the shock process, which allow the error data to determine it. We can see clearly from the table that many of the estimated AR coefficients show high persistence even though those errors are stationary.

Table 4.6 Stationarity of Residual and AR parameters

Shocks	ADF p-value	KPSS statistic	Conclusion	Estimated Coefficient
Government spending	0.1873	0.238410	Trend Stationary	0.9292
Preference	0.3118	0.191114	Stationary	0.9048
Labour supply	0.0712*	0.242881	Trend Stationary	0.9745
TFP – General sector	0.9905	0.963698***	Nonstationary	-0.6121
TFP – Housing sector	0.8919	0.932474***	Nonstationary	0.5483
Housing Demand	0.0246**	0.120453	Stationary	0.7895
Monetary policy	0.0172***	0.052904	Stationary	0.7710
Labour demand - General	0.0647**	0.210822	Trend Stationary	0.8923
Labour demand - Housing	0.1262	0.213745	Trend Stationary	0.9893
Capital demand - General	0.0635**	0.095722	Trend Stationary	0.9017
Capital demand - Housing	0.1710	0.167694	Trend Stationary	0.9207

Notes:

1. p-value with *,** and *** rejects the unit root process at 10%, 5% and 1%

2. KPSS with ** (***) rejects stationarity at 5% (1%)
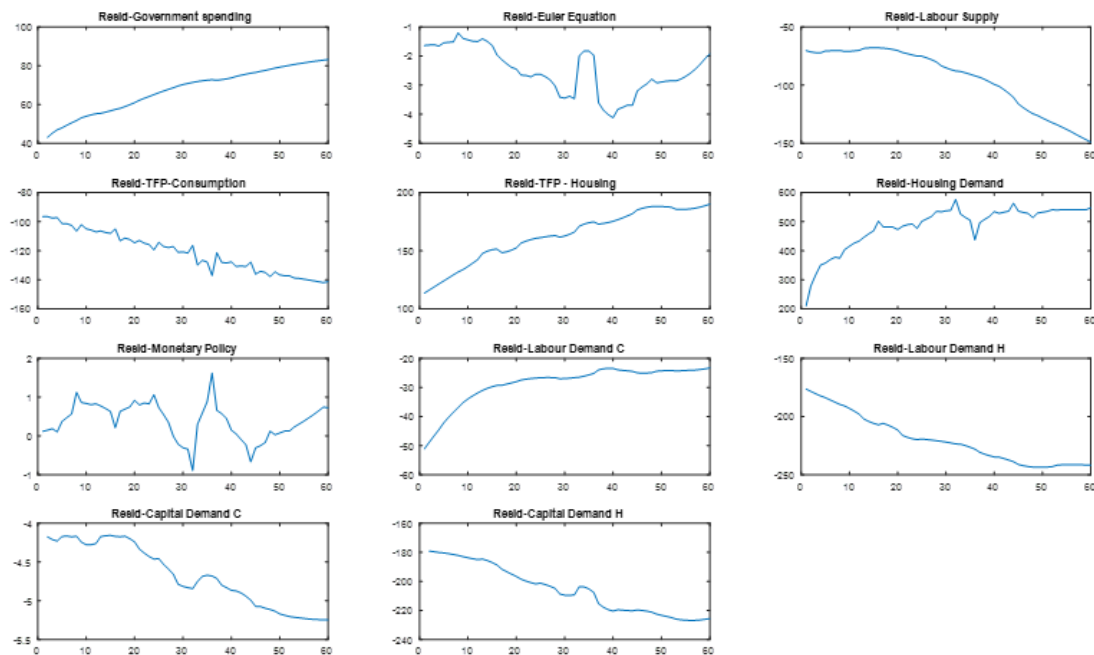
Fig. 4.1 Structure Shocks - Model with Collateral Constraint

4.4 Standard Analysis

4.4.1 Impulse Response Functions

In this section, I evaluate the role of collateral constraint by comparing the structural impulse response functions generated from the estimated benchmark model with those from the estimated model including collateral constraint. In order to make these two models comparable, I give them the same scaled shock (0.1 standard error). In the following, I will analyse the impulse response to housing demand shock, monetary policy shock and productivity shock in the general sector respectively. The impulse responses of key macroeconomic variables such as housing-related variables to traditional shocks are worth mentioning. The key macroeconomic variables are total GDP, general goods consumption, housing consumption, housing price, inflation, as well as output in different sectors. The dashed line shows the impulse

response of the model with collateral constraint, while the solid line represents the response of the benchmark model.

Housing Demand shock – According to Iacoviello and Neri (2010), the housing demand shock can be interpreted as the change in households' preference of purchase housing. It implies unexpected changes in individual households' preferences caused by the social and institutional changes or the availability of resources needed to purchase housing.

Figure 4.2 demonstrates information about the responses of housing demand shock for the two versions of the model. We can see clearly from the figure that all variables move in the same directions in both benchmark model and model with collateral constraint. However, the model with collateral constraint reacts more magnitudes when there is 0.1 standard error of housing demand shock hitting the economy. More specifically, there is an immediate increase in the housing price and housing demand when a positive housing demand shock occurs. It also raises the output of housing to meet the extra housing demand. The impulse responses of selected variables to housing demand shock in both models are in line with the main findings in many previous works of literatures.

As mentioned in the beginning, the housing demand shock can be thought as the variations in housing demand due to the social and institutional changes. In China, the housing institution reforms can be explained as the important institutional change. There is no housing market before the reforms. A gradual and persistent housing institution reforms had been launched since 1980. Hence, the demand for housing increased. The supply of housing raised in order to meet the extra demand. Overall, the reforms in the housing market simulated the whole economic growth, which is a significant fundamental economic change. The more wealth the households get, the better living conditions they desire. Therefore, the demand for housing simulates the change in the housing market and economic growth.

I also want to explore one aspect of the spillovers effect that mentioned in Iacoviello and Neri (2010). The spillover focused on in this chapter is the relationship between housing

wealth and the general consumption. According to Iacoviello and Neri (2010), they use the US data to study the housing market spillovers. Their empirical results show that the collateral constraints alter the transmission mechanism, which amplifies the response of general consumption. Hence, this propagation mechanism shows through the impulse responses functions (IRFs) they obtained. From their IRFs of housing demand shock, the collateral constraint presents the key feature of explaining the spillovers effect, which implies housing demand shock lead to an increase in general consumption. However, my results show that there is no obvious positive spillovers effect from the housing wealth to the general consumption in China. This is maybe because the total income effect is greater than the substitution effect according to the estimated parameters.
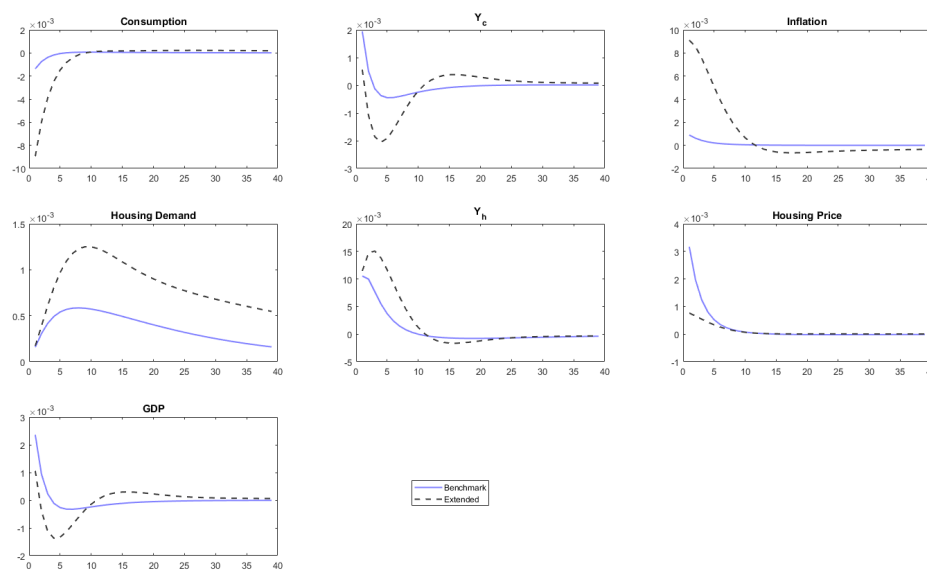
Fig. 4.2 Impulse Response to a 0.1 standard error Housing Demand Shock

Monetary Policy shock – Figure 4.3 shows the response of monetary policy shock. In general, As the figure reflects, a tightening of monetary policy decreases all components of real aggregate demand and real housing prices in both models. The positive monetary policy shock discourages the investment and consumption in both sectors, which decrease the total

output. The decrease of housing output and housing demand shift the pressure to housing price, which lowers the housing price as well. However,compared with the benchmark model, this effect is not obvious on some variables in the housing sector. The lower consumption also affects the changes in inflation.

