Modelling Shadow Banking System and Housing Market in China

by

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Abstract

Given the lessons learned from the financial crisis and housing crash in Japan and the US, as well as the strong connection between the shadow banking sector and property market in the second-largest economy, China, it is essential to understand the mechanism of a model that contains both shadow banking activities and the housing market. Therefore, the first objective of this thesis is to model the Chinese banking and housing sector and understand the underlying mechanism. The second objective is related to a methodological issue. In recent years, many researchers, especially in mainland China, have been exploring the Chinese shadow banking system. Most researchers either only calibrate or use Bayesian estimation to estimate their model. However, none of the approaches test the model against real data. Different models can tell different stories and potentially provide different policy implications. However, if the model is rejected by the actual data, all the results and policy suggestions might become insignificant. Therefore, in my research, I adopt two different estimation approaches, Bayesian estimation and Indirect Inference approach, to first provide some understanding about Chinese shadow banking system, and second, to discover whether my model can or cannot be rejected by the actual data.

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Abbreviations

ABC	Agricultural Bank of China	ICBC	Industrial and Commercial Bank of China
ABCP	Asset-backed Commercial Papers	LTV	Loan-to-value
ABS	Asset-backed Securities	MBS	Mortgage-backed Securities
ACFIC	All-China Federation of Industry and Commerce	MMMFs	Money Market Mutual Funds
ADB	Asian Development Bank	MPK	Marginal Product of Capital
AMLF	Asset-backed Commercial Paper Money Market Mutual Fund Liquidity Facility	MPL	Marginal Product of Labour
AR	Autoregressive	NBS	National Bureau of Statistics
ARI	Account-receivable Investment	NPLs	None-performing Loans
BCOM	Bank of Communications	P2P	Peer-to-peer
BHCs	Bank Holding Companies	PBoC	People's Bank of China
BOC	Bank of China	PDCF	Primary Dealer Credit Facility
CBIRC	China Banking and Insurance Regulatory Commission	PIMCO	Pacific Investment Management Company
CBRC	Chinese Banking Regulatory Commission	POEs	Private-owned Enterprises
CCB	China Construction Bank	PRC	People's Republic of China
CCP	Chinese Communist Party	PSBOC	Postal Savings Bank of China
CDOs	Collateralised Loan Obligations	RBC	Real Business Cycle
CEO	Chief Executive Officer	Repo	Repurchase Agreement
CFO	Chief Financial Officer	RMB	Renminbi
CIRC	China Insurance Regulatory Commission	ROA	Return on Assets
CMOs	Collateralised Mortgage Obligations	SELs	SOE Entrusted Lenders
CPC	Central Committee of Communist Party of China	SIVs	Special Investment Vehicles
CPFF	Commercial Paper Funding Facility	SIVs	Special Investment Vehicles
CPI	Consumer Price Index	SMBs	Small-and-medium Banks

CRA	Community Reinvestment Act	SMEs	Small-and-medium Enterprises
DSGE	Dynamic Stochastic General Equilibrium	SOEs	State-owned Enterprises
DTCC	Depository Trust Clearing Corporation	SPVs	Special Purpose Vehicles
DVP	Delivery Versus Payment	SVAR	Structural Vector Autoregressive
FASB	Financial Accounting Standards Board	TAF	Term Auction Facility
FHA	Federal Housing Administration	TALF	Term Asset-backed Securities Loan Facility
FOCs	First Order Conditions	TBR	Trust Beneficiary Rights
FRED	Federal Reserve Bank of St. Louis	TFP	Total Factor Productivity
FSB	Financial Stability Board	TSLF	Term Security Lending Facility
GC	General Collateral	US	United States
GDP	Gross Domestic Product	VAR	Vector Autoregressive
GRP	Gross Regional Product	WMPs	Wealth Management Products
GSEs	Government-sponsored Enterprises	WTO	World Trade Organisation

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Chapter 1 Introduction

1.1 Background and Motivation

Since April 2019, China has been the second-largest economy in the world, ranking number one exporter of goods to the United States (17.4% of the total U.S imports) and followed by Canada and Mexico. China was also the third-largest importer of US goods[1] (6.2% of the total U.S. exports). The voluminous level of trade between China and the United States suggests a strong connection between these two economies. The latest financial crisis that originated in the United States in 2008 had spread swiftly and strongly to the Chinese economy, substantially decreasing Chinese real GDP growth rate from 14.2% in 2007 to 9.7% in 2008 and 9.4% in 2009[2]. The Chinese government had to stimulate the economy immediately by injecting a four trillion RMB package to offset the potentially detrimental effects.

One of the main causes of the US financial crisis was the massive use of securitisation, mainly by bundling subprime mortgage loans to new financial products. The enormous default risk in these financial products was largely neglected by the credit rating agencies and the public since the market believed housing was the most solid investment in the economy. Borrowers could borrow money continuously from the bank if the housing price kept increasing. This contributed to a housing bubble that

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[1] Top Trade Partners – April 2019, U.S. CENSUS BUREAU, https://www.census.gov/foreign-trade/statistics/highlights/toppartners.html

[2] China NBS / *Bulletin on Reforming China 's GDP Accounting and Data Release System*: stats.gov.cn (12-Jan-17)

rapidly accumulated within a few years and eventually burst when borrowers began to default. Securitisation was the main characteristic of the US shadow banking system, which clearly states that shadow banking was one of the key culprits of the latest credit crunch (Fagan, 2011).

In recent years, there have been increasing concerns whether the financial crisis might repeat in China. Chinese shadow banking sector has been dramatically growing. According to the Financial Stability Board[3], the year-on-year growth rate has been more than 30% since 2014, compared with 10% growth in the rest of the world. Moody's estimation[4] shows that the total share of shadow banking assets to GDP peaked 87% at the end of 2016 and gradually lowered to around 73% in 2018. Shadow banking normally relies on short-term liabilities to support long-term loans, and it has been the main source of financing for private-owned enterprises (POEs), especially small-and-medium-sized enterprises (SMEs) in China. Due to the lack of regulation and monitoring, risks can be accumulated in the sector very quickly. However, regular traditional banking can be intertwined with shadow banking, which can raise the degree of systemic risk that shadow banking poses. Moreover, codependency between China and other countries suggests that crisis in China would impose significant negative impact internationally, especially in countries like the United States that has large trading volume with China.

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[3] Shadow banking in China: a looming shadow, February 2017, http://www.caixabankresearch.com/en/shadow-banking-china-looming-shadow

[4] Moody's: Shadow banking activity in China continues to contract, but de-risking of financial sector likely to moderate, Aug 2018, https://www.moodys.com/research/Moodys-Shadow-banking-activity-in-China-continues-to-contract-but--PR_387952

Chapter 1 Introduction

Both the U.S. and the Japanese financial crises originated from the crash of the housing market. As measured by the Case-Shiller U.S. home price index, the national housing price in the U.S. grew by more than 100% between 1995 and 2006[5]; residential property prices[6] increased by approximately 95% between 1980 and 1990 in Japan; while in China, the house price index appreciated by more than 230% from 2008 to 2018[7]. This raised another substantial concern related to the gigantic Chinese housing market, which is similar to the property bubbles that developed in Japan before 1991 and in the U.S. before 2006. Housing prices have experienced tremendous growth in the recent decade. Chen and Wen (2017) document the data for thirty-five major cities in China and show that the average annual growth rate of real housing prices has maintained 17% for the past 10 years, while the average income growth rate and gross domestic product (GDP) growth rate are only 11% and 10% respectively.

Since 2010, funds from the shadow banking sector were frequently tied into the real estate sector. The reason was that authorities in China restrict bank lending to the public after the stimulation package in order to prevent a potentially overheated economy. This mainly affects the property developers (Hsu et al., 2015). The majority of the real estate sector is comprised of small-and-medium-sized developers; therefore, after the tightened regulation, they found difficulty in obtaining finance and turned to the shadow banking sector for loans. Consequently, this triggered a simultaneous

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[5] See FRED Economic Data https://fred.stlouisfed.org/series/CSUSHPINSA

[6] See FRED Economic Data https://fred.stlouisfed.org/series/QJPN628BIS

[7] See CEIC https://insights.ceicdata.com/Untitled-insight/views

boom in the Chinese shadow banking sector and housing market.

Given the lessons learned from the financial crisis and housing crash in Japan and the US, as well as the strong connection between the shadow banking sector and property market in the second-largest economy, China, it is essential to understand the mechanism of a model that contains both shadow banking activities and the housing market. Therefore, the first objective of this thesis is to model the Chinese banking and housing sector and understand the underlying mechanism. The second objective is related to a methodological issue. In recent years, many researchers, especially in mainland China, have been exploring the Chinese shadow banking system. Most researchers either only calibrate or use Bayesian estimation to estimate their model. However, none of the approaches test the model against real data. Different models can tell different stories and potentially provide different policy implications. However, if the model is rejected by the actual data, all the results and policy suggestions might become insignificant. Therefore, in my research, I adopt two different estimation approaches, Bayesian estimation and Indirect Inference approach, to first provide some understanding about Chinese shadow banking system, and second, to discover whether my model can or cannot be rejected by the actual data.

1.2 Research Logic and Findings

1.2.1 Research Logic

It is impossible to construct a sophisticated model that can fulfil my research objectives in one step; therefore, my research logic is to start with a simple model and

gradually add ingredients into the framework. Eventually, I developed three models sequentially in this thesis. Each of the models can be viewed as a more general case then the previous one and closer to reality. The first model studies an important segment of the Chinese shadow banking sector by focusing on one of the two largest shadow banking instruments, entrusted loans. Private-owned enterprises (POEs), especially small-and-medium-sized enterprises (SMEs) largely rely on entrusted loans to obtain external finance, since they can rarely obtain access to bank credit.

Ehler et al. (2018) claim that the Chinese shadow banking sector is the 'shadow of the banks'. This indicates a strong interconnected relationship between shadow banking activities and conventional banking sector. Hence, my second model is built upon the first one by adding another important shadow banking instrument, wealth management products (WMPs), and shadow banking activities in the conventional banking sector. Building both WMPs and entrusted loans in one model captures more than 70% of total shadow banking assets in China and constructing commercial banks' shadow banking activities allows my model to perfectly reflect the key feature of the Chinese shadow banking system. Lastly, the third model aims to incorporate housing market into the model, developed from the previous two models.

1.2.2 Research Findings

The first part of research findings focuses on the mechanism and implications of my models, and the second part answers the methodological issue. My models indicate that, first, tighter banking regulation pushes the economy away from traditional bank

loans towards shadow banking channels; second, contractionary monetary policy exerts a more negative impact on SMEs' output than that of SOEs, and the existence of shadow banking sector dampens the contractionary monetary policy; thirdly, positive fiscal policy, i.e. four trillion RMB government spending, only temporarily increases GDP in China. However, it crowds out private investment in the SMEs sector, which plays a detrimental effect on SMEs' retained earnings or net worth accumulation and slows down economic growth in the following periods.

In terms of the methodological issue, I ran indirect inference estimations on both the second and third models. To avoid duplication, it is sufficient to start running the test from the second model rather than the first model since the second is a more sophisticated framework, purely focusing on the shadow banking sector. In addition, the second model framework is closer to reality and more general, compared to the first one. The third model needs to be tested since it not only has the shadow banking sector but also incorporates the housing sector. The estimations show that the results are relatively robust in both models, and most of the estimated parameters are similar in both models. The Indirect Inference tests show that, although adding a housing sector in the model can dramatically improve the model performance against the real data, it still cannot pass the test. The reason for obtaining these results may be because the model still lacks some important components that are key to explaining the information in the data, or it may be on account of the nature of these models itself. All my models are Dynamic Stochastic General Equilibrium models, which are too complicated to pass the test. The experience is that the more complicated the model is,

the more difficult to pass the test. Both Professors Lucas and Prescott used to claim that likelihood ratio tests reject too many good models. The Indirect Inference is an even more powerful test than Likelihood Ratio (Le et al., 2015). It is not too surprising that none of my models can pass the test. However, if the model fails to explain the data, there is no doubt that all policy implications suggested by the model need to be cautiously applied.

1.3 Thesis Structure

Before addressing my model frameworks, I focus in Chapter 2 on a detailed review into the background of shadow banking sectors in both the U.S. and Chinese markets, including definition, structure and development of the shadow banking systems. In addition, I discuss the 2007-2009 financial crisis and the risks related to the shadow banking system in China, in which I review the crisis in the peer-to-peer platform (one of the shadow banking instruments). The three model frameworks are introduced in the subsequent three chapters. Specifically, the first model, in Chapter 3, investigates the entrusted lending market in a 'financial accelerator' type DSGE model. The second model, in Chapter 4, includes both WMPs and commercial banks' shadow banking activities. The housing market is incorporated into the framework in Chapter 5 with the inclusion of the shadow banking system introduced in the previous two chapters. Chapter 6 concludes.

Chapter 2 Shadow Banking System and Related Literature

In this chapter, I first review the definition and development of both US and Chinese shadow banking system (Sections 2.1 to 2.3). The reason for considering these two countries is that shadow banking system is the largest in the US compared to other countries, while the system is the fastest growing in China in the recent decade. Development of the shadow banking sectors shares some common factors in both countries, but at the same time, there are considerable differences since both countries remain different economic structure. Hence, to understand the similarities and differences, it requires me to carefully demonstrate and review the evolution of the system in detail (Section 2.1 to Section 2.3). In Section 2.4, I discuss the reason for adopting the DSGE framework to conduct the underlying research. Prior research has been applying different methodologies to study the shadow banking system, so it is essential to explain why I use this type of model framework. Section 2.5 provides literature about modelling the shadow banking system. Furthermore, the theoretical frameworks in this research are estimated by using different estimation techniques, including Bayesian estimation and indirect inference technique. One of the advantages of using the Bayesian approach is to use prior knowledge. An increasing amount of research has studied the shadow banking sector, both in China and the US, in recent years. Therefore, it is relatively convenient to estimate our model by incorporating knowledge from previous research. However, Bayesian approach does not test the model framework with the actual data; instead, it normally concludes which model is

more likely to be better than another, but the better model does not mean that it can mimic the real data. Hence, the purpose of using indirect inference estimation is to occupy this gap, since Indirect Inference provides a classical statistical inferential framework for judging whether the model is rejected or not rejected by the actual data. Thus, in Section 2.6, I review the estimation procedure of both Bayesian and indirect inference estimation. Section 2.7 concludes.

2.1 What is 'Shadow Banking'

From the lesson of the global financial crisis in 2007, it is well accepted that the 'shadow banking system' can become a source of systemic risk, both directly and indirectly. It can directly affect the economy in supplying credit or liquidity and indirectly influence the system because of its interconnectedness with the regular banking sector.

To understand the function of the shadow banking system, it is necessary to know what the shadow bank is and the difference from the traditional banking system. In the conventional system, banks engage in size, maturity and credit risk transformation through the process of funding loans with deposits (Matthews and Thompson, 2005). Lenders or depositors of the banks often have smaller quantities of funds compared to the requirements of borrowers. Therefore, size transformation implies that banks gather small size deposits from a mass of depositors and lend to borrowers who need large size loans. Maturity transformation refers to the use of short-term deposits to

finance long-term loans. Credit risk can be transferred by banks since lenders prefer safe assets, while borrowers may use borrowed funds to invest in the risky project. Deposits are insured fully or partially (if the size is bigger than the cap in one bank account); hence, it is treated as a low-risk asset for lenders. While loans usually contain higher risk, banks can charge a higher interest rate and monitor the behaviour of the borrowers to control the risks (although it is difficult in practice). Furthermore, the central bank acts as the so-called 'lender of last resort', meaning that it offers loans to banks when they experience financial difficulty or near bankruptcy.

The term 'shadow banking' was first invented by the executive director Paul McCulley of Pacific Investment Management Company (PIMCO) in 2007 at Federal Reserve System annual meeting. According to the financial stability board (FSB) in April 2011, the 'shadow banking system' can be broadly defined as 'credit intermediation involving entities and activities (fully or partially) outside the regular banking system'. It is a useful benchmark at the global level. However, one should understand the limitations of this definition. Pozsar and Singh (2011) and Cetorelli and Peristiani (2012) argue that some entities, such as leasing and finance companies, corporate tax vehicles, leasing and finance companies, etc., may be covered by this definition since they do intermediate credit, yet are commonly thought of as non-shadow banking entities. Second, shadow banking activities are defined primarily outside the regular banking system, but in practice, shadow banking does operate within banks; for example, securitisation, repo, collateral operations of dealer banks, etc. (the definition of different financial products will be discussed in the following sectors).

One main difference of the shadow banking is that it is removed from the official public-sector enhancements; in other words, it has no access to a solid backstop that the traditional banking system always has, which is the central bank. Risks can be diversified in the conventional banking system by using the law of large numbers (a mass of depositors), monitoring, as we mentioned above, while shadow banking distributes undesirable risks across the financial system (Claessens and Ratnovski, 2014). For example, securitisation can strip credit and liquidity risks from assets through tranching and supplying liquidity puts (Pozsar et al., 2010; Pozsar, 2013; Gennaioli et al., 2012) or the use of collateral can also decrease counterparty credit exposures in the repo market (Gorton, 2012; Acharya and Öncü, 2013). However, even if these undesirable risks can be distributed, the systemic ones remain in the system, such as the systemic liquidity risk in securitisation, bankruptcy risks of the large borrowers themselves, etc.

Despite the limitations of the definition, shadow banking in different countries also has different structures. It can be mainly divided into two different types, indirect shadow banking activities and direct/straightforward activities. China's shadow banking system relies more on direct lending, while countries like the USA and some European countries frequently use indirect shadow banking instruments, such as securitisation. Therefore, in the following sectors, we will carefully review the shadow banking systems in two important economies, the US and China.

2.2 Shadow Banking in the US and the 2007-2009 financial crisis

2.2.1 Why Do Shadow Banks Exist in the US?

The name 'shadow bank' was invented in 2007, but its formation can be traced back to earlier decades. The existence of shadow banks can be broadly explained by three reasons that are empirically intertwined with each other, which are financial innovation in terms of aggregate money supply (Gorton and Metrick, 2012), regulatory arbitrage and technology changes (Gorton et al., 2010; Acharya et al., 2011; Acharya et al., 2014; Buchak et al., 2018), and agency problems in financial markets (Mathis et al., 2009; Xia and Strobl, 2012).

2.2.1.1 Financial Innovation Regarding Aggregate Money Supply

Before we discuss the shadow banking sector, it is helpful for us to clarify financial innovation in the traditional banks, since it should be more familiar to one with limited knowledge about shadow banking. The earliest forms of money are commodity money that comprised of gold or silver. However, it was replaced by fiat money which is intrinsically useless (Wallace, 1980). Fiat money plays a crucial role in our daily life, and it is the most well-known financial innovation in terms of the money supply. In the early 1800s, money was backed by the promise of convertibility into gold or silver coin, and this gold standard was broken when the Bretton Woods system collapsed in the 1970s. The value of money is based on confidence; the loss of confidence would then cause severe financial panics in the economy. The idea of confidence might sound

strange nowadays since fiat money is one of the most common things that everyone has. But thinking back to the time that was just invented, people were willing to hold this paper note only if the issuer promised that it could be converted into a commodity. It works similarly today, if the value of the money is stable, one is confident to use the same amount of money to buy the same goods that they used to buy. However, if the faith were lost, people would feel panic about whether they could still use the money to buy the same commodities.

During the period from 1837 to 1862, the so-called 'Free Banking Era', only state-chartered banks existed, and there was no federal regulation in the banking system. If the initial capital is adequate, any banker can enter the banking sector, but state or federal government bonds with a face value equal to the value of notes are required to deposit. Reserve requirement, interest rates were regulated heavily by the states. Unfortunately, even if the states had tried diverse ways to stabilise the notes, half of the free banks resulted in failure. It was difficult to maintain confidence during that period because of a reduction in state debt (Jaremski, 2010; Rogoff, 1985). The solvency of a bank was seriously doubted, and depositors would insist on banks to fulfil their obligation to convert deposits into specie. However, banks had a limited specie in reserve, they were unable to solve the problem, and bank run happened. To stabilise market confidence, in 1863 and 1864, the National Banking Act was announced. Explicitly, it stated that banknote is replaced by a national currency backed by the U.S. Treasury bonds and state-banks gradually converted to national banks (White, 1982). Nevertheless, the issue of confidence remained because the treasuries

fluctuated in value until the central bank acted as a lender of last resort following the Great Depression in 1933.

In the cases above, bank deposits (both state-issued and national currency) are all financial innovation in the composition of the money supply. It is secured by the general assets of the bank, and it should be converted into specie once their depositors request. If banks could not meet the obligation, the central bank acts as the lender of last resort. Regarding the shadow banking system, over the past few decades, we have seen many financial innovations in the market. Investors can invest in diverse financial products rather than only deposit their money in a bank account or treasury bills. For example, a) money market mutual funds (MMMFs), b) asset-backed commercial papers (ABCP), c) asset-backed securities (ABS), d) repo (repurchase agreement). The compositions of the aggregate money supply became much more complicated. These innovations had boomed up the economy before the financial crisis, but it also made the financial system far more difficult to understand and vulnerable.

a) Money market mutual funds (MMMFs)

This was first created in 1971 in response to Regulation Q, which is interest rate ceiling on deposits and limit deposit insurance. MMMFs have been treated as safe as bank deposits, but with a more attractive interest rate (Cook and Duffield, 1979). It is open-ended mutual funds that gather money from investors and invest into short-term securities, such as treasury bills, commercial papers and repurchase agreements (repo),

in which the overnight repo is one of the primary investments of MMMFs. This investment is secured by collateral, mainly U.S. Treasury obligation, and equivalent to banknotes. The innovation of MMMFs is that it transforms uninsured deposits from investors into an instrument that resembles an insured deposit.

In 2008, the size of MMMFs in the U.S. peaked at around $3.5 trillion. However, following the bankruptcy of Lehman Brothers, the run on MMMFs was triggered as the net asset value dropped below the stable level, which is $1.00 per share (Wermers, 2011). There are two types of investors who invest in MMMFs, institutional investors and retail investors. Wermers (2011) shows that, during the crisis, institutional investors were more likely to run than retail investors, and they can be viewed as a transmission channel for a contagious run. Regarding the risk taken by MMMFs, Kacperczyk and Schnabl (2013) explore the question as to how risk-taking behaviour differs between stand-alone MMMFs and mutual funds organised by conglomerates. They conclude that, in the run-up to the crisis, MMMFs in conglomerates took more risk, while a stand-alone MMMFs took more risk during the crisis.

b) Asset-backed commercial paper (ABCP)

ABCP is a form of short-term borrowing with maturity between 1 and 270 days. It is an alternative option for customers, offered by financial institutions, by pooling the customer's assets to back the paper (Covitz et al., 2013). Variety assets can be included in asset pools, for example, trade receivables, consumer receivables, auto loans and

leases, student loans, corporate loans, etc. ABCP can be categorised as either single-seller or multi-seller programs. If the source of all assets come from one entity, such as a single banking institution or finance company, it is a single-seller program. If assets are supported by different entities, it is a multi-seller program.

The ABCP program is issued by a bankruptcy-remote special purpose vehicle (SPV), such as ABCP conduits or special investment vehicles (SIVs). It is normally sponsored by a highly rated bank or other financial institution. The SPV purchases assets (i.e. receivables, etc.) into the ABCP program, which is funded by selling commercial paper to investors. The assets must normally be diversified to meet the rating standard of credit rating agencies. At the maturity date, investors can be repaid by the issuance of additional commercial paper or the cash flow received from receivables.

ABCP issuers (SPVs) commonly receive unconditional enhancements from commercial banks. It is exempted from the potential bankruptcy because of the backup lines of credit and liquidity. Similarly to traditional banking regarding maturity transformation, shadow banking, by using the example of SIVs, also conducts maturity transformation. On the liability side of SIVs balance sheet, it is short-term borrowing, while on the asset side of SIVs are securitised assets, such as asset-backed securities (ABS), including mortgage-backed securities (MBS), collateralised debt obligations (CDOs), collateralised loan obligations (CLOs), and collateralised mortgage obligations (CMOs), which are usually medium-term notes or long-term notes. SIVs were first created in 1988. It was used to move the financing part of Citigroup from

on-the-balance to off-the-balance. SIVs can be closely associated with a particular financial institution or operate independently. After the financial crisis in 2009, SIVs have stopped operating.

As mentioned above, ABCP is sponsored by high rated banks or finance companies. But what if the sponsor went bust? American Home declared bankruptcy, which is the sponsor of a single-seller mortgage conduit. Since then, the ABCP market has experienced a run. Covitz et al. (2013) document an investor run on over 100 ABCP programs based on the data from the Depository Trust Clearing Corporation (DTCC), which is one-third of the entire market. Most runs of the ABCP programs were associated heavily with a subprime mortgage, weaker liquidity support and lower credit ratings. Following the crisis, the sharp decline amount of ABCP outstanding resulted from the general deleveraging process. Economy activities decreased to a lower level that led to a reduction in receivables, which used to be assets of ABCP conduits. The total size of outstanding is less than $250 billion in the ABCP market.

c) Asset-backed security (ABS)

An ABS is collateralised by a pool of financial assets, including receivables, loans or mortgages (Gorton and Metrick, 2009). For example, if a student loan (originating from a commercial bank) is securitised by a trust company, the payment of the loan from the student will flow to the investor who purchased this ABS through the trust. Securitisation is the heart of shadow banking, and it is the most important financial

innovation in the past decades. The credit originator can sell the pool of these assets to another entity, as well as transferring the risk.

The ABS is again issued by a bankruptcy-remote SPV that typically conducts credit risk and liquidity transformation. Risks can be transformed through diversification, and illiquid assets can become liquid by pooling such illiquid assets. However, during economic downturns, the liquidity of the ABS becomes more illiquid. As mentioned previously, one particular form of ABS is CDO. CDO is the pool of assets such as mortgages, bonds and loans. When the collateral is agency mortgage-backed securities, it is called collateralised mortgage obligation (CMO); while the collateral is syndicated loans, it is called collateralised loan obligation (CLO). CMO was first issued by Salomon Brothers, and First Boston in 1983 and CDO was issued by Drexel Burnham Lambert in 1987. The scale increased to the issuance of $893 billion in 2006 and peaked in 2007 but collapsed during the credit crunch between 2007 and 2009 (Agarwal et al., 2011).

d) Repurchase agreement (Repo)

Another important shadow banking instrument is the repurchase agreement which implies the sale of security combined with a deal to buy back the security or portfolio by the seller on a specified future date at a prearranged price (Fleming and Garbade, 2003). Most of the repo contracts are short-term between one-and-ninety-days maturity. Repos are over-collateralised loans, in which posting more collateral than is

needed to achieve more favourable credit rating. The difference between the sale price of the repo and the value of the underlying collateral is named as 'repo haircut'. A typical repo transaction starts from a cash provider (such as MMMFs, asset manager etc.) who wants to obtain specific securities as collateral to hedge or speculate the fluctuated value of the securities. They purchase the securities and transfer their cash to a collateral provider with an agreement that the collateral provider will repurchase the securities later. The earliest form of the repo is the bilateral repo market (Copeland et al., 2012), specifically, delivery versus payment or DVP repo. Initially, all reports are bilateral; the collateral provider receives cash and delivers the securities to cash provider simultaneously.

Another form of the repo is the so-called tri-party repo, which specifically relates to a clearing bank, a bank which is a member of the clearinghouse, acts as an intermediary between two entities (Copeland et al., 2014). It is the clearing bank's responsibility to administrate the transactions, and the transactions also appear on their balance sheets. More specifically, the clearing bank maintains both cash from cash providers and securities from security dealers, then the bank sets up the tri-party contract and passes the securities to cash provider as well as transferring money to the dealers' account. When the contract matures, the clearing bank conducts the transaction oppositely. In the U.S., the tri-party repo is the primary source of funding for security broker-dealer, and the lender is normally the MMMFs and other cash-rich investors. Generally, the tri-party repo is included in the general collateral (GC) market, which implies the investors may care more about the underlying collateral than the securities itself. The

volume reached above $2.8 trillion in 2008 and around $1.8 trillion in 2017.

To briefly summarise this sub-section, all the financial innovations, as discussed above, in the shadow banking sector are legally operated with very complex structures, which made the U.S. economy challenging to understand and vulnerable to the financial crisis.

2.2.1.2 Regulatory arbitrage and technology changes

One of the leading hypotheses of explaining the existence of the shadow banking sector is regulatory arbitrage. The traditional banking sector has been heavily regulated, most importantly, the regulatory capital requirements that restrict their leverage (first introduced in the Basel I officially and modified in Basel II and Basel III). The rise of any new form of financial contracts is often driven by regulatory arbitrage; this has been a long-standing idea agreed by researchers traced back decades ago (Silber, 1983; Miller, 1986; Kane, 1988). The description provided by Pozsar et al. (2010) shows that shadow banking has a similar order of magnitude on its total liabilities compared to conventional banking. By using near-monies, i.e. MMMFs, etc., shadow banks can refinance bank assets with higher leverage. Consequently, the effective leverage on loans in the U.S. economy has been dramatically increased along with the existence and development of the shadow banking system.

In the face of the costs of the crisis in 2008, the suggestion of heightened capital requirements has emerged. However, regulatory reforms in the shadow banking system remain silent (Adrian and Ashcraft, 2012), which encourages even more regulatory arbitrage opportunities in shadow banking with lighter regulation. Buchak et al. (2018) examine whether the regulatory burden is a driving force on the reduction of traditional mortgage banking. They show that 50% of loans in the conforming market and 75% of loans insured by the Federal Housing Administration (FHA) originated by shadow banks, in which the FHA loans allow lower-income and less creditworthy households to borrow money (riskier borrowers). They further argue that, in the U.S., since Fintech (financial technology) companies account for approximately a quarter of shadow bank loan in 2015, it implies online origination technology also plays an important role in circumventing heavily traditional banking regulation.

The U.S. shadow banks rely heavily on government-sponsored enterprises (GSEs) and FHA guarantees. Levitin and Wachter (2011) study the role of implicit guarantees for the supply of mortgages by using a quantitative assessment. Buchak et al. (2018) also suggest that the increased regulatory burden of traditional banks accompanied by GSEs and FHA guarantees, to some extent, may contribute to the rise of the shadow banking sector. Moreover, the rapid expansion of ABCP market resulting from the changes in regulatory capital rules since 2004 in the U.S. (Acharya et al., 2011). The financial accounting standards board (FASB) suggests that the bank should consolidate the assets of ABCP conduit on the balance sheet in January 2003. Nevertheless, U.S. banking regulators refused to include the assets from conduits in

the measurement of risk-based capital.

2.2.1.3 Agency problems in financial markets

Another area explains the existence of shadow banking related to agency problem and informational friction. Ashcraft and Schuermann (2008) explore several important informational frictions, including asymmetric information between the lender and originator, between the lender and investors, between the servicer and investors, etc. Investors rely more on the credit ratings of security when they are planning to invest. However, over-reliance on credit ratings can create issues. Mathis et al. (2009) endogenous the reputation in a dynamic model of ratings and find that credit ratings are less accurate during a boom time, meaning that credit ratings may send incorrect information about security when we experience economic growth. The reason is that rating agencies also need to compete for the contract. To secure more contracts in good time, they might be less restrictive on analysing the risks of security. Otherwise, the issuer may turn to another agency.

Similarly, Strobl and Xia (2012) compare the ratings issued by an issuer-paid rating agency and investor-paid rating agency. They conclude that it is particularly severe when the agency is issuer-paid. Specifically, firms with more short-term debt, lower past bond issues rated and a newly appointed CEO (chief executive officer) or CFO (chief financial officer) are more preferred by issuer-paid rating agencies. Cohen and Manuszak (2013) document the fact that variables should not affect a CRA's

(community reinvestment act) view of the credit risk of the conduit; however, variables could affect the incentives of issuers and CRAs in the presence of rating shopping.

2.2.2 The Mechanism of Shadow Banking in the US

Securitisation and wholesale funding are the centres of the shadow banking system in the U.S. As we mentioned in the previous section, loans, mortgages and leases can be securitised and converted into tradable shadow banking instruments, while wholesale funding is an alternative method that banks use to finance operation besides bank deposits. The source of wholesale financing includes federal funds, foreign deposits and brokered deposits (Adrian and Ashcraft, 2016). When banks face difficulty in attracting regular depositors (because of the low-interest payment on deposits), apart from the securitisation, they may turn to this alternative way (wholesale funding) to raise money. Shadow banking system is complex. To understand the mechanism of shadow banking, it is essential to know how securitisation works and the wholesale funding market, in addition to the subsegment of shadow banking, including internal, external and independent, and government-sponsored shadow banking.

2.2.2.1 Securitisation

It is common knowledge that commercial banks collect deposits from depositors and lend out money to borrowers. Deposits are the liability of the bank and loans are the asset on the bank balance sheet. The spread between the deposit rate and the loan rate

is the net interest of the bank (Matthews and Thompson, 2005). In the 1920s, commercial banks were permitted to invest in the stock market by using money from depositors apart from making bank loans. However, in 1929, the Wall Street crashed alongside share prices plummeting, which rendered banks unable to fulfil their obligation to their depositors. Banks run resulted, and the U.S. economy entered the Great Depression. To remove commercial banks from investment banking businesses, the Glass-Steagall Act was introduced in the early 1930s. It implies that commercial banks can only take depositors money to make loans but not purchase securities.

In contrast, investment banks cannot take money from depositors. Instead, they can assist their customers in accessing debt and equity capital market. After the implementation of the act, the U.S. entered a relatively stable economy (Kroszner and Rajan, 1994). Nevertheless, the profit of the banks had dramatically reduced, and the separation between activity of commercial banks and investment banks became increasingly blurred. Financial communities had never ceased lobbying for the act to be repealed. Investment banks had persistently endeavoured to access the strength of the commercial bank's deposits, while commercial banks had wanted to enter the security market to make a higher profit. In 1999, the Glass-Steagall Act was officially repealed. Large commercial banks merged with large investment banks (Crawford, 2011).

Initially, securitisation was created to culminate the interests of commercial and investment banks. Specifically, investment banks purchase loan books from

commercial banks and set up a conduit (such as SPV). Subsequently, loan books are passed to SPV, as well as risks being removed from commercial bank balance sheets (Acharya and Richardson, 2009). As mentioned in the previous section, SPV is the institution that issues bonds. This institution bundles the loan books to issue bonds and then sells the bonds to investors (these bonds can be ABS, MBS, etc.). Hence, the funding would transfer from the bondholders to the investment bank via the SPV. The investment bank then returns the money to the commercial banks, which can be used to meet the obligation of repay interests to depositors and further lend out to other mortgage borrowers.

The core operation of commercial banks has been changed due to securitisation. Initially, commercial banks can only have money to lend out contingent upon successfully attracting depositors. However, since loan books can be securitised, commercial banks can attract more money from bondholders if they can issue more loan books that can be bundled and construct to bonds. Loan books are separated into different elements or tranches, and the loan books from the borrowers with lower repay probability is segmented into 'Inferior' quality tranches. Similarly, medium-quality borrowers can be classified as 'Medium' tranches, and the loan book with very high-quality borrowers is known as 'Good'.

Banks can charge a higher interest rate on the 'Inferior' loans and securitise all the 'Medium', and 'Good' loan books that can be used to back the bond that is issued by the SPV. Since the process of the securitisation can be very complicated, bondholders

are unable to understand the nature of each bond. Instead, they use information disclosed by the credit rating agencies, which effectively rate each security that is considered as a correct assessment on the bonds. The safest security is rated as 'AAA' rating.

Furthermore, to prevent unexpected events, investment banks purchase insurance against potential risks. In particular, the insurance companies (such as A.I.G) sell credit default swaps (formal insurance contract) to investment banks in case the securitisation goes wrong (although before 2007 nobody believed it could go wrong). Insurance companies receive premiums regularly paid by investment banks (Acharya and Richardson, 2009). Interestingly, insurance companies can also use the money they earn and invest in securities.

The non-technical discussion above explains the function of securitisation. Now, we turn to the demand side of these securitised bonds. In the 1930s, the traditional banking system faced a potential bank run since deposits were not protected. However, this ended in 1934 in the USA (Calomiris and White, 1994) with the introduction of federal deposit insurance (deposit insurance capped at $100,000 per account). It operates satisfactorily for retail investors, but not for institutional investors with large cash holdings. Therefore, it is less safe for institutional investors to deposit their money into a bank account. Instead, institutional investors, such as MMMFs and pension funds, prefer to receive collateral from the bank, which is securitised bonds (created by the mechanism that we introduced above). These collaterals can be asset-backed securities

with a very high rating that work similarly to deposit insurance - briefly describing, banks corporate with the conduit to issue securities which are essentially bundled by loan books. Banks use these securitised bonds as collateral to borrow money from institutional investors and then lend out the funds to borrowers (Gorton and Metrick, 2010).

We have discussed the general mechanism of the securitisation intuitively. In the following, we will describe shadow credit intermediation in the wholesale funding market in more comprehensive detail.

2.2.2.2 The shadow credit intermediation process

Shadow banks conduct similar business to traditional banks via a more complicated and 'shadowy' process. Pozsar et al. (2010) explain the credit intermediation chain that consists of seven steps, including loan origination, loan warehousing, ABS issuance, ABS warehousing, ABS CDO issuance, ABS intermediation and wholesale funding. Other finance companies, besides commercial banks, can perform loan contracts. After loan contracts are originated, single or multiple conduits will conduct loan warehousing, and broker-dealers' ABS syndicate desk will take over and issue ABS by pooling or structuring all the loan books. Once the ABS issuance is completed, the warehousing will be facilitated through trading books and further convert into CDOs by broker-dealers' syndicate desk. The next step is ABS intermediation, performed by limited-purpose finance companies, structured investment vehicles

(SIVs), securities arbitrage conduits and credit hedge funds. The whole process is conducted in the wholesale funding market, and the source of the funding is mainly from institutional investors, such as money market mutual funds and other large cash pools. The authors emphasise that first step (loan origination) and the last step (wholesale funding) are essential in the chain. However, shadow credit intermediation does not have to include all the other five steps, or it can contain more than five by repeating some of the steps; for example, repackage ABS CDOs into the so-called CDO squared, which make the product even more complicated. Intuitively, the whole credit intermediation cannot be implemented without the initial loan contracts (loan origination), and it also cannot be conducted if there is no one to purchase the products (wholesale funding); nevertheless, the procedures that transfer the original loan contracts to tradable shadow banking products (e.g. CDOs) can be adjusted based on different situations.

2.2.3 The Financial Crisis in 2007-2009

The series run of ABCP conduits first signalled the collapse of the shadow banking system and the activities of securitisation were terminated entirely in the following. Five largest investment banks suffered in substantial lost and struggled for survival, during which Lehman Brother declared bankruptcy, Goldman Sachs and Morgan Stanley converted to banking holding companies, Bear Stearns and Merrill Lynch were acquired by J.P. Morgan and Bank of America respectively. A large number of shadow banking institutions exited the market, such as SIVs and CDOs (Adrian and Achcraft,

2016).

To prevent further spillover effect of the shadow banking distress and to stabilise the collapsing system, the Federal Reserve decided on solving the liquidity problem, while the U.S. Treasury's initiated programs to mitigate credit problems. Money market investors pulled out their funding because of the deterioration of the asset quality of the ABCP conduits and SIVs. The sponsoring BHCs had to seek other sources of funding, even from the unsecured market, such as the Libor market. As a result of the disruption in Libor market, the Federal Reserve initiated the Term Auction Facility (TAF) to provide funding to commercial banks, mainly replacing the term funding lost in the ABCP market (Armantier, et al., 2008). Foreign banks also gain access to term funding from the TAF via the Fed's discount window by using the foreign exchange swaps.