In the benchmark model, the Taylor Rule in our model affect the consumption through the Euler equation and therefore influence the demand for housing. As the results, it triggers the housing price. However, in the model with collateral constraint, the interest rate also comes in the borrowing constraint (see Equation 4.3), which add another channel to affect the whole economy. It implies that the tightening monetary policy shock also affects impatient households borrowing, which decreases the collateral capacity and amplifies the negative response of consumption.
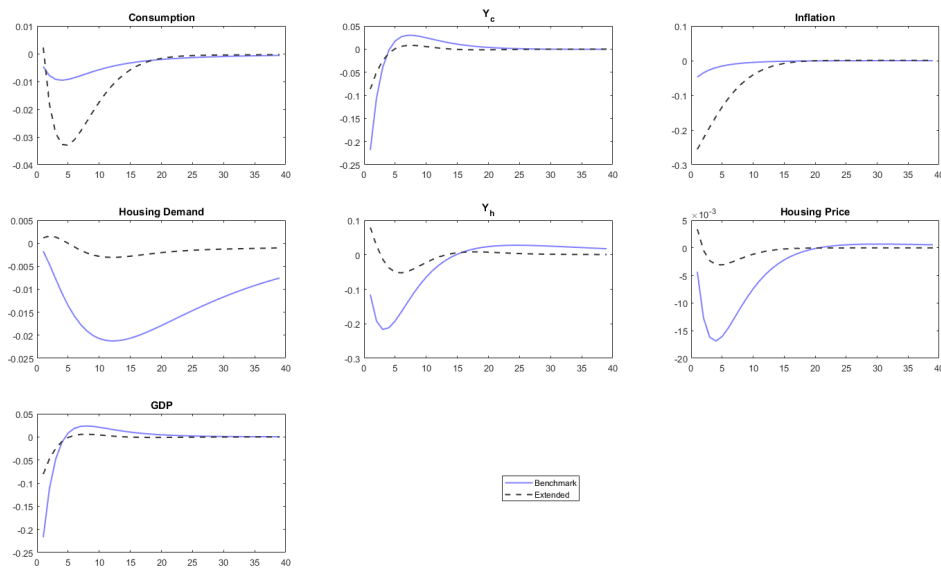
Fig. 4.3 Impulse Response to a 0.1 standard error Monetary Policy shock

General sector Productivity shock – One of the features in my model is I treat the productivity shock in both sectors as non-stationary. In this part, I focus on the impulse response of general sector productivity shock. Figure 4.4 shows the impulse response of

key variables to a positive productivity shock in the general sector. The non-stationary productivity shock has the permanent effect, which influences the macroeconomic variables including output, consumption, housing demand and these variables become more persistent afterwards lasting over 40 quarters. In response to a 0.1 standard error technology shocks, output in the general sector and total GDP react positively to the realisation of technological progress. Inflation decrease due to the decreasing in marginal cost and the increasing in the supply of general goods with a positive productivity shock.

The positive productivity shock also lowers the real housing price. we can see clearly from the figure that the consumption in the model with collateral constraint increase less than the consumption in the benchmark model. The reason maybe because the decreasing of housing price drops the collateral capacity of impatient households, which implies the impatient households borrow less. The less borrowing induces them to consume less. Therefore, the collateral constraints alter the transmission mechanism, which amplifies the response of general consumption.
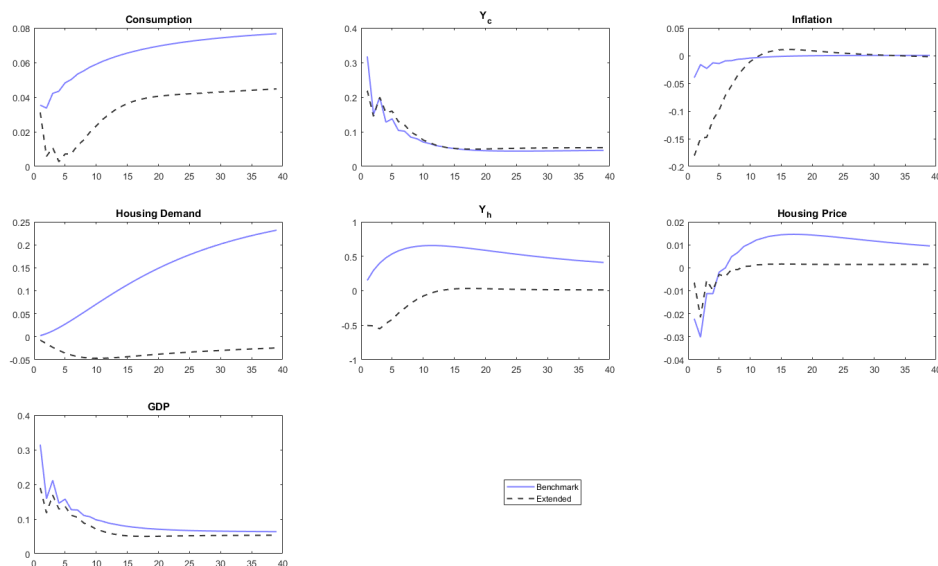

Fig. 4.4 Impulse Response to a 0.1 standard error Productivity Shock in General Sector

4.4.2   Variance Decomposition

In this section, I focus on answering the same question as in Chapter 3 but using the model with collateral constraint. The question is what drives fluctuations in the housing market. Variance decomposition is also employed to investigate the contributions of shocks to future forecast uncertainties. Table 4.7 shows the variance decomposition of GDP, inflation, consumption and housing price at different horizons, which are computed based on the model with collateral constraint using estimated coefficients reported in Section 4.3.3.

In terms of housing prices, we can see clearly from the Table 4.7 that the productivity shock in general sector plays a significant role in driving the cyclical fluctuation in housing price no matter in short run or in the long run. It explains 92.42% of the variance in housing price in the first year and about 95% in the long run. However, the other shocks like housing demand shock, capital and labour demand shock play a minor role in explaining the real housing price. The housing demand shock only accounts for 1.16% of the variance in the real housing price in the short run and decrease in the long run with 0.53% in the long run. That is because the rapid technological change in China leads to the economic boom. The increasing wealth leads the households in China tend to use their income to purchases houses when the state and companies no longer to allocated urban houses treated as welfare goods. Although the housing demand shock is the main driven force in fluctuating housing price in previous literature, in my research, the productivity shock dominates housing price in China. In empirically, this idea is also supported by Bian and Gete (2015). They believe China has experienced significant development involving fast productivity progress. Higher productivity leads to higher households' income, which raises the higher demand for housing. And also, Kahn (2008) argues that the productivity growth in the U.S. is a key driver of medium to long-term movements in housing prices. In addition, the price of the new house is also affected if the productivity growth in the construction sector is slower than in other sectors. This idea is also approved in the case of Canada by Sharpe et al. (2001). And Moro

and Nuño (2012) also argue that this is usually the case for most countries such as Germany, Spain, the U.K. and the U.S.