The deterioration in the repo market occurred following the collapse of the ABCP conduits. Bear Stearns could not obtain funding through tri-party repo market after March 2018; the Federal Reserve then introduced the Primary Dealer Credit Facility (PDCF) to solve these funding difficulties (Armantier et al., 2008). Specifically, primary dealers were permitted to obtain funding from the Fed and effectively gain access to the lender of last resort. Furthermore, Fleming et al. (2010) also explain the detail of the Term Security Lending Facility (TSLF) by which the exchange of agency mortgage collateral by Treasury collateral is allowed.

In September 2008, followed by the bankruptcy of Lehman Brother, money markets suffered a run, which further resulted in the funding shortage of ABCP, CP and repo issuers. Two facilities were introduced by the Federal Reserve to mitigate the issue, including the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF) and the Commercial Paper Funding Facility (CPFF) (Adrian, 2010). As can be seen from the name of these facilities, their purpose is to offer to fund commercial paper issuers and replace the money market funding.

Also, the Term Asset-Backed Securities Loan Facility (TALF), described by Ashcraft and Pozsar (2012), was created to meet the credit needs of households and small-and-medium businesses. It was mainly aimed to provide support of the ABS collateralised by student loans, credit card loans, residential mortgage servicing advances, commercial mortgage loans etc.

The series of the facilities can be briefly summarised as providing the last-resort lending to the shadow banking system during the financial crisis. The purpose of it, as previously mentioned, is to mitigate deterioration and prevent the further spillover effect of the collapse of the shadow banking system.

2.3 Shadow Banking in China and the Collapse of P2P Platform

In this subsection, we will focus on both the banking and shadow banking systems in China, and the outline addresses a) the structure of the Chinese traditional banking

sector; b) the evolution of China's SMEs and why they need shadow banking; d) the status of the shadow banking sector; e) shadow banking instruments.

2.3.1 The Structure of the Chinese Traditional Banking Sector

Before understanding the shadow banking sector, it is essential to know the structure and status of the conventional banking sector in China. According to the latest data released by the China Banking and Insurance Regulatory Commission, Chinese bank assets reached RMB 254.3 trillion ($ 37 trillion) in 2018, which account for more than 300% of the Chinese GDP.

The PBoC was the only bank that functioned as both central bank and commercial bank in 1978. Since then, China's banking sector has grown rapidly. In the early 1980s, the government established four state-owned banks in addition to the PBoC. The four big banks comprise the Bank of China (BOC), the Agricultural Bank of China (ABC), the China Construction Bank (CCB) and the Industrial and Commercial Bank of China (ICBC). The Bank of Communications is known as the fifth-largest bank in China which was restructured and re-commenced operations in 1987. Joint-stock commercial banks were founded both by the government and the private sector during the late 1980s and early 1990s; for example, the China Everbright Bank and CITICS. The state partially owns them but with much less share compared to the 'Big Five' (Elliott and Yan, 2013). To separate policy lending and commercial lending, three policy banks

were created after 1994, which are the Agricultural Development Bank of China, the

Export-Import Bank of China and the China Development Bank.

The share of total assets of the 'Big Five' banks ranks first in the Chinese traditional

banking system. However, it has fallen from 78% to about 41% from 2003 to 2014

(Fungáčová et al., 2018) and further shrank to 35% in mid-2018. Joint-stock

commercial banks rank the second largest category of banks, which accounted for

approximately 18% of total banking assets by the end of 2014 (Fungáčová et al., 2018).

Besides foreign banks that do not account for a significant part of the Chinese banking

system (2%), the remaining banks include 349 commercial township banks, 85 rural

commercial banks, 223 rural cooperative banks and approximately 2650 rural credit

cooperatives operating by the end of 2010 (Martin, 2012).

2.3.2 The Evolution of China's SMEs and Why They Need Shadow Banks

In China, 96% of registered firms are small-and-medium-sized enterprises (SMEs)

(National Bureau of Statistics [NBS], 2014) and they contribute more than 60% of

China's GDP and 65% of employment (Asian Development Bank [ADB], 2014). The

concept and classification of SMEs have been modified along with the development

and restructuring of both state and private sectors. Before 1978, all registered

'enterprises', regardless of scale (large, medium or small), were state or collectively-

owned by the government at different levels. However, this is no longer the case since

the reform era began. Individual entrepreneurs took advantage of the loosening policy

environment and engaged in petty commerce and trading during the early reform era; for example, private restaurants, retail stores and rural household factories (Solinger, 1984). Nevertheless, private entrepreneurs that officially registered with more than eight employees were still not allowed before 1988. Therefore, before this period, if private entrepreneurs did not want to subject numerical limits on employees, they could only disguise themselves as 'red hat enterprises', which implies they had to register as 'collective enterprises.'

The legal boundaries for China's private enterprises were relaxed in the 1990s and the ideological climate transferred towards profit-oriented activities. Private entrepreneurs in partnership with local government officials began to flourish (Tsai, 2007). Following the official ideological slogan of building 'market socialism with Chinese characteristics', almost one-third of Chinese Communist Party (CCP) members were involved in private businesses, termed the so-called 'red capitalists.' Following removal of the major political barrier to large scale private enterprises, i.e. the official legitimation of red capitalists, restructuring policy of the state sector, known as 'grasping the large, letting go of the small' resulted in the privatisation of smaller SOEs (Garnaut et al., 2005). More than 85% of small-and-medium-sized industrial SOEs conducted restructure by the end of 2003 (Zeng, 2013). Since then, the government has started to categorise enterprises into seven different types of industries, according to revenues, total assets and unemployment based on 'Temporary Regulations on the Classification of Large, Medium, and Small Enterprises'. In 2011, China's authorities, including the Ministry of Industry and Information Technology,

National Development and Reform Commission, National Bureau of Statistics and the Ministry of Finance, jointly presented the 'Standards of Classifying SMEs' that further differentiated among fourteen sectors and first introduced the concept of 'microenterprises.' Table 1 shows detail of the standard of how business size is distinguished by firms' operating income and a number of employees in fourteen different sectors in China.

However, official statistics do not differentiate SMEs by ownership type, which implies some SMEs are state-owned rather than private entities. The NBS's Third National Economic Census[8] (2014) reports that there were 8.2 million 'corporate enterprises' by the end of 2013, and 7.5 million were controlled by either state or private entities in the mainland of China (excluding Hong Kong, Macau and Taiwan). By using 7.5 million as the base number of SMEs in total, regardless whether state or privately owned, Tsai (2017) estimates there are approximately 95% SMEs privately controlled, which implies 7.06 million are privately owned, 220,000 firms are state-owned, and the remaining SMEs are collectively controlled. Tsai (2017) further shows that private firms (both large and SMEs enterprises) have outperformed SOEs in return on assets (ROA) consistently since 1999.

SMEs are the backbone of the economy, but especially small and micro enterprises face severe financing constraints in acquiring bank credit due to heavy regulation from the central bank. In contrast, state-owned enterprises (SOEs) are inefficient and

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[8] http://www.stats.gov.cn/english/pressrelease/201412/t20141216_653756.html

constitute the core of China's zombie firms but receive more than 75% of loans from commercial banks (Lardy, 2014; Tsai, 2015). The reasons are the market-wide expectation that the central government would compensate creditors in the case of a default and the five biggest banks are not allowed to lend to SMEs, other than SOEs (Lu et al., 2005). All-China Federation of Industry and Commerce (ACFIC) conducted a national survey in 2010 and found that only 10% of small enterprises and 5% of micro firms could obtain bank loans. Similarly, an NBS survey in 2011 shows that only 15.5% of small and micro companies have access to bank credit. Hence, SMEs must rely on alternative sources of credit to operate their business: this has brought the shadow banking sector into the spotlight. SMEs financing and bank-dominated financial system that prefer lending to SOEs are thus fundamental triggers of the development of China's shadow banking system.

Supporting the state sector and maintaining social stability has been a political concern for the Chinese government since the 1990s (Lardy, 1998). Local governments have pressured state banks to support SOEs by providing 'cheap finance' to avoid mass unemployment. However, China's big commercial banks have accumulated a large amount of non-performing loans (NPLs) because of stimulus-induced bank lending (Zhang et al., 2012; Weinland, 2015). The heavy bank regulation is another reason interacting with the demand of SMEs financing that pushes business away from traditional banking towards shadow banking. There are two main policies that affect

Table 1 Standards of Classifying SMEs

Sectors	Medium		Small		Micro	
	Operating Income (RMB)	Number of Workers	Operating Income (RMB)	Number of Workers	Operating Income (RMB)	Number of Workers
Agriculture, Forestry, Animal Husbandry and Fishery	5m-20m	--	500k – 5m	--	< 500k	--
Manufacturing Industry	20m-400m	300-1000	3m-20m	20-300	< 3m	1-20
Construction Industry	60m-800m	--	50m-60m	--	< 50m	1-10
Wholesale Businesses	50m-400m	20-200	10m-50m	5-20	< 10m	1-5
Retail Industry	5m-200m	50-300	1m-5m	10-50	< 1m	1-10
Transportation Industry	30m-300m	50-300	2m-30m	20-300	< 2m	1-20
Warehousing Industry	10m-300m	100-200	1m-10m	20-100	< 1m	1-20
Postal Industry	10m-300m	100-1000	1m-10m	20-100	< 1m	1-20
Hotel Service Industry, Catering Industry	20m-100m	100-300	1m-20m	10-100	< 1m	1-10
Information Transmission Industry	10m-1b	100-2000	1m-10m	10-100	< 1m	1-10
Software and Information Service Industry	10m-100m	100-300	500k-10m	10-100	< 500k	1-10
Real Estate Industry	10m-2b	--	1m-10m	--	< 1m	--
Estate Management	10m-50m	300-1000	5m-10m	100-300	< 5m	1-100
Leasing and Business Service Industry	80m-1.2b	100-300	1m-80m	10-100	< 1m	1-10

Source:http://www.gov.cn/zwgk/2011-07/04/content_1898747.htm

bank credit: the first is the legal ceiling of bank lending volumes or the loan-to-deposit ratio imposed by the People's Bank of China (PBoC); the second is the prohibition of lending funds to certain risky industries, such as real estate, coal mining, and shipbuilding, issued by the Chinese Banking Regulatory Commission (CBRC). Commercial banks are not allowed to lend more than 75% of the total stock of their deposits. However, shadow banks do not subject to such limitations and can also lend to risky enterprises.

Shadow banking system plays an essential role in the Chinese economy. The benefits are to satisfy the demand of SMEs financing and fuel economic growth; otherwise, it is difficult for SMEs to contribute more than 60% of the GDP if the private sector is excluded from official credit. However, less restriction in the shadow banking sector also comes with substantial economic costs, which may cause financial instability. Besides financial consequence, political consequences also play a minor role in SME financing. The result of Tsai's (2017) field interviews during 1996-2016 show that use of party-state resources to support capitalist ventures has always been of concern. Loan officers believe that the problem is contained within the public sector if an SOE defaults on a loan. However, bank managers explain that if it were loaned to SMEs, they might be criticised by their superiors.

2.3.3 The Status of the Shadow Banking Sector

The share of China's shadow banking assets to the global financial assets ranks the

second largest (16%) that follows the US shadow banking, with 31% (FSB, 2016)[9].

According to the latest report from Moody's[10] (2018), the total stock of shadow

banking assets reached RMB 62.1 trillion ($ 10 trillion) by the end of September in

2018, which accounts for 70% of the country's GDP.

There are several notable differences between the US and China's shadow banking

system. Firstly, the traditional banking sector plays a dominant role in driving the

growth of shadow banking in China. Dang et al. (2015) point out that due to high

inflation, real deposit rate in traditional banks is close to zero and even negative in

recent years, which discourages depositor from saving money in a bank account. To

compensate for the reduction in bank deposits, banks create the so-called wealth

management product (WMPs) to attract more funds by structuring them off banks'

balance sheet. WMPs offer higher interest payment and propagate mainly by

traditional banks, which is more attractive than the bank deposit and creates the

impression that it is subject to small risks.

Secondly, the reason for banks creating WMPs on the off-balance-sheet is to

circumvent burdensome bank regulation from the central bank. This consists of one of

the motivations for the development of the US shadow banking, regulatory arbitrage.

Since shadow banking funds are not subject to the loan-to-deposit ceiling, in principle,

banks can lend out all the funds collected from WMPs. Also, there is no reserve

requirement on shadow funds; therefore, by conducting shadow banking activities and cooperating with shadow banks, traditional banks can extend their credit without restricted regulation and exempt from most of the macro-prudential policies. The role of foreign financial entities can be neglected since domestic institutions act the dominant role in conducting shadow banking activities. Furthermore, due to the main driving force of shadow credit activities in China is the traditional banks, China's shadow banking is normally labelled as the 'shadow of the banks' (Ehlers et al., 2018).

From the funding demand side of the firms financing, shadow banking provides an essential source for private enterprises, especially for SMEs who usually can hardly gain access to bank credit. Since the majority of SMEs have higher productivity compared with SOEs, sufficient funding from the shadow banking sector for them can lead to economic gains (Hale and Long, 2011; Lu et al., 2015; Tsai, 2016).

The last difference is the complexity of the structure of the system. Unlike the US, securitisation and wholesale funding are barely operated in China's shadow credit intermediation. China's shadow banking normally involves one or two steps in the whole intermediation process, whereas the US contains seven steps (Pozsar et al., 2010; Adraina and Aschcraft 2016). In the meantime, since WMPs are mainly sold by the traditional banking sector, this creates a vague impression for households that banks should provide compensation in case of default. However, there is no such legal obligation (Ehlers et al., 2018).

2.3.4 Shadow Banking Instruments

2.3.4.1 Wealth Management Products

As already mentioned above, one of the main shadow banking instruments is WMPs. WMPs are investment products that provide higher yields than formal deposits, and the return is based on the performance of a pool of underlying assets. Although mainly operated by traditional banks and viewed as a close substitute for bank deposits, it is not risk-free (Elliot et al., 2015). According to the latest report from the Global Economics & Markets Research[11] (2018), the total outstanding value of WMPs issued by banks was RMB 29.5 trillion in 2017. Large state-owned banks used to be the leading participant in WMPs market; however, in recent years, there has been a shift towards joint-stock banks. The share of outstanding WMP by joint-stock banks accounts for 40.5% and followed by state-owned banks 33.8%. In addition, smaller city commercial banks expanded their WMPs issuance activity overtime to reach 16%. Agriculture banks and foreign banks remained relatively more minor players in the business that accounts for 5.3% and 1.3% respectively.

WMPs are rarely recorded on banks' balance sheets since banks use another financial institution as a 'channel' firm, usually trust companies. Specifically, trust companies issue WMPs and pass on to banks who propagate the products. Investors purchase WMPs via banks, and the funds are transferred to the trust companies to keep the

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[11] https://www.uobgroup.com/web-resources/uobgroup/pdf/research/MIR-20180808.pdf

transaction off the banks' balance sheet. Trust companies then lend out the money to a company that cannot gain access to bank credit due to heavy regulation (Perry and Weltewitz, 2015). The channel firm acts as a passive administrator while the bank retains control over the investment decisions and can extend credit to certain risky sectors without the restriction of the loan-to-deposit ratio.

2.3.4.2 Entrusted Loans

These are loans made from one company that often has excess cash to another company that cannot obtain approval for bank loans. Meanwhile, companies with easy access to bank credit can borrow from banks and re-lend the money out at much higher rates. These companies are usually SOEs (Elliott et al., 2015). Commercial banks prefer SOEs for loans because they are low risk. The market-wide expectation in China is that the central government would compensate creditors in case of a default in SOEs (Lu et al., 2005). However, there are no such guarantees for SMEs. In addition, large commercial banks are state-owned themselves and managers at these banks can be exempted from being criticised for making bad loans to SOEs. Hence, one of the routes for the shadow banking system is that SOEs obtain 'cheap loans' and then on-lend excess funds to SMEs. Several large SOEs, for example, Baosteel (steel company) and China Shenhua (coal miner), have engaged in the entrusted lending business in the past years.

According to the Moody's estimation[12] in 2017, almost 70% of shadow banking assets fall into two categories, entrusted loans and wealth management products (WMPs). Specifically, the size of entrusted loans and WMPs reached RMB13.8 trillion and RMB 29.54 trillion, which jointly accounts for 48% of Chinese GDP. The growth rates of entrusted loans were 21% and 4.5% in 2015 and 2016.

2.3.4.3 Bankers' Acceptances

These are certificates issued by banks that promise and specify the amount of money, the date, and the person to whom the payment is due in the future. The duration is usually six months and backed by the deposit in a bank. The holder of these certificates is permitted to trade prior to the maturity date at a discounted rate (Elliott et al., 2015). It is called undiscounted bankers' acceptance if the trade does not occur before the due date. An example of using bankers' acceptances as a form of 'money' is commercial transactions, such as purchases of inventory. Buyers who own the bankers' acceptances can use these to purchase inventory from sellers and sellers can claim money from the bank that issued the certificate. These instruments are included in the shadow banking because borrowers can take a loan based on the discounted value of the bankers' acceptances and re-deposit the money into their bank account to further back a larger certificate. Thus, the borrower can create considerable leverage by 'double' using the same amount of deposit.

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[12] https://www.moodys.com/research/Moodys-China-shadow-bank-activity-stops-growing-records-first-ever--PR_374868

2.3.4.4 Interbank Entrusted Loan Payment

There is another form of entrusted loans that operate in the interbank market, which is the so-called interbank payment. This is a loan made by one bank to another bank or nonbanking financial institutions, usually from state banks to small banks (Sun, 2018). It is initially motivated by different risk weight. Specifically, lending money to a financial institution contains a lower risk than lending to an enterprise. The credit risk weight of interbank payment is 25% compared to the loans to firms, which is 100%. State banks can lend money to another financial institution and then on-lend to enterprises as entrusted loans.

2.3.4.5 Trust Products

Traditionally, trust companies are subject to the relatively looser regulation in comparison to the heavy banking regulation, and they issue trust products that aim to create the credit channel to riskier borrowers with limited access to bank credit, especially smaller private firms (Ehlers et al., 2018). However, since 2007, regulators have begun to transform trust companies into professional third-party wealth managers and proposed a series of regulatory measures that changed the framework under which trust companies could operate (Zhu and Conrad, 2014). There are three main products issued by trust companies, including single-investor trust products, collective-investor trust products and non-pecuniary property trust products, and the share of each product account for 50%, 36% and 14% respectively in 2016.

Single-investor trust product implies there is only one large-scale investor, such as securities firms, pension funds and insurance companies. These investors want to invest in a small number of underlying assets but prefer to hold them off their balance sheet. While collective-investor trust product channels a large number of assets and various investors who are usually wealthy individuals and retail investors, a single client can invest in physical or other illiquid assets via non-pecuniary property trust products. This product is typically used to achieve bankruptcy isolation instead of investment management purposes (Ehlers et al., 2018).

2.3.4.6 Online Shadow Banking Platforms

E-commerce (electronic commerce) refers to commercial transactions conducted on the internet. More than 40% e-commerce transaction takes place in China nowadays, which is in a leading position in the world. The most famous companies in the rapidly growing e-commerce ecosystem are Alibaba Group and Tencent (Woetze et al., 2017). 'Ant', which is an online platform associated with Alibaba, provides a small-loan program to SMEs without the need for a banking license and it also obtains permission to securitise these loans (Montlake, 2013). Alibaba also set up a money-market product similar to a bank account, named Yu'e Bao, which requires no minimum amount on the account for each customer but offers higher-yield than banks' deposit rate (Lu et al., 2015). Customers can either save their money into their Yu'e Bao account and earn interest rate or use it to do normal commercial transactions. Since Alibaba has accumulated a considerable customer base, it can easily obtain an enormous amount

of cash and use the money to conduct investment, such as lending money to SMEs and other borrowers.

Peer-to-peer lending (P2P) platform is another type of online shadow banking service. It is a method that directly connects borrowers and lenders. The world's first P2P online platform, Zopa, was founded in the UK in 2005, while credit ease.cn (Yi Xin) is the first P2P platform in China, which was launched in 2006 (Huang, 2018). In June 2018, total outstanding loans reached RMB 1.3 trillion (Liu, 2018). The majority of P2P platforms were able to pool funds from investors and grant loans to borrowers before 2018. However, the regulation became much tighter after the collapse of the P2P industry in 2018, which we will discuss in detail in the next section.

2.3.4.7 Microfinance Companies

These companies are licensed financial institutions that help encourage credit for rural and small borrowers (Ellott et al., 2015). Using microfinance project to reduce national poverty in China has been an important topic since 1998. However, before 2008, microfinance industry had struggled in unstable legal status, only a few companies having obtained permission to operate microfinance business from the central bank, while other financial entities had conducted informal business between borrowers and fund donors (Britzelmaier et al., 2013). In order to boost the performance of microfinance project, the Chinese communist government had proposed a program in May 2018, which the so-called 'Guiding Opinions' granted legal status for

microfinance companies and developed a platform for private capital to help SMEs, micro-enterprises and individuals (HKEXnews, 2014)[13]. The overall scale of the industry remained very small; by the end of 2015, there were only 8910 microfinance companies with outstanding loans of RMB 941.2 billion (GDS LINK, 2016).

2.3.4.8 Other Instruments

Credit Guarantees: These companies take responsibility for the default risk for borrowers by providing financial guarantees to commercial banks and investors, especially when borrowers are small and medium firms. From 1993 to 2000, the credit guarantee companies mainly served government investment. After China joined the World Trade Organisation (WTO) in 2001, it began to grow rapidly and provided services for SMEs. According to CBRC, there were 6030 credit guarantee institutions by the end of 2010 providing a total guaranteed amount of RMB 1.15 trillion (Li and Lin, 2017) for more than 1.15 million enterprises (Articlebase, 2010). Credit guarantee companies in China participate in shadow banking by lending money directly to risky borrowers. They are considered useful in risk controlling (Scheelings, 2006; Ortiz-Molina and Penas, 2008). However, they have faced increasing difficulties and challenges by disputes and lawsuits (Wang et al., 2015) in the case of failing to guarantee the repayment.

Pawnshops: This is a shadow banking instrument that exists in both legal and illegal

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[13] http://www3.hkexnews.hk/listedco/listconews/sehk/2014/1230/06866_2130394/e114.pdf

business. Individual households and small businesses can use their assets, such as jewellery, electric appliances, watches etc., to exchange for quick cash. This is also the earliest form of the credit institution that first appeared in China in the fifth century (Skully, 1994). It is difficult to obtain data about this segment. However, the share of pawnshops in total shadow banking assets is believed not to be high compared with other instruments (Elliott al., 2015).

Trust Beneficiary Rights (TBRs): This is a simple form of derivative in which the buyer of this product receives returns of the underlying trust. For example, banks can purchase TBRs from a third party, such as trust companies, and this third party then extend funds to corporate borrowers who have difficulty accessing formal bank loans. Hence, banks can clarify this activity as 'investment' on their balance sheet rather than 'loans' (Elliott et al., 2015). The benefit of applying this activity is that banks do not restrict by the loan-to-deposit ratio and can keep a lower level of the NPLs since this activity is not identified as lending behaviour.

2.3.5 The Risk of Shadow Banking Activities and the Collapse of P2P Lending Platforms

Sheng et al., (2015) categorise three layers of shadow banking in China and the underlying risks, including the bank off-balance-sheet financing layer, the credit enhancement layer and the non-bank lending layer.

Banks extend credit through off-balance WMPs to evade regulatory restrictions on

loan-to-deposit ratio, capital and reserve ratio requirements. Consumers who purchase WMPs very likely do not understand the risks associated with the products. In fact, they may not even know where their money has been invested. Hence, the main source is the mismatch between asset risk and investors' tolerance for risk. The second layer of shadow banking relates loans to lower credit companies or borrowers unable to access formal bank credit. Shadow banking in China is greatly intertwined with traditional banking sector; if the loans that extend to risky borrowers face the challenge of repaying the debt, it would be very likely to transfer the risks to traditional banks.

Furthermore, in a case of the reciprocal loan guarantee network, when one business finds difficulty in meeting the obligation, all the other bank loans guaranteed by the business are also exposed at risk, either directly or indirectly. The non-bank lending layer relates risks directly with those shadow banks, such as pawnshops, P2P lending platform, financial leasing companies and microfinance companies. These financial intermediaries do not have rights to access the 'lender of last resort'; thus, they are vulnerable to dealing with massive investment losses. The recent collapse of P2P platforms is an example that reflects the risks contained in the shadow banking system.

In the past decade, the online lending market in China has dramatically undergone growth. As of January 2016, there were 2388 P2P platforms in total, and the trading volume reached USD 67 billion (Huang, 2018). The author explains three reasons for rapid growth in the P2P market, including high online penetration rate, a large supply of available funds and financial constraints of SMEs. China has 730 million internet

users, and online penetration rate exceeds 53.2% by the end of 2016, which helped boost popularity in the e-commerce and online financial platforms. Furthermore, since traditional bank deposit has been gradually losing attraction for Chinese investors, P2P lending normally promises 8-12 per cent interest rates, becoming famous overnight. Compared with traditional banking sector, P2P lending platforms are much friendlier to smaller businesses and become one of the most convenient sources of financing for SMEs; yet with insufficient regulation, this causes a dramatic fall in the industry.

According to the Interim Measures on Administration of Business Activities of Online Lending Information Intermediaries which were jointly announced by CBRC, the Ministry of Industry and Information Technology, the Ministry of Public Security and the State Internet Information Office (2016), P2P platforms should only be information intermediaries, rather than cash pool, and all the platforms need to register with local authorities. The interim measures were first introduced in August 2016, and local government agencies were told to complete the implementation of the framework by June 2018. However, in order to attract more capital locally, provincial governments failed to implement interim measures efficiently. As of the end of August, the work still has not finished. Since there was no established regulatory framework, most platforms had been involved in cash pooling activities and resulted in Ponzi schemes.

Huoq.com (a P2P lending platform backed by SOEs that was founded in December 2016) announced that it went into liquidation in July 2018. Tianfu Lanyu - partly owned by an SOE in Xinjiang Province - owns one-third of Xinjiang Tianfu Lanyu

Optoelectronics Technology, which is the owner of the Huoq.com. However, the platform suddenly disappeared on July 10, and neither investors nor the company could be found them. According to the Home of Online Lending (Wangdai Zhijia), there were only ten platforms considered in trouble in May 2018. However, the number had increased to 63 in June and 163 by the end of July. One hundred and eight P2P platforms were shut down within 42 days (Li, 2018).

Although the P2P lending industry only accounts for approximately 2% of total shadow banking assets in China, it is the riskiest and most unregulated part of the system (Bloomberge, 2018). Experts from China International Capital Corporation predict that only 10% of the P2P platform at present can survive in the next three years. The failure of regulating this industry may trigger systematic risks (Liu, 2018).

2.4 The Reason for Using DSGE Framework

Lucas (1976) criticises that reduced-form models are not reliable for policy evaluation. When a new economic policy is introduced, agents in the economy may also alter their expectations and behaviour, which will change the parameters of the corresponding reduced-form model. Consequently, such model frameworks may provide inefficiently and even no useful information about the actual impact of alternative economic policies. For example, if policymakers want to exploit the trade-off between unemployment and inflation based on a Phillips curve, such as increasing inflation to decrease unemployment, agents will adjust their expectations of high future inflation,

and alter their employment decisions, which will result in a smaller effect on output than policymakers predicted. Once policymakers estimate the model with the new data, they may find that the trade-off was less significant than initially thought. In other words, the negative association between unemployment and inflation does not guarantee low unemployment under alternative monetary policy regime. In order to perform policy evaluation, the solution should use models that are structural and policy-invariant, micro-founded with deep parameters, such as the coefficients of the utility function of consumers and producing sectors. When the micro-foundations are specified correctly, then parameters will have a stable value across different policy regimes.

The first generation of models that has micro-foundations, rational expectations and general equilibrium framework is the real business cycle (RBC) models, which focus on the impact of the technology shock. Although RBC models show the potential of not being subject to the Lucas critique, it leaves no space for monetary policy analysis. By encompassing a role for economic policy with an emphasis on monetary policy, and including various nominal rigidities, DSGE models have been constructed and became the workhorse framework of macroeconomic analysis. Once possible to treat DSGE models to the latest vintage in the evolution of macroeconomic models, it makes certain updates comparison to previous generations. This does not mean that older vintage models should be abandoned, they still have their followers, and indeed, may even be better in some dimensions.

DSGE frameworks have been widely used by researchers both in academic research and in policy institutions, especially in central banks, as the baseline framework of reference for studying fluctuations in economic activities and their association to monetary and fiscal policies. DSGE models are powerful tools that can be widely adopted to examine a variety of macroeconomic phenomena flexibly and for policy discussion and analysis. In addition, it has been proved that DSGE models can fit data successfully (Smets and Wouters., 2003; Christiano et al., 2005). However, considerable criticism has been raised against DSGE models built upon the New Keynesian framework. The arguments mainly focus on the failure of these models to predict the crisis and the lack of financial block in the model structure, which should account for key determinants behind the crisis.

Trichet (2010) discusses the role of DSGE models in the European central bank and points out that ''when the crisis came, the serious limitations of existing economic and financial models immediately became apparent. … Macro models failed to predict the crisis and seemed incapable of explaining what was happening to the economy in a convincing manner. As a policymaker during the crisis, I found the available models of limited help. In fact, I would go further: in the face of the crisis, we felt abandoned by conventional tools.'' He further argues that ''[t]he keys lesson I would draw from our experience is the danger of relying on a single tool, methodology or paradigm. Policy-makers need to have input from various theoretical perspectives and from a range of empirical approaches. Open debate and a diversity of views must be cultivated – admittedly not always an easy task in an institution such as a central bank.''

Dotsey (2013) and Hendry and Mison (2014) highlight that some 'deep parameters', for instance, the degree of price stickiness, turns out not to be deep enough as it displays little stability when the shocks hit the economy. A further reason that DSGE models have been criticised is the lack of effective communication devices. Blanchard (2017) argues that the presence of various distortions makes DSGE models interesting; however, it also makes it difficult to understand about the impact of these distortions on the results and the related reaction, especially for those who do not have experience of building these models. DSGE models are only one of many tools used at many central banks. For example, Brayton et al. (1997) document some more traditional structural models like FRB/US and FRB/Global, which coexist with the use of the number of DSGE models. Levin et al. (1999) and Levin and Williams (2003) emphasis that no policy institutions should place too much faith in any single model. From the perspective of a robustness check, more tools should work better than single tool. Gali (2017) points out several dimensions that need to be filled in DSGE models, including the standard assumptions of rational expectations, infinitely lived representative household and perfect information.

Despite the shortcomings of DSGE models, they still arguably remain the dominant role in macroeconomic research. From the experience of using DSGE models in central banks, although these models are not the perfect forecast tools, the performance remains sufficiently strong. It has been proved that DSGE models are useful in replicating and explaining the historical experience and allow for the estimation of unobservable but important variables, such as the natural rate of interest. In addition,

the models are allowed to conduct counterfactual experiments, which may provide meaningful outcomes for 'what if' analysis. As Coenen, Motto, Rostagno, Schmidt and Smets stress in their comment chapter of the Ebook edited by Gurkaynak and Tille (2017), regardless explicit or implicit, counterfactual analysis is always the core of effective policy experiment. Policymakers constantly ask questions, such as "What risk does a protracted period of low inflation entail for the anchoring of inflation expectations? How have structural reforms affected the Phillips curve and the outlook for inflation? What is the contribution of our new credit easing measures to current credit and money market developments? How will a certain fiscal consolidation package affect the economy and the need for monetary policy action? What would be the impact of a supply-driven rise in oil prices?" There are mainly two reasons estimated DSGE models are suitable to conduct counterfactual analysis: first, structural interpretation is well identified in these models; second, these models fit data reasonably well.

Justiniano, Primiceri, and Tambalotti review the empirical performance related to the DSGE frameworks in the comment chapter. They describe the DSGE models as a staple in the toolkit that connects central banks with the world. Christiano et al. (2005) and Smets and Wouters (2007) demonstrate how estimated medium-scale DSGE models play a useful and successful role in explaining hidden information of aggregate data. From the policymakers' point of view, one important appeal of using DSGE is the ability to combine good empirical analysis and the ability to tell stories behind the economic phenomenon. The substantial progress of estimating DSGE models with

Bayesian technique proves that the estimated results based on DSGE models can provide as accurate a forecasting analysis as the rich parameterised statistical models; for example, VAR models. In the meantime, decomposed forecast error analysis in the micro-founded DSGE frameworks makes it possible for researchers to understand what primitive shocks may play substantial role in the future, which is difficult to implement in those reduced-form models. With these obvious appeals, DSGE models have become the standard tool to interpret historical data, to investigate the sources of economic fluctuations, and to conduct counterfactual policy experiments. The authors point out one growing gap between central bank analysis and academic modelling style. On the one hand, central banks develop DSGE models with increasing scale and complexity to capture more observable variables and shocks. They are trying to explain empirical questions by using one coherent but complicated structure. On the other hand, researchers in academia are trying to simplify the framework and make it more transparency and easy to be interpreted. In this respect, the trade-off between integrating more features into a large-scale framework and simplified models with transparent laboratories is ongoing progress in the field.

Since the latest financial crisis, policymakers around the world have been calling for some comprehensive policy packages that may be helpful in recovering the economy. Fabio Ghironi believes that DSGE models are the most suitable tools. The reason is that DSGE settings can include all different features across various policies and understand how they might with each other. Moreover, the dynamic feature of the model allows researchers to understand the difference between short-run and long-run

effects of various policy implementations and investigate whether different policy packages are complementing or substituting for each other. The stochastic characteristic allows the model to recognise uncertain environment and conduct policy experiments. Each sector in the model, e.g. consumers, firms, governments etc. can make their own decisions without knowing the knowledge of the external environment and business cycle conditions. Finally, the nature of general equilibrium framework is to jointly determine prices and quantities in the goods market, money market and other markets by imposing the constraints and optimality conditions of different sectors in the structural model. Such models do not set any prior assumptions on how price or quantity should be affected by certain policies.

Over the past ten years, the New Keynesian frameworks have kept expanding by encompassing new phenomena and addressing some of the criticisms that we mentioned above. For example, research in recent years has been incorporating financial frictions to the baseline DSGE models (Bernanke et al., 1999; Del Negro and Schorfheide, 2013); heterogeneous agents and incomplete markets are included in the model to address the representative household and perfect information criticisms (Werning, 2015; Kaplan et al., 2018; Auclert, 2019); overlapping generation models are used to replace the infinite lived household in the regular DSGE framework (Gali, 2014; Del Negro et al., 2017; Gali 2017).

To briefly conclude, the criticisms of New Keynesian models notwithstanding, the DSGE models arguably remain the mainstream in the macroeconomic school of

thoughts. The nature of DSGE models allows policymakers to conduct counterfactual analysis with various policy packages in one structural framework. It is not difficult to imagine that millions of criticisms would raise up immediately if central banks or any policy institution claims that they want to build a model that relies on static rather than dynamic, deterministic rather than stochastic, and partial rather than general equilibrium. As Blanchard (2016) concludes "there are many reasons to dislike current DSGE models…[but] they are eminently improvable and central to the future of macroeconomics."

2.5 Literature on Modelling Shadow Banking System

This thesis draws from different strands of literature associated with modelling financial system in DSGE frameworks and related policy implications. As the illustration from the previous section, we know that DSGE models still remain the mainstream of macroeconomics models currently, which originally elaborated from the fusion of the Real Business Cycle (RBC) models and the New Keynesian sticky-price frameworks during 1980s to the early 1990s (Verona et al., 2013). Before the 2007-2009 financial crisis, most of the DSGE model incorporates no role for the financial sector and assume frictionless financial markets so that financial intermediaries play a passive role. The DSGE models used by the most influential central banks to analyses monetary policy, such as the SIGMA model at the Federal Reserve Board (Erceg et al., 2006), the Smets and Wouters model at the European Central Bank (Smets and Wouters, 2003) and the Bank of England's Quarterly Model

(Harrison et al., 2005), all exclude the prominent role of the financial sector.

After learning the lesson from the crisis, many studies argue that financial intermediaries should play more important roles in influencing the performance of the economy through the transmission of central bank policies (Erceg et al., 2006; Harrison et al., 2005; Smets and Wouters, 2003; Wang, Deng, Yang, 2015). The very first attempt to incorporate a frictional financial sector in a New Keynesian DSGE framework is developed by Bernanke et al. (1999), in which risky enterprises use both net worth (internal finance) and bank loans (external finance) to finance capital investment. In their model, financial friction is derived from the spread between the risk-free lending rate and the rental rate of capital, which denoted as the risk premium. Another way to consider financial friction is the consideration of the collateral constraint (Iacoviello, 2005). There are two types of agents assumed in this string of DSGE models, where impatient households use housing as collateral to borrow money from patient households. Imperfect competition in the banking sector is also considered to model the set of banks' interest rate (Kobayashi, 2008; Gerali et al., 2010). Curdia and Woodford (2010) model a time-varying spread between banks' deposit and lending rates. Moreover, the role of bank capital in the transmission mechanism of different macroeconomic shocks are studied in a number of papers; for instance, Van den Heuvel (2008), Gertler and Karadi (2011) and Meh and Moran (2010).

Together with the increasing amount of research that includes financial sector (Gertler and Karadi, 2011; Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2013; Du et al., 2014), the subprime crisis also reminds researchers that the behaviour of the financial intermediaries themselves needs to be analysed carefully. They have been involved in risky activities that surge the development of the US shadow banking system, where the shadow banks are treated as the culprit of the financial crisis. There have been more attempts to include the shadow banks and investigate the related policy implications of the shadow banking sector in the DSGE frameworks in recent decades.

Verona et al. (2013) follow the framework of the financial accelerator model described in Bernanke et al. (1999), Christiano et al. (2010) and modify it with an extra financial intermediator, shadow banking sector. Households are permitted to purchase two types of financial instruments offered by banks, time deposits and corporate bonds, where time deposits are used to finance riskier entrepreneurs through retail banks, and corporate bonds are used to fund safer entrepreneurs via investment banks. In the paper, they argue that a long period of loose monetary policy remarkably amplifies the fluctuations in both real and financial variables when optimism and perverse incentives are taken into account in the financial sector. Thus, the 'too low for too long' interest rate policy creates the preconditions for a boom-bust cycle.

The idea that the growing amount of shadow banking activities increase the difficulty in implementing monetary policy is supported by empirical studies. Sunderam (2013)

presents a model, which includes three types of claims that provide money services, deposits, Treasury bills, and ABCP. Households maximise utility by choosing their consumption level as well as the holdings of three different claims. The author emphasises that the increasing demand for money-like claims [14] is one of the explanations of the rise of shadow banking. Empirically, the paper proves that short-term debt, such as ABCP, indeed has properties of quasi money, which positively correlated with the growth of households' money demand before the 2007-2009 crisis.

Meeks et al. (2017) introduce two types of financial intermediaries, commercial banks and shadow banks in a dynamic general equilibrium model. The key element is that commercial banks purchase claims (make loans) from the economy's ultimate borrowers, nonfinancial firms, then optimally decide how much loan books maintain on their own balance sheet and how much sell it to the shadow banking sector. In turn, shadow banks issue claims against the loans they acquire to fund their purchase. This model consists with the function of the shadow banking activities in practice that we explained in Section 2.2.2, where shadow banks take the raw material of loan books produced by commercial banks and transform it into ABS. Their model indicates that traditional bank credit is negatively associated with shadow bank credit; in addition, traditional bank credit shows procyclical while shadow bank credit is countercyclical. However, they do not control for the loan quality in their shadow banking environment.