The real consumption is the non-housing variable but it does be affected by the housing demand shock. The cyclical fluctuations in consumption are driven mainly by preference shock and housing demand shock, which explain 39.20% and 33.70% of the variance in housing price in the first year. In the long run, the influence of preference shock and housing demand on housing price fluctuations decreases with around 27% and 24% in the long run. The preference shock plays a significant role in explaining the real consumption because the shock influences the inter-temporal Euler equation, which directly affects the real consumption. The reason why housing demand shock also plays a role in explaining the real consumption maybe due to, I believe, the collateral constraint. The borrowing capacity of impatient households mainly depends on the housing price. The change in housing price affects the borrowing, in turn, the consumption.

The following variables in the Table 4.7 GDP, inflation and interest rate are also non-housing variables. However, the housing demand shock plays a minor role in driving the cyclical fluctuations, which account for less than 15% of most variables. The supply shock does affect some variables, but it is not the dominant driving force. However, the contribution of productivity shock in the general sector to the fluctuations in non-housing variables is more important especially for the most non-housing variable in the long run. Technology shock explains 84% of the variances in GDP in the short run and about 91% in the long run. In terms of inflation and interest rate, the shock explains 70%-90% in inflation and 60%-80% in interest rate different horizons.

Technology shock in the general sector plays a significant role in the movements of the key macroeconomic variables. These interesting findings can explain the Chinese economic development. According to Hsu and Zhao (2009), they find that the total factor productivity growth rates are the main reason for the economic volatility especially when China started

its market-oriented reforms. Therefore, technology becomes an engine to promote Chinese economic growth. This is the intuition to explain why the technology productivity shock is quite important when explaining the key macroeconomic variables.

Table 4.7 Variance Decomposition of aggregate variables- Collateral Model

Variable	Gover. Spend.	Intert. Pref.	Lab. Supply	Tech. in General	Tech. in House	House Demand	Monet. Policy	Lab. D. General	Lab. D. House	Capit. D. General	Capit. D. House
1 Year:											
GDP	0.40	0.23	0.20	84.82	3.74	0.35	0.23	1.34	5.99	1.32	1.38
Inflation	0.16	0.32	1.25	70.73	2.27	13.65	0.73	0.68	2.74	1.09	6.39
Consumption	0.54	39.20	0.32	1.00	6.96	33.70	0.30	0.06	1.66	1.29	14.99
Housing Prices	0.11	0.04	0.06	92.42	0.93	1.16	0.86	0.62	2.15	0.68	0.96
5 Year:											
GDP	0.37	0.27	0.15	86.39	6.88	0.24	0.10	0.64	3.62	0.70	0.65
Inflation	0.19	0.20	2.25	81.69	3.19	6.33	0.44	0.35	1.79	0.57	3.01
Consumption	1.42	32.61	1.08	3.72	17.14	28.58	0.30	0.44	1.52	1.09	12.10
Housing Prices	0.17	0.10	0.05	92.32	2.84	0.94	0.57	0.38	1.57	0.47	0.61
10 Year:											
GDP	0.19	0.14	0.09	91.89	4.48	0.12	0.05	0.33	2.02	0.36	0.33
Inflation	0.09	0.09	1.34	91.30	1.70	2.76	0.19	0.15	0.82	0.25	1.32
Consumption	1.65	27.48	1.38	10.59	21.11	24.29	0.25	0.68	1.37	0.92	10.30
Housing Prices	0.09	0.06	0.03	95.16	2.08	0.53	0.32	0.21	0.91	0.27	0.34

4.4.3 Historical Decomposition

I have already discussed the fluctuation of the key macroeconomic variables in terms of variables decomposition. In this section, I focus on the historical decompositions that indicate the contribution of each shock to the volatility of variables over a certain sample period. Figure 4.5 and Figure 4.6 show the historical decomposition of real housing price and real consumption. The results in historical decompositions mirror some common features with those in variance decomposition.

According to the effects of shocks on various aspects of the economy, I classify these 11 shocks (government spending shock, preference shock, housing demand shock, labour supply shock, productivity shock in both housing and general sectors, capital demand as well as labour demand in both sectors and monetary policy shock) into six categories. The preference shock and labour supply shock belong to private shocks. The public shocks contain labour demand shock in different sectors and capital demand shock in the general sector and housing sector. The policy shocks consist of monetary policy shock and government spending shock.The TFP including the technology shock in two sectors. The housing demand shock does not be classified into private shocks category since I want to observe how this shock influence the real housing price and real consumption.

From Figure 4.5, I find that the fluctuation of housing price is mainly driven by the technology shock and public shocks. The contribution of housing demand shock appears less important. The figure also displays that the housing price seems relatively stable during the period 2000-2003 and period 2010-2012, but it fluctuated a lot during the crisis period. It should also be noticed that there was a drop started in 2007, which reflected the stock market boom in 2007 and the market's reaction to the global crisis. The housing market recovered after the crisis and rise dramatically until earlier 2010. The economy increased rapidly these years, which lead households in China earning increasing wealth. They tended to use their wealth to purchase the house since housing market developed these years rapidly. I also

Fig. 4.5 Historical Decomposition of Real Housing Price

find that after 2010, the housing price decreased continuously as lower productivity. These findings are generally in line with Liu and Ou (2017). They show that the housing market triggered another significant slowdown as demand and productivity both continued to fall from 2013 onwards, which the housing price was corrected toward its equilibrium level.

As for the macroeconomy, I focus on the dynamic of consumption. Figure 4.6 shows the historical decomposition of real consumption. We can see clearly from the figure that the fluctuation of real consumption is driven by private shocks like preference shock, housing demand shock and productivity shock, which in line with the finding in variance decomposition. More specifically, during period 2000-2003, the real consumption seems relatively stable. The positive productivity shock increased the real consumption, which implies higher productivity translated into higher household income and higher real consumption. The negative effect can be found during period 2011-2013. The real consumption started to fall since productivity fell. The historical shock decomposition of real consumption further suggests the contribution of collateral constraint, which housing demand shock affected the real consumption dramatically in late 2007. However, during period 2008-2011, the contribution of preference shock appears more important.
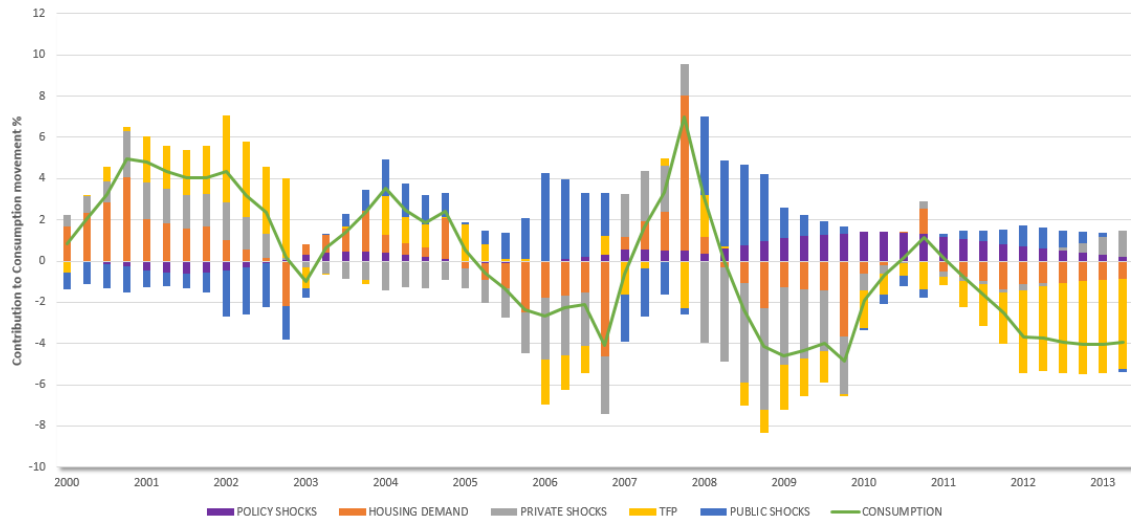
Fig. 4.6 Historical Decomposition of Real Consumption

4.5 Conclusion

The aim of the chapter is that I want to explore whether the model can explain the Chinese housing market well if I include the collateral constraint. Indirect Inference evaluation is employed to answer this question. The testing results show that both benchmark model and model with collateral constraint can match the data, but the model with collateral constraint is obviously inferior to the benchmark model according to the Wald statistic. This implies the benchmark model is the best model using the Wald statistic as a guide. Hence, it should be quite cautioned when choosing the model. In the following, I conduct IRFs, variance and historical decomposition to further study the model with collateral constraint. The results show that the collateral constraint explains the spillover effect from the housing market to the wider economy. The productivity shock in the general sector plays a significant role in the movements of the key macroeconomic variables.