Faia (2012) considers the case that commercial banks can transfer credit risk to

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[14] The term 'money-claim' is used to indicate very short-term, fixed-principle debt owed.

secondary market which reduces the impact of liquidity shocks on bank balance sheets. However, the author argues that although secondary market can release bank capital and amplify the effect of macroeconomic shocks on output and inflation, by providing the channel of capital recycling, secondary market allows banks to take on more risk, which results in financial instability. This brings the moral hazard issue to traditional banking sector. Nevertheless, the paper does not consider the shadow banking sector, which may underestimate the impact of credit risk transfer to the financial system.

Mazelis (2014) builds a DSGE framework that includes both commercial banks and shadow banks and investigates the impact of monetary policy shocks on aggregate loan supply. The author assumes that formal banks have no friction of acquiring deposits from depositors, while shadow bank raises deposits via search and marching for available deposits by households. Thus, the reaction of the same monetary policy shock is different in two different sectors. When monetary policy becomes tighter, commercial banks raise up deposit rates and lending rate, which discourage loan supply and encourage savings. However, since depositors save money both in the traditional bank account and shadow bank account, thus the higher savings aggregately also indicate the higher saving in the shadow banking sector. The key difference is that a higher saving in the non-bank sector reduce funding market tightness for shadow banks, which allows them to increase lending. This opposite behaviour then alleviates credit squeeze and mitigates the fall in loan supply, which in turn offsets the fall in investments and output.

Despite monetary policy rule, this thesis is also closely related to studies that analyse macroprudential policies. For example, Kannan et al. (2012) bring housing market into a DSGE framework and ask whether macroprudential rules can help with the financial stability rather than solely rely on monetary policy and what are the tradeoffs between inflation and output stabilisation and the risk of asset price crashes. The model is extended based on Iacoviello (2005) and Iacoviello and Neri (2010) with financial accelerator effects. They simulate the model and find that macroprudential policies are helpful to alleviate financial shocks that lead to credit and housing price boom; however, there is a possibility in making policy mistakes. Specifically, if the boom is due to financial or housing demand shocks, macroprudential policies can help to stabilise the market and improve welfare; but if the boom results from higher productivity shock, the same macroprudential rules may decrease welfare.

Similarly, Rubio and Carrasco-Gallego (2014) evaluate the implications of interaction among macroprudential policy, LTV ratio, and monetary policy for the business cycle, social welfare and financial stability. They build a DSGE model with a macroprudential Taylor-type rule for the LTV ratio. Unlike the standard LTV ratio that is fixed, their assumption follows the spirit of the Basel III regulation which allows the macroprudential policy responses to the credit boom automatically and may avoid excess credit growth. Social welfare is improved in the cases of macroprudential regulator coordinate and not coordinated with a central bank when both macroprudential and monetary policies exist, especially in the case of a non-coordinated case. In addition, they find that macroprudential authorities would

decrease the LTV ratio when there is positive technology shock or positive housing demand shock, and it stabilises the economic system unambiguously.

Angelini et al. (2014) present a medium-scale DSGE model with another type of macroprudential policy, time-varying capital requirements, and study the effects of the countercyclical capital requirement policy. Similar to Rubio and Carrasco-Gallego (2014), this paper also posits two cases of interaction between monetary and macroprudential policies, i.e. corporative and non-corporative scenarios. Their results suggest that the impacts of time-varying capital requirements on output and inflation volatility can be neglected when the dynamic of the economy is mainly driven by the supply shock, such as TFP shock. In other words, co-existence of both macroprudential and monetary policies is no better than monetary policy only when supply shock is important. In addition, lack of cooperation between macroprudential authorities and central bank may result in higher volatility of the policy instruments. The reason is that both types of policies have different objectives but with similar related variables, such as bank rates and credit; therefore, due to different purpose, different policies may push these variables toward different directions. In a nutshell, an improper macroprudential policy may eventually exaggerate macroeconomic instability. However, if financial shock plays ranks important role in driving economic dynamic, macroprudential would reduce the volatility of output regardless of the cooperation between different policymakers.

Nevertheless, the literature I reviewed above has not touched the macroprudential effects with the existence of the shadow banking system. It is necessary to evaluate the policy implications when shadow banks become larger since shadow banks differ from commercial banks in two aspects. First, they are not restricted by capital requirements; second, they have no liquidity backup, such as deposit insurance from the government, in the case of bankrupt, which may increase the financial instability. For example, Luck and Shempp (2014) find that the size of shadow banking plays a crucial role in determining the stability of the financial system. They build a simple banking model in which regulated banks and unregulated shadow banks exist due to regulatory arbitrage and conclude that if the shadow banking system is independent of the traditional banking sector, then, the shadow bank run would not induce systemic risk. But if the two banking sectors are intertwined with each other, the crash in the risky banking sector may enhance the overall financial instability.

Begenau and Landvoigt (2018) build a tractable general equilibrium model to quantify the benefits and costs of tight bank regulation and study the implications of optimal capital requirements policy with regulated commercial banks and unregulated shadow banks. Consistent with the practical circumstances, their model assumes that commercial banks are insured and can always fulfil the obligation of the interest payment to depositors but subject to capital requirements. On the other hand, shadow banks are not restricted by regulation, but face the probability of bank runs. They calibrate the model and claim that tighter bank regulation (higher capital requirement) drives up the size of the shadow banks along with the underlying risks. However, this

does not mean that the aggregate financial system becomes fragile; instead, riskiness in the shadow banking sector is largely offset by the greater stability in commercial banks. They further conduct the welfare analysis and conclude that when capital requirement reaches approximately 17%, the welfare is maximised with the existence of both commercial and shadow banking sectors. One important aspect of their model that drives the conclusion is that deposits in shadow banks generate liquidity services. Shadow banks become larger in size against the tighter commercial bank regulation. This does not indicate higher leverage in the shadow banking system since higher demand for shadow banking deposits decreases the funding costs, which in turn decreases the incentive to search for higher yields. Another similar practice from Durdu and Zhong (2018) highlights that shadow banks can mitigate the effects of an increase in capital requirements. Using their model, they find that the commercial bank annual default rate decreases from 0.75% to 0.05% in the long run when capital requirements increase by one percentage point. And the higher capital requirements slow down the real economy with a 0.6% decrease in GDP in short-run and 0.2% decrease in long-run. Moreover, total lending declines by 0.9%.

Another important segment of the crisis is the disruption of wholesale funding markets where banks lend to each other. In these models, the source of shadow banking funds is commercial banks. By augmenting the model of Gertler and Kiyotaki (2012) that only considers retail banks, Gertler et al. (2016) incorporate wholesale banking alongside the retail sector, where the credit amount is raised endogenously. Furthermore, they allow for the possibility of wholesale bank runs. The flow of the

funds in the model is that retail banks obtain deposits from households, and endogenously determine the funds provided to wholesale banks. Wholesale banks then allocate the funds to productive nonfinancial sectors. They argue that during the 'normal' times, the existence of wholesale funding increases both efficiency and stability in the banking system. However, the growth of wholesale banking system makes the economy more vulnerable to a crisis.

Nelson et al. (2017) emphasise the securitisation aspect of shadow banks. They develop a macroeconomic model in which risky loan books are offloaded to the shadow banking sector from commercial banks' balance sheet. Then shadow banks bundle it as the form of ABS and sell it in the bond market. Commercial banks can take on higher leverage with the help of the securitisation market since holding ABS instead of loans releases the burdensome regulation in the traditional banking sector. The model reproduces the negative co-movement between the commercial bank and shadow bank, in which a contractionary monetary policy shock persistently slows down the growth of commercial banks but increases the shadow banking activities. Feve and Pierrard (2017) develop a similar model with the interaction between shadow banks and commercial banks. Commercial banks make loans to nonfinancial firms, and at the same time, purchase the ABS issued by shadow banks. The reason is that ABS is tradable and backed by a pool of loan books but subject to less regulation. The authors focus on the regulatory implications and find that commercial banks substitute away from traditional loans and towards ABS to relax regulatory constraints.

Another important paper in the shadow banking literature is Moreira and Savov (2017), who present a microfinance model in which macrocycle is driven by liquidity transformation in the financial sector. The authors consider the issuance of money, which only provides liquidity in the states with lower uncertainty. The dynamic model shows that the buildup of shadow money during low uncertainty times boosts asset prices and economic growth since producing liquid securities requires less collateral. But the cost is the increased fragility, which raises uncertainty and leads to the collapse of the shadow banking sector. The occurrence of the collapse of the sector shrinks the liquidity provision and rises liquidity premia and discount rates, which in turn lower the asset prices and investment.

To combat the spillover effect of the 2007-2009 financial crisis, Chinese authority launched the well-known 'four-trillion' stimulus package that fueled by bank loans. The stimulation plan largely attributes the fast development of Chinese shadow banking activities. Since then, there is a burgeoning literature on the shadow banking system in China, and the relationship between shadow banking and policy implementations in China has also been considered by scholars. Zhou (2011) claims that the existence of the shadow banking sector would weaken traditional monetary policy since he believes funds from regular depositors can, to some extent, flow into the shadow banking sector. In the meantime, the effectiveness of the money supply is dampened through macro-control and generates external effects on the money market. Similarly, Wang (2010) investigates trust wealth investment and concludes that the

transmission mechanism of window guidance [15] is ambiguous with the shadow banking system and new money supply is increased substantially. This would make the central banks' decision less effective. Li (2013) takes the effect of both short periods and longer periods into account. The author finds that money supply is relatively stable in the long-run and would be dramatically affected by the shadow banks. This conclusion suggests that the impact of shadow banking system could be reduced if government adopts credit-oriented policies. By opposing short-term constraints on an SVAR model, Chen and Zhang (2012) indicate that shadow banking can stimulate economic growth as well as money supply significantly but with a negligible impact on inflation.

Hachem and Song (2017) add two features into the standard banking models that engage in maturity transformation. First, big versus small banks, in which big banks can influence the rest of the economy with their operation, while small banks cannot. Second, both types of banks are free to choose to operate the business on a regulated balance sheet or on an unregulated off-the-balance sheet, which features shadow banking activities. The bank regulation they discuss in the paper is liquidity minimum requirement which requires banks to keep the liquid assets to short-term funding ratio above a certain threshold. The theoretical framework predicts that small banks are more constrained by the liquidity requirements; therefore, when the regulation becomes tighter, small banks prefer manage funds on an off-balance sheet vehicle that

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[15] The central bank asks banks to issue or not issue loans to specific industrial sector or companies.

is not subject to liquidity regulation. This activity raises the interest rates on the instruments above the regular deposit rates. Funds are poached from big banks since households find the deposit is less attractive. Big banks can react in two ways: first, they can create their own high return instruments; second, they can tighten interbank market for emergency liquidity which may be against small banks in the case of shortage of liquid asset during bad periods. By applying their theory to the Chinese case, they find that the tight regulation accounts for one-third of credit boom between 2007 and 2014.

Several empirical studies have studied different segments of the Chinese shadow banking system. Acharya et al. (2019) examine the scale and the effect of WMPs on the banking system. By using a large, product-level data, the authors track the response of small-and-medium banks (SMBs) to the competition from the big four banks. The stimulation package is mainly supported by the big four banks. As the loan amount increases, big four banks need to increase the deposit in order to keep obeying the loan-to-deposit ratio. The increasing competition in the deposit market pushes down the level of the SMBs' deposit amount. In order to attract more depositors, SMBs react by issuing more WMPs, which normally offer higher yield compared to the bank deposit. However, this does not finalise the competition; the four big banks also issue more WMPs to regain the depositors, which causes a surge in the development of WMPs' market. The authors confirm that the issuance behaviour of WMPs is regulatory arbitrage and further provides evidence that the rising in the WMPs' market is triggered by the stimulus plan.

Allen et al. (2019) provide a large-sample transaction-level analysis and focus on the second-largest component of the Chinese shadow banking system, entrusted loans. They find that large firms with access to cheap finance from commercial banks tend to be entrusted lenders in the market and most of these firms are SOEs. The entrusted lending activities are very likely to occur during the periods of tight credit regulation. They categorise two types of entrusted loans: affiliated loans that normally indicate the loans between parent companies and subsidiaries and non-affiliated loans that imply no relationship between lenders and borrowers. Furthermore, the pricing of the affiliated loans is very close to the official bank loan rate, while the pricing of the nonaffiliated loans is about twice the average official bank lending rate. Finally, they argue that, unlike other shadow banking instruments, entrusted loans may enhance financial stability. The reason is that entrusted lenders are normally well capitalised and have higher equity ratios than banks. Thus, the large equity provides, to some extent, the safety buffers against potential risk from the risky loans.

Chen et al. (2018) explore the implications of shadow banking for monetary policy. Their evidence shows that commercial banks have not only been operating off-the-balance-sheet shadow banking activities but also engaging in on-the-balance sheet. On the bank's asset side of the balance sheet, there is a special category, named account-receivable investment (ARI), which implies all the bank's non-loan investment. Initially, it only includes central bank bills and government bonds, but ARI is not restricted by the two bank regulations above since it is clarified as an investment rather than a bank loan. By taking advantage of this segment, commercial banks have been

purchasing back the beneficial rights of entrusted loans and report the activity as an investment behaviour instead of lending[16]. Recalling that, initially, commercial banks act only as a middle man to channel funds between companies, but now, once they purchase the beneficial rights, the repayment from the borrowing enterprises will directly go to the bank's on-the-balance sheet. They build a partial equilibrium framework for a banking sector and argue that the tight regulation pushes the commercial banks to increase the risk lending activities, which is the reason that raises the overall shadow banking credit. In addition, they empirically test that nonstate banks to behave differently from state banks in their responses to monetary policy in terms of their shadow banking activities. Specifically, shadow banking activities in state banks react insignificantly against the contractionary monetary policy, while nonstate banks tend to increase shadow banking activities with the purpose of circumventing the tight regulation.

To sum up, in this sub-section, I review both theoretical and empirical literature of modelling and testing shadow banking sectors both in the Chinese and US markets. This thesis is closely related to several different strands of the shadow banking literature, including the effectiveness of different policies, such as monetary, fiscal and macroprudential policies, with the existence of shadow banking system, and the related issues of financial stability.

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[16] Chen et al., (2018) named this as ARIX, which is the investment excluding central bank bills and government bonds.

2.6 Bayesian and Indirect Inference Estimation

2.6.1 Bayesian Approach

Conventional statistical estimations always assume no relationship between variables. Thus, the null hypothesis normally indicates no relationship and no prior knowledge of variables. However, it is often the case that researchers do have some understanding of the relationship between variables, which may be based on earlier research and investigations. It is different from the conventional approach (frequentist framework) that relies on the notion of repeating the same experiment many times. Instead, with the Bayesian technique, researchers can encompass the background knowledge and take it into the process of estimation of parameters. Hence, the key difference between Bayesian and conventional statistics, for example, maximum likelihood, is the different views of unknown parameters in a model.

For example, consider a regression $y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$, where y is the dependent variable, x_1 and x_2 are the independent variables, ε is the residual, α, β_1 and β_2 are the unknown parameters that we need to estimate. Conventional approaches assume that all parameters have only one true fixed value but unknown before estimation. Bayesian methods do not provide on value but rather a probability distribution, which implies each parameter is estimated to have a distribution that includes uncertainty about the value. Such uncertainty is specified before taking the model to the data and is called prior distribution. Then these prior distributions of all

estimated parameters are combined with the observed data that is expressed in terms of the likelihood function to obtain the posterior distribution, which is the estimated results of the parameter values. Thus, these three ingredients, i.e. prior distribution, data and posterior distribution, constitute the Bayes' theorem (Van de Schoot and Depaoli, 2014).

Prior distribution of Bayesian statistics reflects prior knowledge of the underlying parameters, which can be stemmed from previous studies and investigations (O'Hagan et al., 2006). The variance of the prior distribution implies the level of uncertainty about the value of the parameters, the smaller the variance, the more certain about the value of the parameter. There are three types of prior distribution regarding the level of certainty of the parameter value, non-informative priors, weakly-informative priors and informative priors. Non-informative priors simply imply a great deal of uncertainty or have no prior knowledge about the value. Weakly-informative priors contain some useful information but typically have limited influence on the final parameter estimate. Finally, the priors that include the most amount of information about the values are informative priors. The last type of prior has a large impact on the final estimates. After specifying the priors, Bayes' theorem then takes it to the data that contain new and true information and obtain the posterior distribution, which reflects one's updated knowledge about the estimated parameters (Van de Schoot and Depaoli, 2014).

Comparing with the conventional frequentist approach, the major difference is that only Bayes can incorporate background knowledge into the estimation and allow for updating the previous understanding after analysing with the new data. Another advantage of Bayesian statistic is that it does not require testing the same null hypothesis repeatedly. One can pick up the theory from prior literature and conduct further analysis. In addition to theoretical advantages, one practical advantage of using Bayesian methods is that it can deal with small sample size, which is not based on the central limit theorem as in the frequentist approach. The prior distribution only reflects the background knowledge of the theory and is not based on sample size. The maximum likelihood function of the data is scaled by the size of the sample. With more data in the sample, the likelihood function contains more information and may have a larger influence on the final estimation. For a small sample, prior distribution plays heavier role in the estimation, while with large sample, data have a larger impact on the posterior distribution. Many papers have shown the benefits of using Bayesian methods when large data set is not available (Zhang et al., 2007; Lee and Song, 2004; Hox et al., 2012).

Bayesian estimation has been substantially applied in macroeconomics research in the last three decades. Querron-Quintana and Nason (2013) explain the reason that Bayesian method becomes popular is that it offers researcher the chance to estimate and evaluate macro models where frequentist approach often finds challenge to implement, especially for DSGE models. Another attractive aspect of the popularity of the Bayesian approach is the increasing computational power to estimate medium

and large scale DSGE frameworks. In addition, frequentist econometricians argue that DSGE models are misspecified versions of the true model, even though these models are always seen as abstractions of economies. Hence, Bayes' theorem is favoured in estimating DSGE models as it eschews the existence of such true model and claims that all models are false, but one can be better than another.

2.6.2 Indirect Inference Estimation

Berger and Wolpert (1988) state that Bayes' theorem, based on the likelihood principle, does not assume the existence of a true or correctly specified DSGE model. The likelihood principle implies that all evidence about a DSGE model is contained in its likelihood conditional on the data. Therefore, from a Bayesian economist perspective, one model can be more likely to be better compared with the benchmark model. Indeed, there is no model can be literally true since the 'real world' is too complex to be explained by one model, which implies all DSGE models are false or 'misspecified'. Nevertheless, as argued in Le et al. (2015), an abstract model with implied residuals may still be able to mimic the data. For example, a model with the assumption of perfect competition may never exist in reality, but can still be able to predict the behaviour of industries with a high degree of competition. Thus, although the DSGE model maybe just a simplified version of a complex reality, it should be tested on its explanatory power against the real data.

Bayesian estimation can evaluate the model by creating a likelihood ratio, which essentially states that one model is better or worse than the other. It does not directly test the model against the real data. Thus, indirect inference technique is applied in this thesis for judging whether the model is partially rejected or not rejected by the data. Indirect inference estimation has been widely used in history (see Smith, 1993; Gregory and Smith, 1991; Gourieroux et al., 1993; Gourieroux and Monfort, 1996; Canova, 2007). Le et al. (2011) refine the method with Monte Carlo simulation, which is adopted in this research. The basic idea of indirect inference estimation is to compare the simulated data generated from the DSGE model with the actual data. Specifically, a different set of model parameters would generate different simulated moments from the same model. If the simulated moments are sufficiently close to the moments generated by the actual data, the model can be viewed as to pass the indirect inference test, and the set of model parameter that passes the test is the final estimated parameters.

To obtain the moments of the actual data, we need to choose the auxiliary model. Meenagh et al. (2009) demonstrate that the Vector Autoregressive model (VAR) can be used as an approximation of the reduced form of the DSGE models. Hence, we use the VAR model as the auxiliary model and incorporate with the chosen actual data to calculate the moments of the real data. The simulated moments from the model are used to compare with the moments from the auxiliary model. To determine whether two sets of moments are close to each other, we need to compute the Wald statistic. According to Le et al. (2011), there are two different types of Wald statistics: the 'Full

Wald' which considers all endogenous variables in the DSGE model and the 'Directed Wald' which mainly focuses on some aspects of the model performance. One should notice that the more variables and lags are included in the auxiliary model, the higher power of the indirect inference test and the higher chance that the model can be rejected. Therefore, it is arguably sufficient that if we mainly focus on the key endogenous variables in our model, which including output, inflation and interest rate.

The purpose of the indirect inference testing is to find out whether a certain set of model parameters can compute the Wald statistics that pass the critical value, while the indirect inference estimation is aimed to find out at least one set of model parameters that can finally pass the test. This implies to simulate the model and test different sets of parameters a hundred or even a thousand times.

2.7 Conclusion

In this chapter, I explain what is shadow banking (Section 2.1) and review shadow banking systems in both the US and Chinese market (Sections 2.2 and 2.3). Shadow banking activities are mainly operated in the capital market via securitisation before the 2007-2009 financial crisis in the US, while in China, it is undertaken dominately in the traditional banking sector. After the appeal of the Glass-Steagall Act in 1978, commercial banks merged with investment banks in America. However, in order to avoid the same crisis occurring in the Great Depression, combined with the development of the money market funds, the US banks created the way to bundle the

mortgage loan books, issue asset-backed securities and sell it to investors. The main underlying assets of the securities are houses since the market treats it as solid collateral.

The development of the Chinese shadow banking is triggered by the heavy bank regulation interacted with the difficulty of SMEs financing. Ninety-seven per cent of registered firms in China are small- and medium-sized enterprises (SMEs), and they contribute more than 60% of the Chinese GDP. However, they can rarely gain access to funding from the formal banking sector since the status of SMEs is not transparent to the lender and the government has restricted the funding that goes to certain industries. State-owned enterprises (SOEs) obtain more than 75% of loans from commercial banks. Chinese shadow banking activities rely less on securitisation; instead, it is a very good example of direct lending, i.e. the ultimate lender lends money directly to the ultimate borrower. According to the Moody's estimation, total shadow banking assets accounted for more than 70% of Chinese GDP in 2017, in which entrusted loans and wealth management products (WMPs) jointly contributed almost 70% of total shadow banking assets (approximately 50% of the GDP). Therefore, it is sufficient to capture the main picture of the Chinese shadow banking system by considering these two products. The aim of this thesis is to then build the dynamic stochastic general equilibrium (DSGE) frameworks with these two shadow banking activities, in order to understand what the main driving factors for the economy are and how important shadow banking is in China.

In Section 2.4, I carefully explain the reason for using a DSGE framework to conduct this research. DSGE models are still the mainstream model frameworks in studying macroeconomics with policy implications. It is difficult to believe that a static model can be the better choice since it is impossible to understand the policy effect within one period. Similarly, deterministic model is definitely not the choice if we need to take uncertain environment into account. Furthermore, I am interested in the overall reaction in the entire economy rather than only focusing on one sector; therefore, general equilibrium models have, no doubt, outweighed partial equilibrium frameworks.

Section 2.5 provides a literature review of how researchers model both the US and China shadow banking sectors with different policy implications, including monetary, fiscal and macroprudential policies. The estimation techniques are introduced in Section 2.6. I first apply Bayesian estimation in this research because there is similar prior research in this area and it is convenient for me to pick them up and conduct further research. Using indirect inference estimation is to test whether our model is rejected or not rejected by the actual data.

The model frameworks in this thesis are introduced in the following three chapters. Chapter 3 focuses on modelling the entrusted lending market, and Chapter 4 incorporates WMPs into the model framework. Chapter 5 extends the model from Chapter 4 by adding the Chinese housing market.

Chapter 3 Entrusted Loans and SOEs Lending Activities

3.1 Introduction

The first model in the thesis is a framework to study the entrusted lending market. One of the core shadow banking activities is entrusted loans, which are loans made by cash-rich companies to cash-strapped companies through a third party (usually a traditional bank in China). The entrusted loans were the largest component of the Chinese shadow banking system before 2014 and ranked second after the rapid growth of wealth management products (WMPs).

Unbalanced economic structure and the heavy bank regulation by the PBoC are the fundamental triggers of the rapid growth of entrusted loans (Lu et al., 2015). SOEs are large companies in which at least half of the shares are owned by the Chinese government. Since SOEs are perceived as 'safe' and are backed by the government in the case of default, the traditional Chinese banks favour SOEs for loans and often put less effort when evaluating the creditworthiness of SOEs (Elliot and Yan, 2013). However, private-owned enterprises (POEs), especially small-and-medium-sized enterprises (SMEs), face severe restriction of getting access to bank credit. This is because these firms usually lack sophisticated accounting reporting system and proper risk assessment mechanism, which makes it difficult for banks to monitor and evaluates the performance and underlying risks of their business. Moreover, the central government discourages lending to high-risk companies (Elliot et al., 2015). This

further push business away from the formal banking sector to shadow banking system.

Allen et al. (2019) reveal that entrusted loans allow large SOEs which have access to cheap finance from banks to provide liquidity to credit-constraining companies, in particular, SMEs. Their evidence highlights that during the period 2004-2013, 73.8 per cent of lenders who engage in entrusted loans are SOEs. SOEs behave risk-neutral and given their central role in the entrusted lending business, I investigate the following research questions: (1) Does the existence of the shadow banking system reduce the effectiveness of monetary policy in tightening credit constraints faced by SOEs? (2) Does an increase in government spending add to the conventional crowding-out mechanism by worsening the credit conditions of SMEs?

To seek answers to the above research questions, I construct a dynamic stochastic general equilibrium (DSGE) framework with entrusted lending behaviour of SOEs. The model shows that SOEs who receive affiliated loans [17] from their parent companies tend to have a lower marginal product of capital than SMEs who obtain non-affiliated loans from SOEs entrusted lenders. Through running experiments under different levels of bank credit tightness, I find that in the steady-state, SOEs engage more in non-affiliated loans to SMEs when the reserve ratio requirement increases.

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[17] There are two distinct types of entrusted loans, including affiliated and nonaffiliated loans (Allen et al., 2019). Affiliated entrusted loans are loans to subsidiaries from their parent company, while nonaffiliated loans require no prior relationship between lenders and borrowers.

I then estimate the model by using a Bayesian approach for the period 1992Q1-2015Q4. The model dynamic shows that a contractionary monetary policy exerts a more negative impact on the SMEs' output than that of SOEs. This is because SMEs are credit-constrained firms and are required to pay a risk premium to get financed. Instead, SOEs only pay the risk-free rate[18]. When the market becomes tighter, external financial sources become more costly and difficult for SMEs to access, which results in a higher risk premium and lower output. Furthermore, the effectiveness of the monetary policy is lower when SOEs entrusted lenders are free to adjust the allocation of holding affiliated and non-affiliated loans. This implies that when monetary policy becomes tighter, SOEs entrusted lenders can choose to allocate more funds to SMEs in order to generate a higher return on the loans.

The first model also incorporates the transmission mechanism of government spending into the investigation of the shadow banking system. Government spending is vital in China and has a nonnegligible impact on the Chinese economy. The results show that although government spending immediately stimulates the economy, it crowds out private capital investment by SMEs, which further restricts the financial market and makes SMEs pay a higher risk premium when accessing financial sources. Due to the limited capital investment and capital inputs, the only way for SMEs to increase output is through incurring additional costs to hire more labours.

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[18] The main difference between affiliated and non-affiliated loans is the interest rate. Specifically, the interest rate on affiliated loans is lower since lending from the parent company to a subsidiary is less risky. Thus, the lending rate charged by the parent SOEs is set be equal to the risk-free rate of bank loans.

This chapter is organised in the following way. Section 3.2 briefly introduces the background and the literature of modelling shadow banking in China. Section 3.3 presents the New Keynesian framework. In Section 3.4, I calibrate the model and estimate it using Bayesian methods. Section 3.5 concludes.

3.2 Related Literature

Research in this area has grown rapidly in recent years. Elliott et al. (2015) and Ehlers et al. (2018) provide a detailed review about the development, structure, size and potential risks of China's shadow banking sector. Lu et al. (2015) and Tsai (2017) document the heavy reliance of the SMEs on informal financing due to their limited formal credit. Wang et al. (2018) develop a general equilibrium model of China's shadow banking from the perspective of dual-track interest rate liberalisation. The authors argue that if credit misallocation persists and low productivity of SOEs cannot be improved, full interest rate liberalisation does not guarantee a Pareto improvement. Chen et al. (2018) suggest that banks' continuous engagements in risky entrusted loans strongly link shadow banking to commercial banks. They show that the entrusted loan provision increases as the tightening of bank credit resulted from the contractionary monetary policy. Allen et al. (2019) use transaction-level analysis and find that the interest rates of non-affiliated loans indicate market rate, while the rate of affiliated loans is closer to that of the bank loans.

This study differs from the previous literature by incorporating the SOEs risk lending behaviour within a DSGE framework. The objective is to evaluate the impact of bank credit regulation, monetary policy and fiscal policy on China's economy. The model follows the spirit of 'financial accelerator' literature, in which risky firms (SMEs) borrow money by using their net worth as collateral. There is growing interest in BGG type model studying the effect of the shadow banking sector. Verona et al. (2013) follow the framework of the financial accelerator model described in Bernanke et al. (1999), and Christiano et al. (2010)   modify it with an extra financial intermediator, and a shadow banking sector. Households are permitted to purchase two types of financial instruments offered by banks, time deposits and corporate bonds, where time deposits are used to finance riskier entrepreneurs through retail banks, and corporate bonds are used to fund safer entrepreneurs via investment banks. Funke et al. (2015) augment the framework from Funke and Paetz (2012) by adding a shadow banking sector in the China's economy and develop a BGG type DSGE framework to capture the interface between qualitative and quantitative monetary policy versus shadow banking.

Two main DSGE frameworks incorporate financial friction in a macroeconomic model, which are the financial accelerator type (BGG) and collateral-based models, such as Iacoviello (2005) and Iacoviello and Neri (2010). The collateral-based model is not adopted in my models based on two reasons; first, I do not include housing market in my first two models; second, Iacoviello type housing model only consider residential property rather than commercial property. In my third model, the producer sector,

mainly the SME sector use housing as collateral to borrow money. Therefore, the patient and impatient households sectors are not appropriate in my model framework.

Differing from the standard framework, for example, Bernanke et al. (1999), my model includes two production sectors, i.e., SOEs and SMEs, where SOEs can borrow at the risk-free rate, while SMEs need to pay extra risk premium. My model differs from their approach since SOEs are the centre and the shadow banker in the entrusted lending business. Wang et al. (2018) include a competitive banking system with the presence of WMPs and trust loans (shadow banking instruments) and focus on interest rate liberalisation. I, instead, treat SOEs as the entrusted lenders 'financial intermediaries' to SMEs and study the effectiveness of the policies under this structure.

3.3 Model Framework

The spirit of my framework is the financial accelerator model proposed by Bernanke et al. (1999). Entrusted loan is embedded in my model by adding a SOEs entrusted lenders sector and two intermediate goods producers, including SOEs producing branches[19] and SMEs, which require external finance to invest in capital. SOEs obtain bank loans from commercial banks and determine the allocation of affiliated and non-affiliated loans in each period. The model features nominal price rigidity and capital adjustment costs. There are seven structural shocks: a reserve ratio shock, a monetary policy shock, a government spending shock, two TFP shocks and two investment-

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[19]   The producing branches can be treated as the subsidiaries of the SOEs entrusted lenders.

specific technology shocks in both SOEs' and SMEs' sectors.

The model contains eight agents. These are; households, commercial banks, SOEs entrusted lenders and producers, SMEs, final goods producers (retailers), government sector and capital goods producers. Figure 1 provides a simplified graphical depiction of the links and process.

Figure 1 Model Structure (Entrusted Loans)
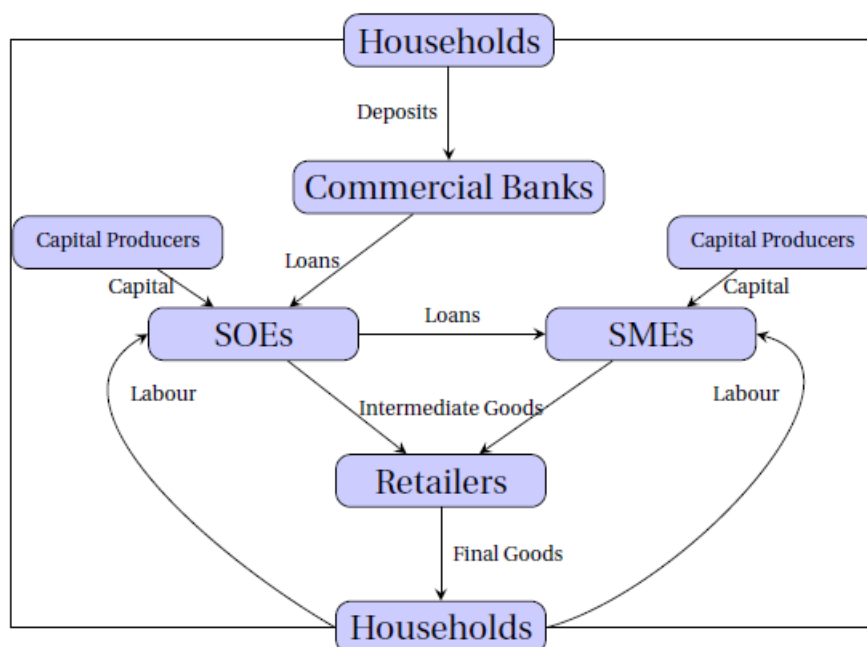
Households live forever, they work, consume, pay tax and deposit money in the commercial banks. I exclude WMPs in the first model by solely focusing on how to link shadow banking activity to the formal banking sector via the SOE-SME link. Commercial banks lend money directly to SOEs entrusted lenders. SMEs play a key role in the model that cannot gain access to bank credit; instead, they borrow from SOEs entrusted lenders. SMEs are assumed to have finite life. The expected lifetime

of an SME is $\frac{1}{1-\gamma}$, in which γ is a constant probability of surviving to the next period. This assumption takes the phenomenon of births and deaths of firms into account. In the meantime, it rules out the probability that an SME can be fully self-financed by accumulating sufficient net worth. Therefore, the core idea of the model is that SMEs can only access external finance from SOEs by paying an extra risk premium. SMEs' net worth accumulated from their profit is the key determinant of the cost of external finance. Firms with higher levels of net worth require less external funding and mitigate the agency problems related to external finance, which in turn decreases the risk premium. Moreover, SOEs producers and SOEs entrusted lenders are just two branches of SOEs; therefore, the producing branch can borrow money from their own branch without paying extra premium.

Both SOEs producing branches and SMEs are intermediate goods producers that use capital and labour inputs. They sell their heterogeneous goods to final goods producers who collect all the intermediate goods and bundle them as final homogeneous goods. Finally, households, capital goods producers and government consume all the final goods. In addition, government spending is financed by tax payment of households, and households are the final owner of all the entities in the economy except the government.

3.3.1 Households

There is a continuum of households indexed by l, who maximises the lifetime utility which is separable in the current level of real consumption, $C_{l,t}$, and leisure $(1 -$

$N_{l,t}$):

$$E_0 \sum_{t=0}^{\infty} \beta^t [\ln(C_{l,t}) + \ln(1 - N_{l,t})] \tag{1}$$

where E_0 is the rational expectation operator, $\beta \in (0,1)$ is the discount factor, $N_{l,t}$ is the hours worked. The l-th household faces an inter-temporal budget constraint in each period,

$$C_{l,t} + D_{l,t} \le w_{l,t} N_{l,t} + R_{t-1}^D \frac{D_{l,t-1}}{\pi_t} - T_t + \Pi_t^{Retail} \tag{2}$$

where $D_{l,t}$ is the level of real financial wealth in the form of real bank deposits with a riskless gross rate of return R_t^D. π_t is the inflation and $w_{l,t}$ is the real wage of labour supply. Households receive the interest payment of their deposits from the previous period and the real lump sum profit from the final goods producers Π_t^{Retail}. Furthermore, households pay the real lump-sum transfer tax T_t every period. To save on notation, I drop the index j on Π_t^{Retail} and T_t as the optimal conditions are the same across different households. Hence, household chooses $C_{l,t}$, $D_{l,t}$ and $N_{l,t}$ to maximise equation (1) subject to the budget constraint (2). The optimization problem can be written as a Lagrangian equation,

$$\mathcal{L} = E_0 \sum_{t=0}^{\infty} \beta^t \left\{ [\ln(C_{l,t}) + \ln(1 - N_{l,t})] \right.$$
$$\left. + \lambda_t^H \left[w_{l,t} N_{l,t} + R_{t-1}^D \frac{D_{l,t-1}}{\pi_t} - T_t + \Pi_t^{Retail} - C_{l,t} - D_{l,t} \right] \right\} \tag{3}$$

The first-order conditions (F.O.Cs) are,

$$\partial C_{l,t}: \qquad \frac{1}{C_{l,t}} = \lambda_t^H \tag{4}$$

$$\partial N_{l,t}: \qquad \frac{1}{1 - N_{l,t}} = \lambda_t^H w_{l,t} \tag{5}$$

$$\partial D_{l,t}: \qquad \lambda_t^H = \beta \lambda_{t+1}^H R_t^D \tag{6}$$

$$\partial \lambda_t^H: w_{l,t} N_{l,t} + R_{t-1}^D \frac{D_{l,t-1}}{\pi_t} - T_t + \Pi_t^{Retail} - C_{l,t} - D_{l,t} = 0 \tag{7}$$

λ_t^H is the Lagrangian multiplier, which is interpreted as the shadow price of income in the equations and the equation (7) is the budget constraint. The consumption Euler equation can be obtained by combining conditions (4) and (6) which implies the inter-temporal substitution in consumption,

$$E_t \left[\beta \left(\frac{C_{l,t+1}}{C_{l,t}} \right)^{-1} \frac{1}{\pi_{t+1}} \right] R_t^D = 1 \tag{8}$$

It states that the marginal utility of consumption in period t equals the present value of the marginal cost of giving up one unit of consumption in period $t+1$ (incorporate with the gross inflation rate π_{t+1}). The wage equation can be obtained by combining equation (4) and (5).

$$\frac{C_{l,t}}{1 - N_{l,t}} = w_{l,t} \tag{9}$$

3.3.2 Commercial Banks

I assume commercial banks collect deposits from households at the gross deposit rate R_t^D and make loans to SOEs with the real risk-free lending rate R_t^L, therefore, aggregately, it satisfies the following profit function,

$$\pi_t^{CB} = B_t R_t^L - D_t R_t^D \tag{10}$$

where B_t is the total loan amount. To motivate a nontrivial but simple banking sector, I impose the reserve requirement of a constant ratio[20], τ, imposed by the regulators; therefore, only a proportion of the total deposits is allowed to be lent out,

$$B_t = \left(1 - \tau \varepsilon^{e_t^\tau}\right) D_t \tag{11}$$

where $\varepsilon^{e_t^\tau}$ is an exogenous reserve ratio shock and e_t^τ follows an AR (1) process.

3.3.3 State-owned Enterprises Entrusted Lenders

Although SOEs entrusted lenders can be a production sector, the main purpose of this paper is to understand their entrusted lending behaviour; therefore, for model convenience, I only target the resource allocation of SOEs entrusted lenders in this section and leave the producing behaviour to their subsidiaries, denoted as SOEs.