Chapter 5

Conclusion

The dramatic rise and the large fluctuation of housing price motivate me to study the Chinese housing market. This thesis addresses two research questions related to the housing market in China: i) the sources of fluctuations in the Chinese housing market. ii) identify whether the model with collateral constraint enables a better performance. A DSGE model using Indirect Inference method is employed to explore these two issues.

Following the above two motivations, I reviewed the literature about the driving forces behind movements in the housing sector and the structured DSGE models with collateral constraint in Chapter 2. In the existing empirical literature, the housing price fluctuation is affected by the economic fundamentals such as construction costs, disposal income and population. There is no consensus among researchers regarding the source of housing price dynamics in the existing empirical literature. There are some limitations when using various econometric models such as omitted variables problem and endogeneity problem. Therefore, a micro-foundation structural model is chosen in this thesis to study the housing market dynamics in China. The increasing researchers have followed Iacoviello and Neri (2010) who use a Bayesian estimated DSGE model to discover the housing market fluctuation. More factors are considered to enrich the model based on their analysis framework. In summary, most of the literature that using a micro-founded DSGE model employing Bayesian estima-

tion have concluded that the housing demand shocks play an important role in explaining the fluctuation of housing price in China. In terms of the model with collateral constraint, I reviewed Kiyotaki and Moore (1997) who first introduced the collateral constraint and Iacoviello (2005) who extend Kiyotaki and Moore (1997) 's work by using housing stock as the collateral.

Chapter 3 focus on answering the first research question: What is the driving force in the fluctuation of housing price. A DSGE model with housing sector and some important features of the Chinese economy is established to address this question. Two features of the Chinese housing sector are considered in this model: i) two sectors on the supply side. ii) the non-stationary productivity shock in both housing and general sector. In order to check whether this model can explain the data behaviour in the Chinese housing market, Indirect Inference evaluation is employed. The testing results show that the model using the calibration value is rejected by the data. Hence, Indirect Inference estimation is used to estimate the model over the period 2000-2014, which find out a set of coefficients that can pass the test. The estimated model can fit the data well when a variety of endogenous variables are added to the auxiliary model, explaining the output, housing price and interest rate that I concerned about. I discovered the housing market using this right estimated model, which can perform well in explaining the data. In terms of the driving force of fluctuations in the Chinese housing market, the variance and shock decomposition suggest that the capital demand shock play a significant major role in explaining the housing price. That maybe because the housing market reform stimulates the Chinese housing industry, which develops some new regime of capital accumulation. These regulation change on the supply side played a key role in housing development.

The increasing interest in the DSGE housing model literature have focused on the collateral constraint on the households' side, which treats as a channel that connects the housing market to the wider economy. Hence, in Chapter 4, I focus on discovering that

whether adding a collateral constraint to a New Keynesian DSGE model enables a better performance. Indirect Inference evaluation is used to examine it. From the modelling point of view, my starting point is the benchmark model that introduced in Chapter 3. In order to examine whether the model with collateral constraint can explain the Chinese housing market well, I include another feature into the benchmark model: collateral constraint. I add this constraint by splitting the households into patient and impatient households. The impatient households in the economy face a binding collateral constraint when participating in loan and mortgage market. Indirect Inference testing results show that the model with collateral constraint cannot provide a better performance in explaining the data. More specifically, both benchmark model and model with collateral constraint model can match the data, but the model with collateral constraint is obviously inferior to the benchmark model according to the Wald statistic. This implies the benchmark model is the best model using the Wald statistic as a guide. Hence, it should be quite cautioned when choosing the model. I also use Monte Carlo experience to show how the power of Indirect Inference. I evaluate the power of Indirect Inference test on both benchmark model and model with collateral constraint. The experience results show that the power is considerably high given a significant falseness. It is also interesting to find that the model with collateral constraint has more power compared with the benchmark model. It might be because the collateral model has more restrictions, so a small change in the parameter will create the more significant overall worse match.

There are two contributions in this thesis. First, the dynamic stochastic general equilibrium model is set up incorporating housing sector and some important features of the Chinese economy. This provides a framework to describe the Chinese housing market in a reasonable detail. Differing from the most previous literature, the productivity shock in both the housing sector and general sector are assumed to be non-stationary. The non-stationary shocks could shed light on some stylized fact in China. Second, the evaluation and estimation strategy followed Indirect Inference method using unfiltered non-stationary data are employed in this

thesis. To my knowledge, there has been no evaluation of DSGE model with housing sector. This is the perspective adopted in this thesis.

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Appendix A

Data

Benchmark Model

The sources of these observables from 2000Q1 to 2014Q4 are from the National Bureau of Statistics of China (NBSC), Ministry of Human Resources and Social Security,P.R.C (MHRSS), the People's Bank of China (PBOC) and the Oxford Economics (OE). In this case where the quarterly data are not available, it is only available on annual basis. I follow Liu and Ou (2017) to convert the annual data into the quarterly data using either the 'quadratic-match sum' or the 'quadratic-match average' algorithms with Eviews. The Table A.1 below summarise all the description and sources of the data used in the evaluation and estimation.

Table A.1 Data Description and Source of Benchmark Model

Symbol	Variable	Source
GDP	Total Output	NBSC
Y_c, Y_h	Output in different sector	Model implied[2]
C	Total private consumption	NBSC
H	Total housing consumption	Model implied[2]
W	Average Wage per person	MHRSS
π	Quarter-on-quarter CPI inflation	NBSC
N[1]	Total Employment	Oxford Economic
N_c, N_h	Employment in two sectors	Model implied[4]
p_h	Real housing price	NBSC
I, I_c, I_h	Investment	NBSC
K, K_c, K_h	capital	Model implied[3]
i	Nominal interest rate	POBC

Notes on Table A.1:

1. The variable N_t in the model represent the aggregate supply of labour hour of household. The measurement of the aggregate supply of labour is the multiplication of supply of labour in each household and the total employment. It is assumed that the working hour in the contract is fixed (around 8 hours). Therefore, the aggregate supply of labour hour can be equal to the total employment. In my research, due to the data limitation in China, the total employment is used to represent N_t in the model.

2. Constructed data: Y_c, Y_h, H

The output in different sectors are constructed following Liu and Ou (2017). The value of housing (Residential investment) is the multiply of the price of housing (p_h) and the quantity of housing (Y_h). In this identification, the value of housing and the price housing

are all available from NBSC. Therefore, it is easy to the quantity of housing (Y_h). The unobservable variable H_t is obtain from the marketing clearing condition in housing sector. The depreciation rate used in calculating H_t following Liu and Ou (2017). The output in general sector (Y_c) is calculated using the definition of GDP.