In each period, the representative SOEs entrusted lender borrows money from commercial banks and choose the number of affiliated loans to an SOE, indexed by j, and the non-affiliated loans to an SME, indexed by i. Recalling the differences between the two types of loans are the underlying risks and interest rates. SOEs charge risk-free rate to their subsidiaries but require a higher rate on non-affiliated loans since SMEs are risky borrowers. SMEs are fraught with risk because their return to capital

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[20] A higher reserve ratio implies a tighter bank credit regulation.

investment is subject to the idiosyncratic shock ω^i, which is a random variable assumed to be log-normally distributed and i.i.d. across time and firms, with $E(\omega^i) = 1$,

$$\log(\omega) \sim N\left(-\frac{1}{2}\sigma_\omega^2, \sigma_\omega^2\right) \tag{12}$$

At the end of period t, the amount of non-affiliated loans to SME i, $B_{i,t+1}^{SME}$, is determined by the difference between the expenditure on physical capital and the SMEs' net worth,

$$B_{i,t+1}^{SME} = Q_t^{SME} K_{i,t+1}^{SME} - Net_{i,t+1} \tag{13}$$

where Q_t^{SME} is the price paid per unit of capital in period t, $K_{i,t+1}^{SME}$ is the quantity of capital purchased, and Net_{t+1} is the net worth accumulated by the survived SME. The amount of the affiliated loans to SOEs follows similar condition,

$$B_{j,t+1}^{SOE} = Q_t^{SOE} K_{j,t+1}^{SOE} \tag{14}$$

where $B_{j,t+1}^{SOE}$ is the amount of the affiliated loans and is determined by the expenditure on capital $Q_t^{SOE} K_{j,t+1}^{SOE}$. SOEs production sectors are different from SMEs because they can easily obtain funds from their parent company without friction which do not require using net worth as collateral to borrow money.

SOE entrusted lenders that act as a financial intermediary to SOEs and SMEs face an opportunity cost of funds between t and $t+1$, which equals to the risk-free rate, R_{t+1}^L. The idiosyncratic risk involved in lending is perfectly diversified in equilibrium in our model; thus, the optimal contract arrangement is determined by the following

equation,

$$\left[1 - F\left(\overline{\omega}^i\right)\right] R_{t+1}^{NA} B_{i,t+1}^{SME} + (1 - \mu) \int_0^{\overline{\omega}} \omega^i R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME} dF(\omega)$$

$$+ R_{t+1}^L B_{j,t+1}^{SOE} = R_{t+1}^L \left(B_{i,t+1}^{SME} + B_{j,t+1}^{SOE}\right) \tag{15}$$

which implies the total expected return on both non-affiliated and affiliated loans equals the opportunity costs of the total funds[21]. The first item on the left-hand side of the equation implies the yield on the non-defaulted loans to SMEs. $F\left(\overline{\omega}^i\right)$ is the default probability with a continuous and once-differentiable CDF function. R_{t+1}^{NA} is the contractual rate on the non-affiliated loans. The SME is able to repay the loan if the idiosyncratic shock is higher or equal to the threshold, $\overline{\omega}^i$. That is, $\overline{\omega}^i$ is defined by,

$$\overline{\omega}^i R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME} = R_{t+1}^{NA} B_{i,t+1}^{SME} \tag{16}$$

when $\omega^i \geq \overline{\omega}^i$, the SME repay the promised amount $R_{t+1}^{NA} B_{i,t+1}^{SME}$ and keeps the difference, i.e. $\omega^i R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME} - R_{t+1}^{NA} B_{i,t+1}^{SME} = (\omega^i - \overline{\omega}^i) R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME}$. While it declares bankrupt and exits the market if $\omega^i < \overline{\omega}^i$. The second item thus implies the value left in the account of the bankrupt SME subject to a monitoring cost[22], μ. The idea here is SOE entrusted lender needs to pay an extra cost to observe the borrower's realised return on capital, i.e. the monitoring cost equals $\mu \int_0^{\overline{\omega}} \omega^i R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME}$, in

---

[21] The total funds of SELs, B_t, are obtained from the commercial banks, which equals $B_{t+1}^{POE} + B_{t+1}^{SPB}$ aggregately.

[22] This is the so-called 'costly state verification' (CSV), and there are several important contributions in business cycle literatures that incorporate with CSV, such as Townsend (1979), Williamson (1987), Carlstrom and Fuerst (1997), Fisher (1999), Christiano, Motto and Rostagno (2004), Arellano et al. (2012) and Jermann and Quadrini (2012).

which R_{t+1}^K indicates the capital return. Equation (15) indicates that SOEs entrusted lenders are risk-neutral as the risk in the portfolio is perfectly diversified.

3.3.4 Small-and-medium Sized Enterprises

Before turning to the optimization problem in the SME sector, one needs to be clear that the key difference between SMEs and SOEs is the financial condition. SOEs can borrow funds at a risk-free rate, while SMEs cannot. SMEs need to pay an extra risk premium to offset the potential loss in case of a default. Hence, the purpose of this sector is to first determine the risk premium for a specific loan contract and solve the maximization problem. SMEs are permitted to keep the retained profit once they fulfil the interest payment to SOEs. Therefore, the expected return of a surviving SME from the capital investment can be defined as,

$$E\left\{\int_{\overline{\omega}}^{\infty} \omega_i R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME} dF(\omega) - [1 - F(\overline{\omega}_i)]\overline{\omega}_i\, R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME}\right\} \qquad (17)$$

The expectation operator E indicates the expected return on investment, R_{t+1}^K. The first part in equation (17) implies the total return from the investment and the second part is the interest payment on the loans with the non-default probability $1 - F(\overline{\omega}_i)$. The above equation can be simplified as,

$$[1 - \Gamma(\overline{\omega}_i)]R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME} \qquad (18)$$

Where

$$\Gamma(\overline{\omega}_i) = \int_{\overline{\omega}}^{\infty} \omega_i dF(\omega) + G(\overline{\omega}_i) \qquad (19)$$

And

$$G(\bar{\omega}_i) = \int_0^{\bar{\omega}} \omega_i dF(\omega) \tag{20}$$

Rearranging the SOE entrusted lenders' participation constraint (15),

$$\int_{\bar{\omega}}^{\infty} \omega_i dF(\omega) + (1 - \mu) \int_0^{\bar{\omega}} \omega_i dF(\omega) = \frac{R_{t+1}^L}{R_{t+1}^K} \frac{B_{i,t+1}^{SME}}{Q_t^{SME} K_{i,t+1}^{SME}} \tag{21}$$

Combining with the notation in equation (19) and (20), the constraint can then be written as,

$$\Gamma(\bar{\omega}) - \mu G(\bar{\omega}) = \frac{R_{t+1}^L}{R_{t+1}^K} \frac{B_{i,t+1}^{SME}}{Q_t^{SME} K_{i,t+1}^{SME}} \tag{22}$$

Where $\Gamma(\bar{\omega}) - \mu G(\bar{\omega})$ represents the net share of profits going to the SLB. The optimization problem is then to maximise the objective function (18) of the SME, i, subject to the participation constraint of the SOE entrusted lenders (22), and the Lagrangian is,

$$\mathcal{L} = [1 - \Gamma(\bar{\omega}_i)] R_{t+1}^K Q_t^{SME} K_{i,t+1}^{SME}$$
$$+ \lambda_t^{SME} \left[\Gamma(\bar{\omega}) - \mu G(\bar{\omega}) - \frac{R_{t+1}^L}{R_{t+1}^K} \frac{B_{i,t+1}^{SME}}{Q_t^{SME} K_{i,t+1}^{SME}} \right] \tag{23}$$

Simplifying the notation by denoting $s_t = \frac{R_{t+1}^K}{R_{t+1}^L}$, and $\aleph_t = \frac{Q_t^{SME} K_{i,t+1}^{SME}}{B_{i,t+1}^{SME}}$. The F.O.Cs with respect to $\bar{\omega}_i$, $\aleph_t$ and λ_t^{SME} are,

$$\partial \bar{\omega}_i: \qquad \Gamma'(\bar{\omega}_i) = \lambda_t^{SME} [\Gamma'(\bar{\omega}) - \mu G'(\bar{\omega})] \tag{24}$$

$$\partial \aleph_t: [1 - \Gamma(\bar{\omega}_i)] s_t + \lambda_t^{SME} [\Gamma(\bar{\omega}) - \mu G(\bar{\omega})] s_t = \lambda_t^{SME} \tag{25}$$

$$\partial \lambda_t^{SME}: \quad [\Gamma(\bar{\omega}) - \mu G(\bar{\omega})] s_t \aleph_t = \aleph_t - 1 \tag{26}$$

Rearranging equation (26), we can obtain a critical link between capital expenditure and financial conditions, which indicates the risk premium, denoted as s_t, of the non-affiliated loan contract,

$$s_t = E_t \left(\frac{R_{t+1}^K}{R_{t+1}^L} \right) = \frac{1 - Net_{i,t}/Q_t^{SME} K_{t+1}^{SME}}{\Gamma(\bar{\omega}) - \mu G(\bar{\omega})} \tag{27}$$

Equation (27) indicates the relationship between risk premium and the net worth (or retained earnings) of an SME, i, in period t. The risk premium is defined as the spread between the expected return on capital, R_{t+1}^K, and the risk-free rate, R_{t+1}^L. The risk premium s_t is greater than 1 and it is clearly seen that the higher the net worth, $Net_{i,t}$, the lower the risk premium the SME needs to pay with ceteris paribus laws. $1 - Net_{i,t}/Q_t^{SME} K_{t+1}^{SME}$ indicates the firm's leverage ratio. Intuitively, firms with more retained earnings tend to have lower default probability as they can use more internal finance instead of external funds, or equivalently, firms with less probability of default can take on debt with a lower cost of funds.

I then need to determine the net worth accumulation of the SMEs. In each period, SMEs face a survival ratio[23], γ, therefore $(1 - \gamma)$ SMEs exit the market. Let V_t be equity in period t, then the aggregate net worth in period $t + 1$, Net_{t+1} is given by,

---

[23] This assumption is to rule out the case that one SME may accumulate net worth sufficiently in the future and never require borrowing from the financial intermediary. Empirically, it is well accepted that substantial number of start-ups firms end in failure and this is a common situation globally, for example, Hall and Woodward (2010) investigate the extreme cross-sectional dispersion in entrepreneurs' payoffs.

$$Net_{t+1} = \gamma V_t \tag{28}$$

with

$$V_t = R_t^K Q_{t-1}^{SME} K_t^{SME} - \left[R_t^L + \frac{\mu \int_0^{\bar{\omega}} \omega R_t^K Q_{t-1}^{SME} K_t^{SME} dF(\omega)}{B_t^{SME}} \right] B_t^{SME} \tag{29}$$

where γV_t is the equity held by entrepreneurs at $t - 1$ who are still in business at t.

Entrepreneurial equity V_t equals gross earnings of capital investment,

$R_t^K Q_{t-1}^{SME} K_t^{SME}$, on holdings of equity from $t - 1$ to t, less repayment of borrowings

(repayment of the loans, $R_t^L B_t^{SME}$ plus the risk premium). The ratio of defaults costs

to quantity borrowed reflects the premium for external finance,

$$\frac{\mu \int_0^{\bar{\omega}} \omega R_t^K Q_{t-1}^{SME} K_t^{SME} dF(\omega)}{Q_{t-1}^{SME} K_t^{SME} - Net_t} \tag{30}$$

After determining the risk premium and net worth of SMEs, I then turn to the

production phase, SMEs borrow money from SOEs entrusted lenders and purchase

capital in period t for use in the following period $t + 1$. Capital and hired labour are

used to produce intermediate goods, $Y_{i,t+1}^{SME}$, which follows a Cobb-Douglas function,

$$Y_{i,t+1}^{SME} = A_{t+1}^{SME} \left(K_{i,t+1}^{SME} \right)^{\alpha_1} \left(N_{i,t+1}^{SME} \right)^{(1-\alpha_1)} \tag{31}$$

where A_{t+1}^{SME} is an exogenous TFP shock in the SME's sector. $K_{i,t+1}^{SME}$ is the amount of

capital purchased by the SME in period t, $N_{i,t+1}^{SME}$ is the labour demand, and α_1 is the

income share of capital. SMEs maximise profit by selling intermediate goods to the

final goods producers, paying the wage and interests on the loans. At the end of each

period, they sell back undepreciated capital to the capital goods producers. The profit

function of the SME, i, is

$$
\pi_{i,t+1}^{SME} = \frac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^{w}} Y_{i,t+1}^{SME} - w_{t+1}N_{i,t+1}^{SME} - R_{t+1}^{K}B_{i,t+1}^{SME}
$$
$$
+ Q_{t+1}^{SME}\left(1 - \delta^{SME}\right)K_{i,t+1}^{SME}
$$
(32)

Recalling that $B_{i,t+1}^{SME} = Q_{t}^{SME}K_{i,t+1}^{SME} - Net_{i,t+1}$ (the amount the SME borrows depends on

the value of the capital investment minus the net worth they have). X_{t+1} is the relative

price of intermediate goods which is between the aggregate wholesale price P_{t+1}^{w} and

the nominal price for the final good P_{t+1}. $\dfrac{P_{t+1}^{w,SME}}{P_{t+1}^{w}}$ is the relative wholesale price of

goods produced in the SME sector which is between the sectoral wholesale price and

the aggregate wholesale price. w_{t+1} is the real wage. Assuming SMEs need to sell

the undepreciated capital back to the capital goods producers at the end of the period

$t + 1$, hence, they need to purchase new capital for the production in the subsequent

period.

Taking the F.O. Cs with respect to $K_{i,t+1}^{SME}$ and $N_{i,t+1}^{SME}$, we obtain,

$$
\partial K_{i,t+1}^{SME}: E_t\left(R_{t+1}^{K}\right) = \frac{MPK_{i,t+1}^{SME} + Q_{t+1}^{SME}\left(1 - \delta^{SME}\right)}{Q_{t}^{SME}}
$$
(33)

$$
\partial N_{i,t+1}^{SME}: w_{t+1} = (1 - \alpha_1)\frac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^{w}}\frac{Y_{i,t+1}^{SME}}{N_{i,t+1}^{SME}}
$$
(34)

Where $MPK_{i,t+1}^{SME}$ represents the marginal product of capital in the SMEs' sector, which

is equal to $\alpha_1 \dfrac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^{w}}\dfrac{Y_{i,t+1}^{SME}}{K_{i,t+1}^{SME}}$. δ^{SME} is the capital depreciation rate. Equation (33) states

the expected gross return to holding a unit of capital from period t to $t + 1$. R_{t+1}^{K} is

the return on capital investment. Equation (34) states the marginal product of labour

in the SMEs' sector.

3.3.5 State-owned Enterprises

In each period t, the SOE j purchases physical capital by borrowing money from

their parent company at the risk-free rate R_{t+1}^L. Combining capital, $K_{j,t+1}^{SOE}$ with the

hired labour, $N_{j,t+1}^{SOE}$, in period $t+1$, SOE produces intermediate output and resell the

underappreciated capital back to the capital good producers. The Cobb-Douglas

production function is specified as,

$$Y_{j,t+1}^{SOE} = A_{t+1}^{SOE}\left(K_{j,t+1}^{SOE}\right)^{\alpha_2}\left(N_{j,t+1}^{SOE}\right)^{(1-\alpha_2)} \tag{35}$$

where A_{t+1}^{SOE} is the exogenous technology shock, which is the same across all SOEs,

and it follows an AR (1) process. α_2 is the income share of capital in SOES' sector.

The profit function of the SOE producing sector is given by,

$$\pi_{j,t+1}^{SOE} = \frac{P_{t+1}^{w,SOE}}{X_{t+1}P_{t+1}^w}Y_{j,t+1}^{SOE} - w_{t+1}N_{j,t+1}^{SOE} - R_{t+1}^L B_{j,t+1}^{SOE}$$
$$+ Q_{t+1}^{SOE}\left(1-\delta^{SOE}\right)K_{j,t+1}^{SOE} \tag{36}$$

Where $B_{i,t+1}^{SOE} = Q_t^{SOE}K_{i,t+1}^{SOE}$, indicating that SOEs do not need to accumulate net worth to

finance their capital investment. $K_{j,t+1}^{SOE}$ is the capital purchased in period t for the use

in period $t+1$. $N_{j,t+1}^{SOE}$ is the labour hired in period $t+1$. $\frac{P_{t+1}^{w,SOE}}{P_{t+1}^w}$ is the relative price

between SOEs wholesale price and the general wholesale price level. w_{t+1} is the real

wage which is the same across different sectors (both SOEs and SMEs). The capital

return in the SOEs sector equals the risk-free lending rate, R_{t+1}^L, since the producing

sector borrow money from their own lending branch (SOEs entrusted lenders) without

any friction. δ^{SOE} is the capital depreciation rate in the SOEs sector. Q_t^{SOE} implies

the price of the capital and the undepreciated capital is sold back to the capital goods

producers at the end of period $t+1$ at price Q_{t+1}^{SOE}. Taking the F.O.Cs with respect

to $K_{j,t+1}^{SOE}$ and $N_{j,t+1}^{SOE}$ yield,

$$\partial K_{j,t+1}^{SOE}: R_{t+1}^L = \frac{MPK_{j,t+1}^{SOE} + Q_{t+1}^{SOE}\left(1 - \delta^{SOE}\right)}{Q_t^{SOE}} \tag{37}$$

$$\partial N_{j,t+1}^{SOE}: w_{t+1} = (1 - \alpha_2) \frac{P_{t+1}^{w,SOE}}{X_{t+1}P_{t+1}^w} \frac{Y_{j,t+1}^{SOE}}{N_{j,t+1}^{SOE}} \tag{38}$$

Equation (37) implies the gross return to holding a unit of capital in the SOEs, which

equal to the risk-free lending rate from the commercial banks. δ^{SOE} is the

depreciation rate and $MPK_{j,t+1}^{SOE}$ is the marginal product of capital in SOE's sector,

which takes the form as $\alpha_2 \frac{P_{t+1}^{w,SOE}}{X_{t+1}P_{t+1}^w} \frac{Y_{j,t+1}^{SOE}}{K_{j,t+1}^{SOE}}$. Comparing the gross capital return in SMEs

sector, i.e. equation (33), when capital inputs are homogeneous across sectors, the

marginal product of capital of private firms is clearly higher than that of state firms as

$R_{t+1}^K > R_{t+1}^L$. Intuitively, this implies a higher efficiency in the credit-constrained

firms; in other words, the MPK in the SMEs' sector is higher than the state sector.

Equation (38) indicates the real wage level equals the marginal product of labour in

the SOEs' sector.