3. Constructed data: K_c, K_h, K

The total capital and the capital in different in different sectors are calculated following Caselli(2004) using the capital accumulation equation (3.13). The investment can obtain from NBSC. The depreciation in each sector follow Liu and Ou (2017).

4. Constructed data: N_c, N_h

Follow Barsky et al. (2007)'s assumption and the identification equation (3.44) to construct N_c and N_h. Barsky et al. (2007) assume that factors flow freely across industries, nominal wages and rental prices will be equal in each sector. That means the capital-to-labour ratios will equalize across industries since the production function is homogeneous of degree one no matter which sector have sticky prices and which one have flexible prices. Consider the identification equation, there are two equations and two unknown, it is easy to solve for N_c and N_h

Model with Collateral Constraint

Five more variables are introduced in this model due to the inclusion of the collateral constraint by splitting the households into two types. They are consumption of patient households (C_{pt}), consumption of impatient households (C_{It}), housing demand of patient households (H_{pt}), housing demand of impatient households (H_{It}) and impatient households borrowing (B_{It}). The rest variables are the same as that used in Chapter 3, which sample period covers from 2001Q1 to 2014Q4. These five variables cannot be obtained from database directly. Hence, the observables and model equations are used to construct these variables. The identification and steady state ratio following Andrés et al. (2013) are used to calculate consumption and housing demand of different type of households. The unfiltered data also used in this chapter to do the evaluation and estimation. The reason why using unfiltered data have already been discussed in the last chapter. Table A.2 below summarise the variables and source of the data used in this model.

Table A.2 Data Description and Source of Model with Collateral Constraint

Symbol	Variable	Source
GDP	Total Output	NBSC
Y_c, Y_h	Output in different sector	Model implied[2]
C	Total private consumption	NBSC
C_p	Patient households consumption	Model implied[5]
C_I	Impatient households consumption	Model implied [5]
H	Total housing consumption	Model implied[2]
H_p	Patient households housing consumption	Model implied[6]
H_I	Impatient households housing consumption	Model implied[6]
B_I	Total borrowing of Impatient households	Model implied[7]
W	Average Wage per person	MHRSS
π	Quarter-on-quarter CPI inflation	NBSC
N[1]	Total Employment	Oxford Economic
N_c, N_h	Employment in two sectors	Model implied[4]
p_h	Real housing price	NBSC
I, I_c, I_h	Investment	NBSC
K, K_c, K_h	capital	Model implied[3]
i	Nominal interest rate	POBC

Notes on Table A.2: The detail of Note 1 to Note 4 can be found in Appendix A benchmark model.

Note 5: Model implied data: C_p, C_I. The identified equation of total consumption goods $C_t = C_{pt} + C_{It}$ along with the ratio of consumption of patient and impatient households following Andrés et al. (2013) are used to construct consumption of different type of households.

Note 6: Model implied data: H_p, H_I. They are calculated applying the same logic like calculating C_p, C_I. Using total housing demand together with the ratio of housing demand of patient and impatient households by Andrés et al. (2013) to calculate housing demand of patient and impatient households.

Note 7: Model implied data: B_I. The total borrowing of impatient households can be obtained from the binding borrowing constraint (equation 4.3). The data on the right-hand sides of equation 4.3 are available. Hence, it is easy to get B_I

Appendix B

Impulse Responses of Main Variables

Benchmark Model

Fig. B.1 Government Spending Shock
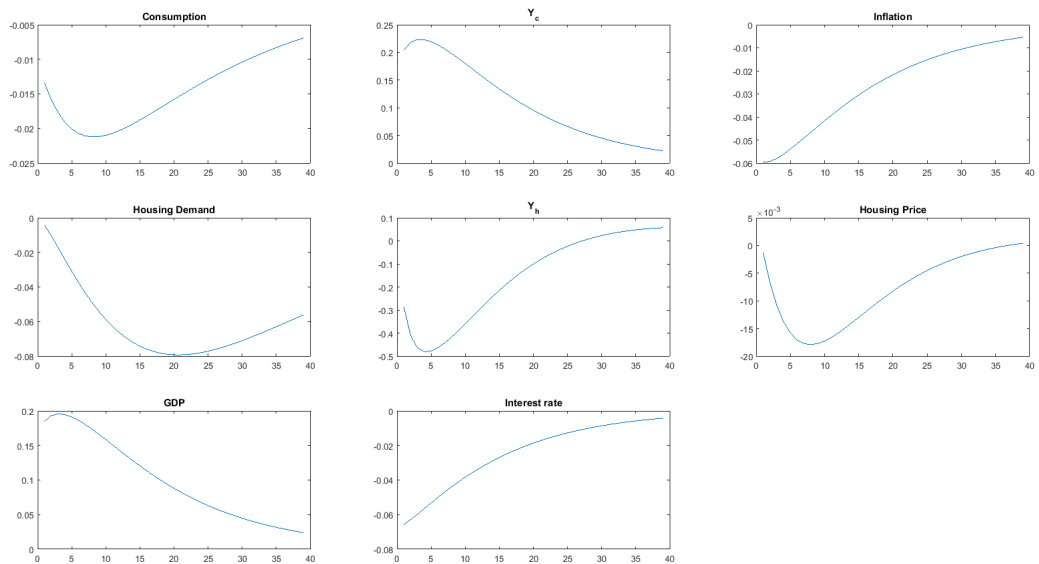
Fig. B.2 Preference Shock
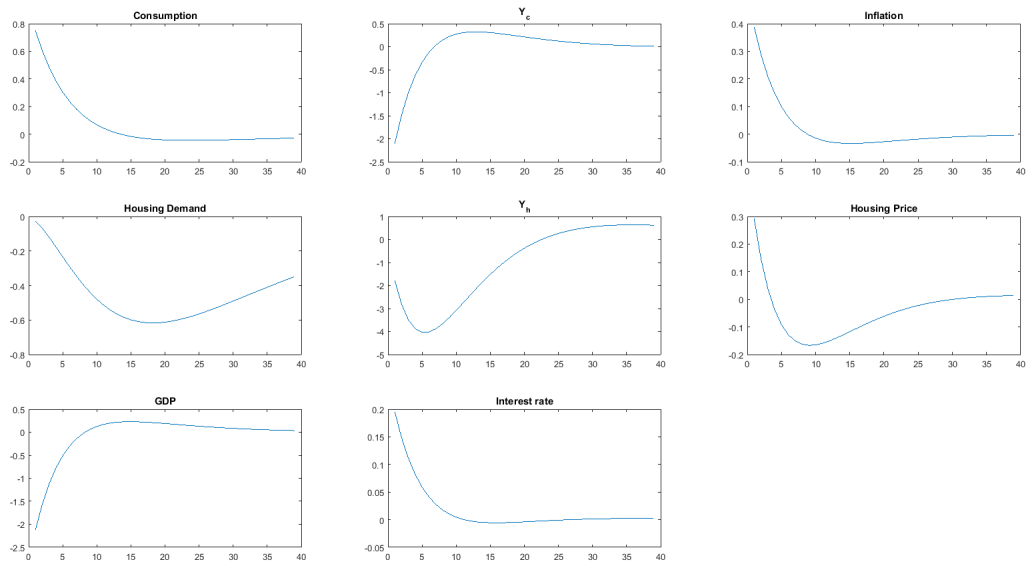
Fig. B.3 Labour Supply Shock
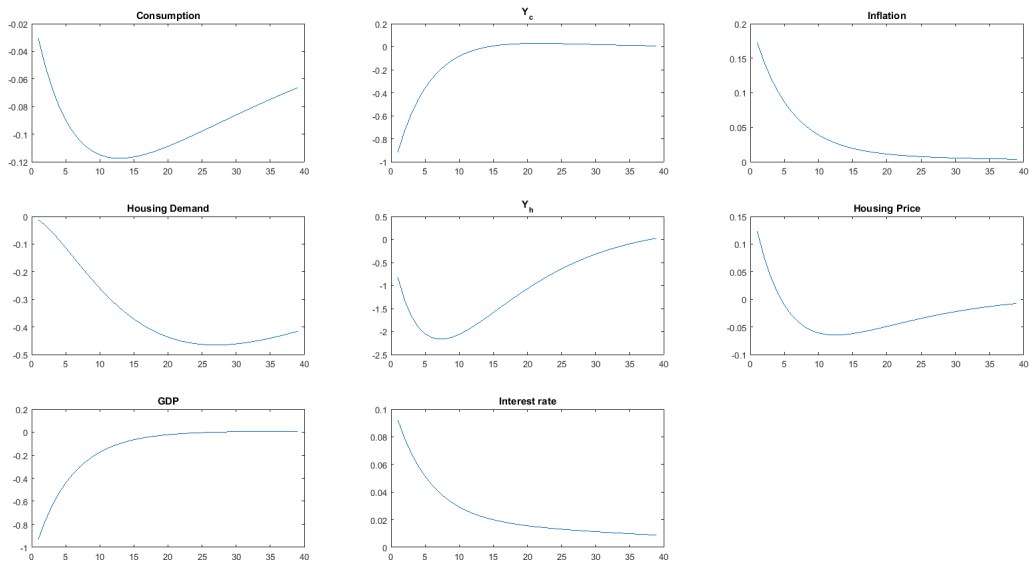
Fig. B.4 Productivity Shock in Housing Sector
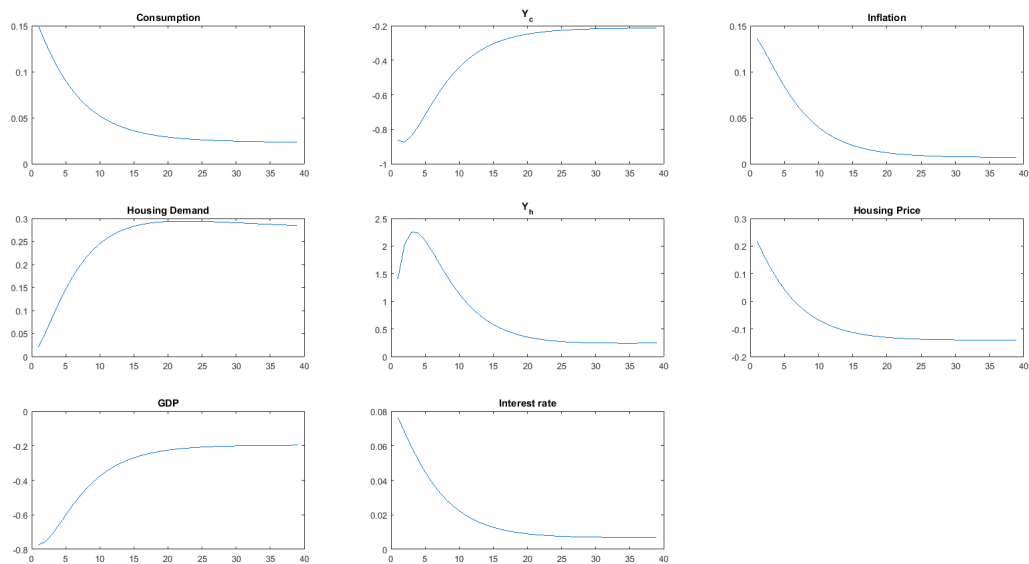
Fig. B.5 Labour Demand Shock in General Sector
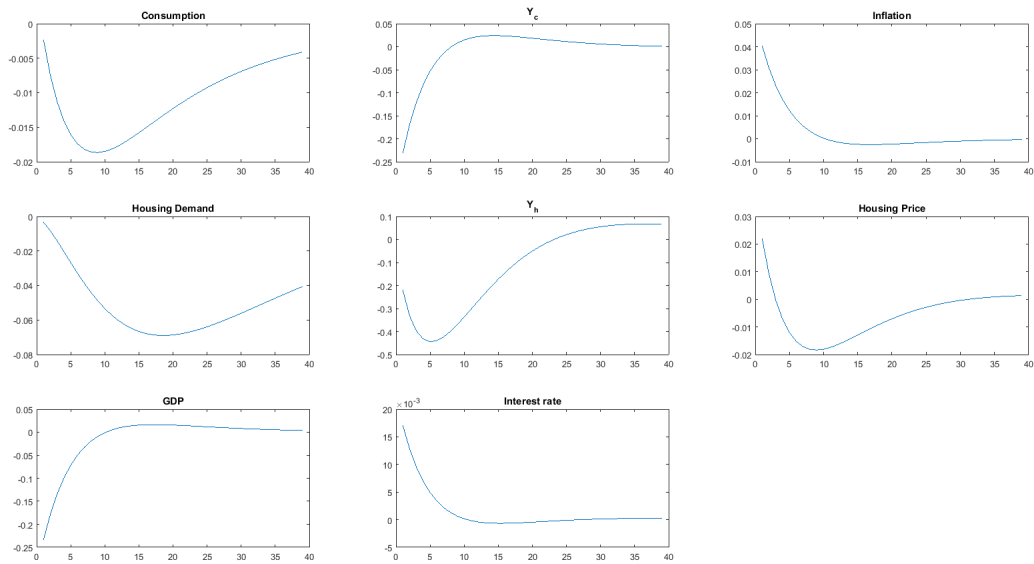
Fig. B.6 Capital Demand Shock in General Sector
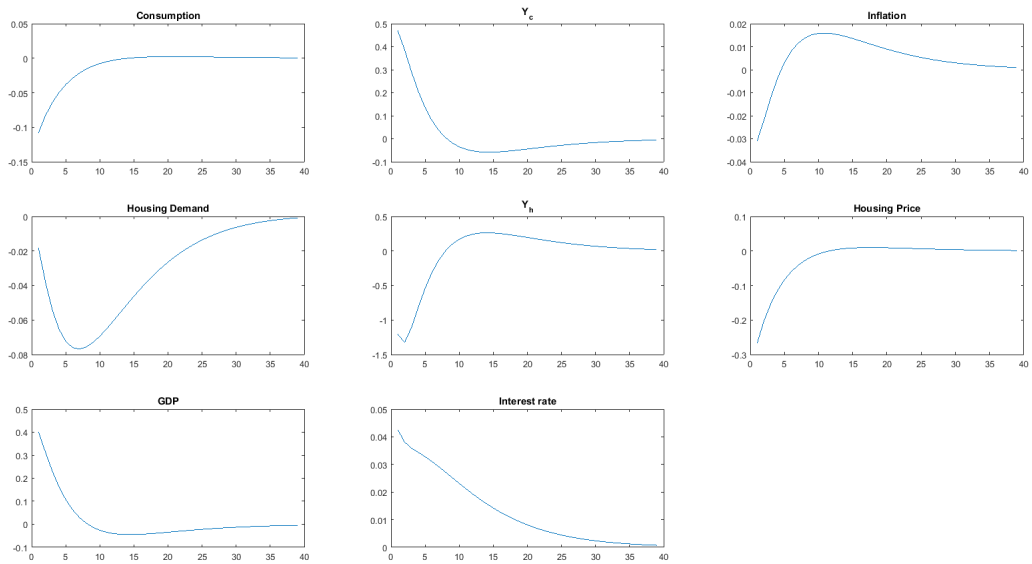
Fig. B.7 Capital Demand Shock in Housing Sector
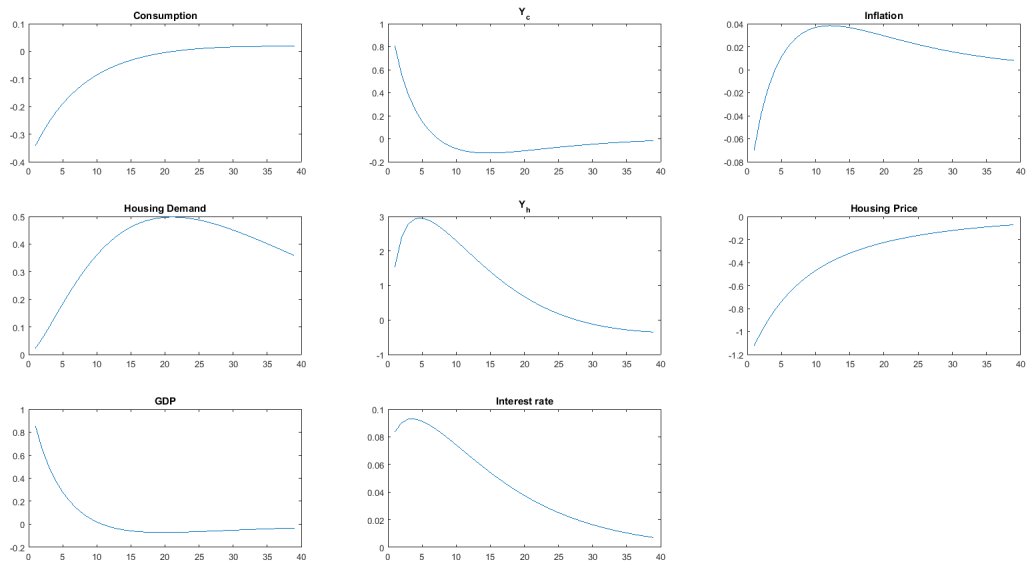
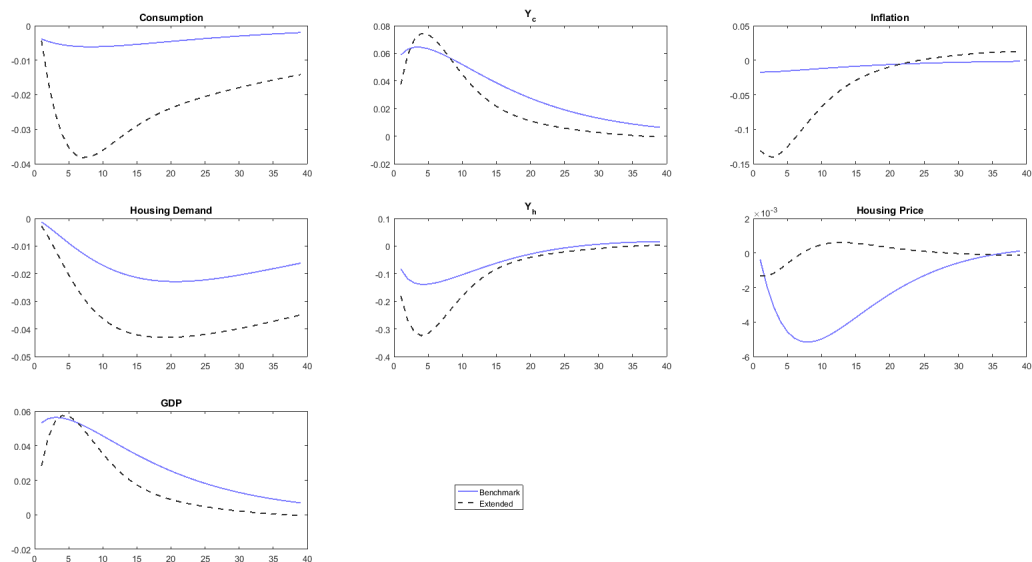# Model with Collateral Constraint

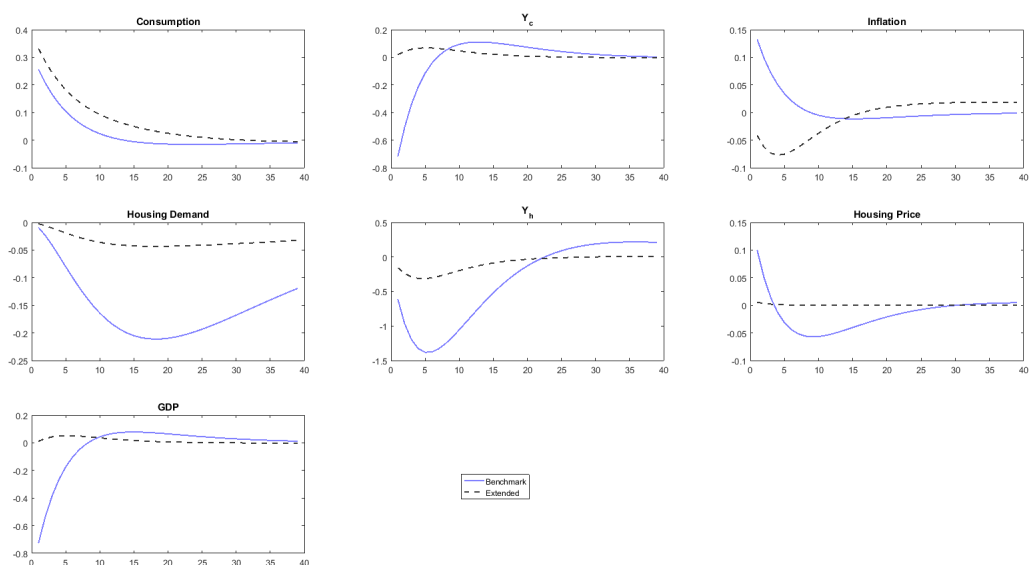Fig. B.8 Government Spending Shock
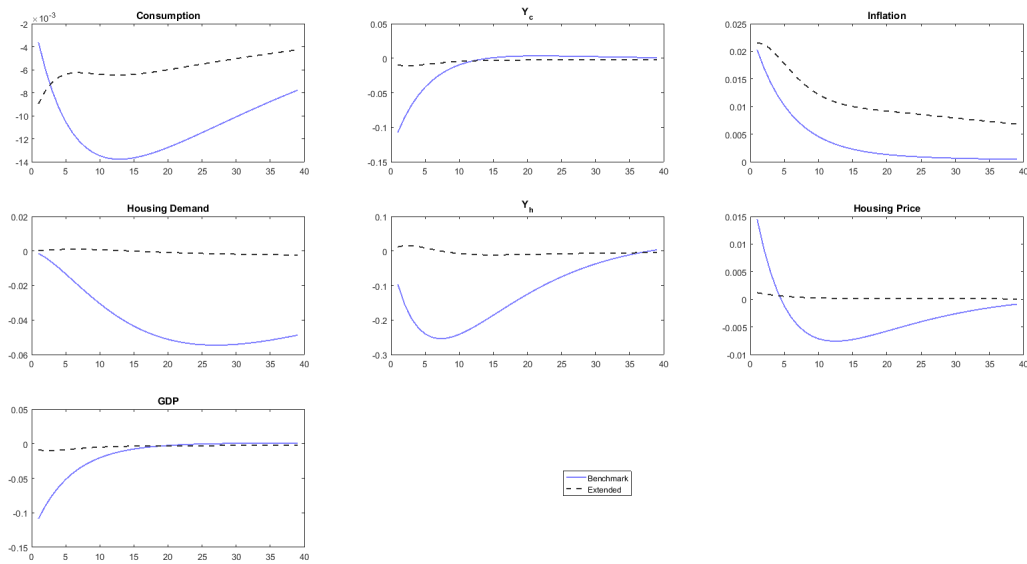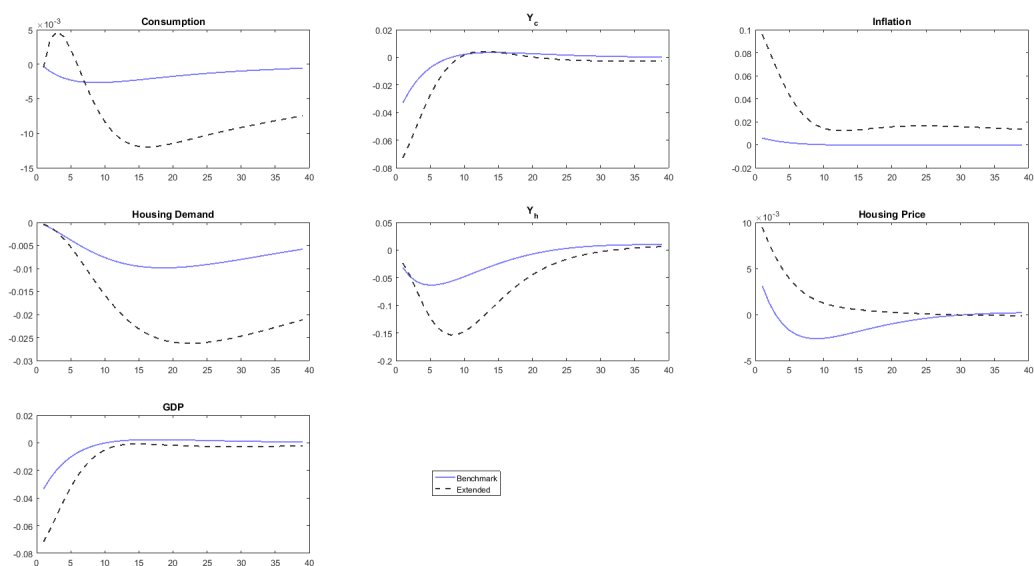

Fig. B.9 Preference Shock

Fig. B.10 Labour Supply Shock

Fig. B.11 Productivity Shock in Housing Sector
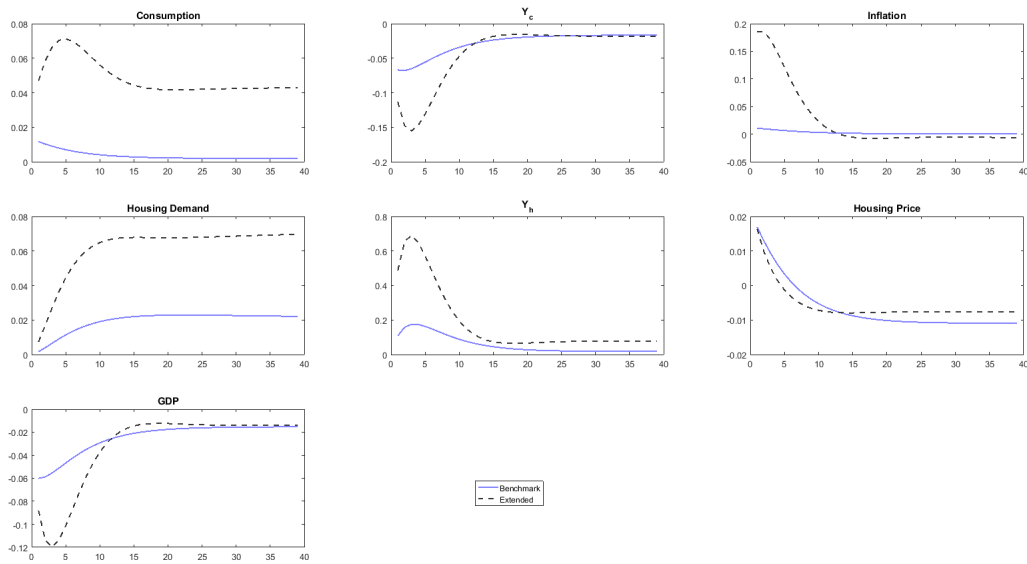
Fig. B.12 Labour Demand Shock in General Sector

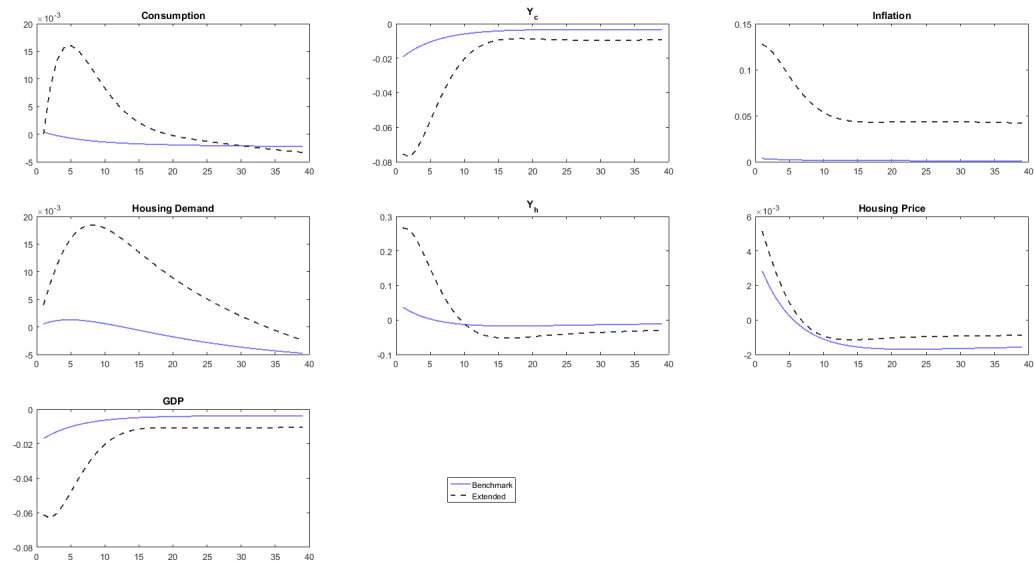## Fig. B.13 Labour Demand Shock in Housing Sector
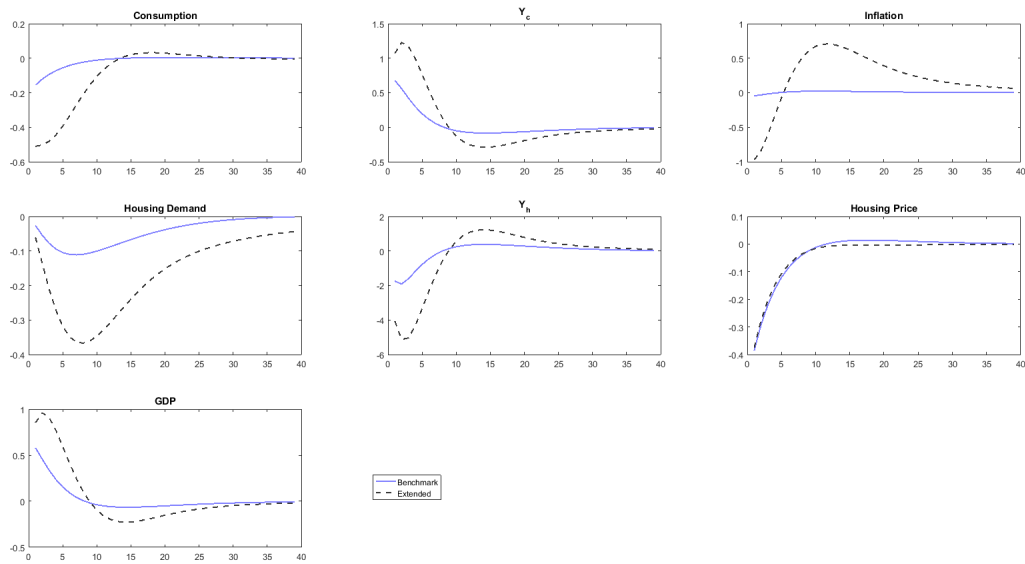
Fig. B.14 Capital Demand Shock in General Sector

Fig. B.15 Capital Demand Shock in Housing Sector