3.3.6 Capital Goods Producers

There is a representative capital goods producer who purchases final output as materials inputs, I_t^{SOE} and I_t^{SME}, and produce new capital goods for both SOEs and SMEs. the new capital goods are sold at price Q_t^{SOE} and Q_t^{SME}. The profit function is,

$$\pi_t^I = K_{t+1}^{SOE} Q_t^{SOE} + K_{t+1}^{SME} Q_t^{SME} - I_t^{SOE} - I_t^{SME} \tag{39}$$

Subject to the capital accumulation with adjustment costs in both sectors, which implies increasing marginal adjustment costs in the production of capital,

$$K_t^{SOE} = (1 - \delta_1) K_{t-1}^{SOE} + e_t^{ISOE} \left[I_t^{SOE} - \frac{\phi_K^{SOE}}{2} \left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE} \right)^2 K_{t-1}^{SOE} \right] \tag{40}$$

$$K_t^{SME} = (1 - \delta_1) K_{t-1}^{SME} + e_t^{ISME} \left[I_t^{SME} - \frac{\phi_K^{SME}}{2} \left(\frac{I_t^{SME}}{K_{t-1}^{SME}} - \delta^{SME} \right)^2 K_{t-1}^{SME} \right] \tag{41}$$

e_t^{ISOE} and e_t^{ISME} are the investment-specific shocks, which both follow AR (1) processes. The Lagrangian equation is,

$$
\begin{aligned}
\mathcal{L} = {}& K_{t+1}^{SOE} Q_t^{SOE} + K_{t+1}^{SME} Q_t^{SME} - I_t^{SOE} - I_t^{SME} \\
& + \lambda_t^{ISOE} \left[(1 - \delta_1) K_{t-1}^{SOE} + e_t^{ISOE} \left[I_t^{SOE} - \frac{\phi_K^{SOE}}{2} \left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE} \right)^2 K_{t-1}^{SOE} \right] \right. \\
& \left. - K_t^{SOE} \right] \\
& + \lambda_t^{ISME} \left[(1 - \delta_1) K_{t-1}^{SME} + e_t^{ISME} \left[I_t^{SME} - \frac{\phi_K^{SME}}{2} \left(\frac{I_t^{SME}}{K_{t-1}^{SME}} - \delta^{SME} \right)^2 K_{t-1}^{SME} \right] \right. \\
& \left. - K_t^{SME} \right]
\end{aligned}
\tag{42}
$$

The F.O.Cs with respect to I_t^{SOE}, I_t^{SME}, K_t^{SOE} and K_t^{SME} are,

$$\partial I_t^{SOE}: \lambda_t^{ISOE} e_t^{ISOE} \left[1 - \phi_K^{SOE} \left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE} \right) \right] = 1 \tag{43}$$

$$\partial I_t^{SME}: \lambda_t^{ISME} e_t^{ISME} \left[1 - \phi_K^{SME} \left(\frac{I_t^{SME}}{K_{t-1}^{SOE}} - \delta^{SME} \right) \right] = 1 \tag{44}$$

$$\partial K_t^{SOE}: Q_t^{SOE} = \lambda_t^{ISOE} \tag{45}$$

$$\partial K_t^{SME}: Q_t^{SME} = \lambda_t^{ISME} \tag{46}$$

Combining equations (43) with (45), and equations (44) with (46) respectively yield the Tobin's Q equations,

$$\frac{1}{Q_t^{SOE}} = \left[1 - \phi_K^{SOE} \left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE} \right) \right] e_t^{ISOE} \tag{47}$$

$$\frac{1}{Q_t^{SME}} = \left[1 - \phi_K^{SME} \left(\frac{I_t^{SME}}{K_{t-1}^{SME}} - \delta^{SME} \right) \right] e_t^{ISME} \tag{48}$$

3.3.7 Final Goods Producers: Retailers

To incorporate sticky prices in the model, I introduce a unit mass of monopolistic competitive retailers. They purchase intermediate wholesale goods from SMEs and SOEs at aggregate wholesale price P_t^W, then bundle them into the homogeneous final products. Let $Y_{z,t}$ be the quantity of output sold by a retailer z, measured in units of wholesale goods, then the total final usable goods, Y_t, are the following composite of individual retail goods,

$$Y_t = \left[\int_0^1 (Y_{z,t})^{\frac{\epsilon-1}{\epsilon}} dz \right]^{\frac{\epsilon}{\epsilon-1}} \tag{49}$$

where $\epsilon > 1$ is the elasticity of substitution among different types of intermediate goods that captures the markup to the intermediate goods' prices. The wholesale output,

$Y_{z,t}$, is composed of sectoral output according to,

$$Y_{z,t} = [a(Y_{i,t}^{SME})^\rho + (1-a)(Y_{j,t}^{SOE})^\rho]^{\frac{1}{\rho}} \tag{50}$$

where a implies the weight of using SMEs' goods in bundling the final goods and ρ is the substitutability between two types of intermediate goods. Final output can be transformed into consumption good that purchased by households, capital goods producers and government or used up in monitoring costs and reserve requirement at the price P_t. the corresponding price index is given by,

$$P_t = \left[\int_0^1 (P_{z,t}^W)^{1-\epsilon} dz\right]^{\frac{1}{1-\epsilon}} \tag{51}$$

Following the Calvo (1983) price setting, I introduce sticky-price in the retail sector. With probability $(1-\theta)$, a given retailer is assumed to be able to reset its price (P_t^*) at period t.

$$\sum_{k=0}^{\infty} \theta^k E_t[\Lambda_{t,k} \frac{P_t^* - P_{t+k}^W}{P_{t+k}} Y_{t+k}^W(z)] \tag{52}$$

The expected discounted profit is maximised by the stochastic discount factor, $\Lambda_{t,k} \beta \frac{C_t}{C_{t+k}}$, which is the ratio of marginal utility between period $t+k$ and t incorporate with the probability of being able to adjust the price, P_t^*. there is no sticky-price if $\theta = 0$. the nominal marginal cost of a retailer is the general wholesale price $P_{z,t}^W$, therefore, the objective is to maximise equation (52) by choosing the optimal reset price. Taking the F.O.C with respect to P_t^*, we obtain,

$$\sum_{k=0}^{\infty} \theta^k E_t \left\{ \left[\Lambda_{t,k} \left(\frac{P_t^*}{P_{t+k}} \right)^{\epsilon} Y_{t+k}^W(z) \left[\frac{P_t^*}{P_{t+k}} - \left(\frac{\epsilon}{\epsilon - 1} \right) \frac{P_{t+k}^W}{P_{t+k}} \right] \right] \right\} = 0 \tag{53}$$

Rearranging the equation above, we obtain the function for the optimal reset price,

$$P_t^* = \frac{\epsilon}{\epsilon - 1} \frac{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k} \left(P_{t+k}^W P_{t+k}^{-(1-\epsilon)} Y_{t+k} \right)}{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k} \left(P_{t+k}^{-(1-\epsilon)} Y_{t+k} \right)} \tag{54}$$

Or

$$P_t^* = \frac{\epsilon}{\epsilon - 1} E_t \sum_{k=0}^{\infty} (\beta_D \theta)^k \left(P_{t+k}^W \right) \tag{55}$$

Where P_{t+k}^W can be treated as the marginal cost of the retailer. According to the aggregate price level (51), we can split it into a combination of the optimal reset price and the previous price[24],

$$P_t = \left[\int_0^1 [(1 - \theta)(P_t^*)^{1-\epsilon} + \theta P_{t-1}^{1-\epsilon}] dz \right]^{\frac{1}{1-\epsilon}} \tag{56}$$

Which can be simplified as,

$$P_t = [(1 - \theta)(P_t^*)^{1-\epsilon} + \theta P_{t-1}^{1-\epsilon}]^{\frac{1}{1-\epsilon}} \tag{57}$$

Dividing both sides by P_{t-1}[25],

$$\frac{P_t}{P_{t-1}} = [(1 - \theta) \left(\frac{P_t^*}{P_{t-1}} \right)^{1-\epsilon} + \theta \left(\frac{P_{t-1}}{P_{t-1}} \right)^{1-\epsilon}]^{\frac{1}{1-\epsilon}} \tag{58}$$

---

[24] All firms that can reset their price will choose the same level, and the rest of firms will have the same aggregate price level as the previous period.

[25] We need to allow for the existence of steady state inflation (zero steady state inflation in the linearization), by dividing the lagged price level, the steady state is then well defined.

Defining $\frac{P_t}{P_{t-1}} = 1 + \pi_t$, equation (58) becomes,

$$1 + \pi_t = [(1-\theta)\left(\frac{P_t^*}{P_{t-1}}\right)^{1-\epsilon} + \theta]^{\frac{1}{1-\epsilon}} \tag{59}$$

Substituting equation (55) into equation (59) and log-linearising the inflation equation around the zero-inflation steady state[26], we are able to obtain the New Keynesian Phillips curve,

$$\tilde{\pi}_t = \beta E_t \tilde{\pi}_{t+1} + \frac{(1-\theta)(1-\theta\beta)}{\theta}(-\tilde{x}_t) \tag{60}$$

Where $\tilde{x}_t = \widetilde{p_t - p_t^w}$ implies the relative price between the aggregate wholesale price and retail price. The aggregate resource constraint takes the form as,

$$Y_t = C_t + I_t + G_t + \tau D_t + \mu \int_0^{\overline{\omega}} \omega R_t^K Q_{t-1}^{POE} K_t^{POE} dF(\omega) \tag{61}$$

Where $I_t = I_t^{SOE} + I_t^{SME}$ and $\mu \int_0^{\overline{\omega}} \omega R_t^K Q_{t-1}^{POE} K_t^{POE} dF(\omega)$ reflects aggregate monitoring costs.

3.3.8 Government Sector and Monetary Policy

To close the model, I specify the government budget constraint by assuming that government spending is financed by households' tax payment,

$$G_t = T_t \tag{62}$$

and it follows the AR (1) process. In addition, there is a central bank implement monetary policy according to the conventional Taylor rule,

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[26] The detailed log-linearisation process is included in the appendix.

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_m} \left[\left(\frac{\Pi_t}{\Pi}\right)^{a_\pi} \left(\frac{Y_t}{Y}\right)^{a_y}\right]^{1-\rho_m} e_t^m \tag{63}$$

where R_t, Π_t are the nominal interest rate and inflation rate, respectively. The parameter ρ_m captures the degree of interest rate smoothing, a_π and a_y are the elasticities of the policy target with respect to inflation and output gap. e_t^m is a random shock to the nominal interest rate.

3.4 Data and Bayesian Estimation

In the empirical analysis, I estimate our model with China's quarterly data by Bayesian methods. Based on the estimation results, I investigate the implications of impulse responses.

3.4.1 Data Description

The sample period for the estimation is 1992Q1-2015Q4 due to the data availability. I use eight observable macroeconomic variables, as there are eight structural shocks in the model. Five common macroeconomic variables are used in the estimation, including GDP, consumption, investment, labour and inflation, and three variables of our interests[27], risk premium, capital investment return in SMEs' sector and SOEs output in real term. The sources of GDP, consumption, inflation and labour are from Datastream[28].

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[27] We consider these observed variables because the SOEs' lending activities to SMEs are the centre of this paper.

[28] The codes of the variables are provided in the appendix.

All the data are seasonally adjusted, and nominal variables are converted to the real terms by using the consumer price index. I then take natural logarithm on the real GDP, real consumption, real investment, real SOEs' output and labour and times 100[29].

3.4.2 Calibrated Parameters

I first calibrate some parameters that are difficult to identify from the data (Table 2). The values I choose are consistent with literature about the Chinese economy. The discount factor β is set to be 0.99, which can be used to pin down the steady-state quarterly real deposit rate of 0.01 or four per cent expressed at an annual frequency. The steady-state reserve ratio is set to be 0.15, which is the average value of the reserve ratio in China between 1992-2015. I choose the quarterly depreciation rate equals 0.035 to be consistent with the literature, which implies an annual rate of 14% (Li and Liu, 2017). I take the steady-state government spending to total output, G/Y, to be 0.14, which is the historical average of nominal consumption over nominal GDP ratios between 1992-2015. There is no literature for the parameters regarding the CES aggregator in the retailers' sector, therefore, I choose the weight parameter $a = 0.5$, which implies the final goods producers have no preference between SMEs and SOEs intermediate goods, and the substitutability of the goods ρ is set to be 0.95. The value of the survival ratio is calibrated as 0.97 (Zhuang et al., 2018). The risk spread, $R^K - R^L$, equal to four hundred basis points, which is the average value of the risk premium in our data. I set a higher value of realised payoffs lost in bankruptcy, μ equals 0.2

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[29] This converts the fraction number to percentage.

(Carlstrom and Fuerst, 1997), as previous literature provides no relevant information about the magnitude of the parameter value in the Chinese market.

Table 2 Calibrated Parameters

Parameters	Values	Definitions
β	0.99	Discount Factor
τ	0.15	Reserve Ratio in Steady State
δ^{SME}	0.035	Quarterly Depreciation Rate in SMEs' Sector
δ^{SOE}	0.035	Quarterly Depreciation Rate in SOEs' Sector
G/Y	0.14	Government Spending to GDP Ratio
a	0.5	Weight Parameter in Retailers' CES Aggregator
ρ	0.95	Substitutability in Retailers' CES Aggregator
γ	0.97	Quarterly Survival Ratio in Steady State
$R^K - R^L$	0.04	Quarterly Risk Premium in Steady State
μ	0.20	Monitoring Cost in Steady State

3.4.3 Estimated Parameters and Priors

The rest of the parameters are estimated by using Bayesian methods in Dynare. The prior densities, means and standard deviations are shown in Table 3. I follow most of the literature to set the priors in order to capture the main features of the Chinese economy. The serial correlation parameters of the shock processes (ρ^τ, ρ_a^{POE}, ρ_a^{SOE}, ρ_k^{POE}, ρ_k^{SOE}, ρ^s, ρ^G) are all follow Beta distributions with mean 0.5, and standard deviations 0.2. All the standard errors of the innovations are assumed to have Inverse-gamma distribution with a mean of 0.010 and degree of freedom 2, which implies an infinite standard deviation (Li and Liu 2018).

The prior of the parameter determines nominal price rigidity, θ, follows Beta density with mean 0.5 and standard deviation 0.2, which is different with Li and Liu[30] (2017)

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[30] In their paper, the prior they use for this parameter suffers unbounded density in Dynare (Beta density with mean 0.5 and standard deviation 0.1).

and implies the expected duration between price changes is about 2 quarters[31]. Chinese research, such as Liu (2008), Tong (2010) and Li and Liu (2017) calibrate the capital share in the Cobb-Douglas function since they only have one intermediate goods producer. As different levels of capital intensity may be observed between two producing sectors, my analysis is different from their approach and choose to estimate these parameters. The priors of α_1 and α_2 are Beta (0.4,0.10) and Beta (0.5,0.10), the capital share in SOEs is set to be 0.50 to reflect a higher level of capital intensity in the state sector. Our model uses the same investment adjustment cost function with Bernanke et al. (1999), therefore, I follow their assumption to set the prior means for ϕ_K^{SME} and ϕ_K^{SOE} as 0.25 and allow wide variation in estimating these values by setting the standard deviation as 1.5. As for the monetary policy rule, the parameters ρ_m, a_π, a_y are all conventional with one exception that the prior mean of a_y is set to be 0.5, indicating a higher reaction on output stabilisation in China (Funke et al., 2015).

3.4.4 Posterior Estimates

The capital shares in SMEs and SOEs are estimated to be 0.4236 and 0.4519, indicating a higher level of capital intensity in the state sector. Our estimates favour a strong rigidity in nominal price setting (θ=0.8256), which is close to 0.84 in Zhang (2009). In terms of the monetary policy, the mean of the coefficient on the lagged

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[31] Bils and Klenow (2004) find the duration is between 6 months and 1 year. We choose 2 quarters, which suggests that $\theta = 0.5$.

interest rate is estimated to be less persistent, 0.5283, and the mean of the long-run

reaction to inflation appears to be lower, 1.2248, then the prior. While the reaction to

Table 3 Prior Distributions

Parameters	Prior Density	Prior Mean	Prior Standard Deviation
α_1	Beta	0.4	0.10
α_2	Beta	0.5	0.10
θ	Beta	0.5	0.20
ϕ_K^{SME}	Normal	0.25	1.5
ϕ_K^{SOE}	Normal	0.25	1.5
a_π	Normal	1.5	0.15
a_Y	Normal	0.5	0.05
ρ_m	Beta	0.5	0.20
ρ^τ	Beta	0.5	0.20
ρ_a^{SME}	Beta	0.5	0.20
ρ_a^{SOE}	Beta	0.5	0.20
ρ_k^{SME}	Beta	0.5	0.20
ρ_k^{SOE}	Beta	0.5	0.20
ρ^s	Beta	0.5	0.20
ρ^G	Beta	0.5	0.20
σ^m	Inverse-Gamma	0.01	2
σ^τ	Inverse-Gamma	0.01	2
σ_a^{SME}	Inverse-Gamma	0.01	2
σ_a^{SOE}	Inverse-Gamma	0.01	2
σ_k^{SME}	Inverse-Gamma	0.01	2
σ_k^{SOE}	Inverse-Gamma	0.01	2
σ^s	Inverse-Gamma	0.01	2
σ^G	Inverse-Gamma	0.01	2

the output gap is slightly higher with a mean value of 0.5256. This is consistent with

the scenario in China that the PBoC assigns a higher weight to stabilizing output. The

parameters of the adjustment costs are estimated to be lower than the prior mean with

the values of 0.1700 (ϕ_K^{POE}) and 0.2030 (ϕ_K^{SPB}).

Table 4 Posterior Distributions

Parameters	Posterior Mean	Posterior Standard Deviation
α_1	0.4236	0.0031
α_2	0.4519	0.0029
θ	0.8256	0.0125
ϕ_K^{SME}	0.1700	0.0073
ϕ_K^{SOE}	0.2030	0.0018
a_π	1.2248	0.0079
a_Y	0.5256	0.0027
ρ_m	0.5283	0.0024
ρ^τ	0.5526	0.0064
ρ_a^{SME}	0.5457	0.0088
ρ_a^{SOE}	0.7032	0.0097
ρ_k^{SME}	0.9837	0.0030
ρ_k^{SOE}	0.6010	0.0025
ρ^s	0.7604	0.0144
ρ^G	0.4835	0.0051
σ^m	0.8619	0.0457
σ^τ	4.6991	0.1339
σ_a^{SME}	3.6357	0.1827
σ_a^{SOE}	2.3407	0.1154
σ_k^{SME}	5.7795	0.1135
σ_k^{SOE}	2.6479	0.0625
σ^s	2.7604	0.0758
σ^G	4.2909	0.0820

Regarding the parameters of the exogenous shock processes, I find that investment shock in SMEs' sector, productivity shocks in the state sector and risk premium shock are estimated to be the most persistent with mean values of coefficient of 0.9837, 0.7032 and 0.7604 respectively. While the productivity shock in the private sector has relative lower persistence with an AR (1) coefficient of 0.5457. The posterior means of the government spending shock is 0.4835, the investment shock in SPBs is 0.6010, and the reserve ratio shock is 0.5526, which also appears to be less persistence.

3.4.5 Credit Allocation of with Different Level of Bank Credit Tightness

The other and perhaps more important, reason for the rapid growth in China's shadow banking is regulatory arbitrage. This is a major reason for the rapid growth of shadow banking in China since 2012, when the Chinese authorities started to counter inflation after the large-scale stimulus program in response to the global financial crisis 2008–2010. Furthermore, PBoC raised the bank reserve requirement ratios 12 times in 2010 and 2011 to a record high of 21.5 per cent for large institutions in June 2011. To explain the effect of bank credit tightness on the decision of the SOE entrusted lenders' credit allocation, I run experiments under different levels of reserve ratio but keep everything else the same. The higher value of the reserve ratio implies a tighter level of bank credit regulation.

Table 5 Bank Credit Tightness

	$\tau = 0.05$	$\tau = 0.10$	$\tau = 0.15$
B/Y	171%	109%	78%
B^{SOE}/B	83%	81%	80%
B^{SME}/B	17%	19%	20%

Table 5 shows the steady-state values of the total quantity of bank loans to GDP ratio (B/Y), the share of the affiliated loans in the total credit, B^{SOE}/B, and the ratio of non-affiliated loans to total, B^{POE}/B. The steady state value of bank loans to GDP ratio decreases from 171 per cent to 78 per cent when the reserve ratio increases from 5 per cent to 15 per cent, permanently. However, the proportion of non-affiliated loans to SMEs increases from 17 per cent to 20 per cent. The finding from our model indicates that tighter bank, while reducing overall credit availability increases SOE

engagement in more lending to SMEs, partially muting the effect of tighter regulation on SMEs.

3.4.6 Nowcasting Versus Data

To see the performance of our model, I implement nowcasting on the main macroeconomic variables, including output, consumption, investment and inflation. Blue lines depict the mean estimate of the filtered endogenous variables, which implies the best guess for the variables at the estimated periods between 1992Q1 and 2015Q4 (96 quarterly periods) given information up to the current observations. The orange lines are the filtered raw data. It can be seen that the nowcasted variables from our model track the real data very well during the estimated periods (Figure 2).

Figure 2 Nowcasting Versus Data
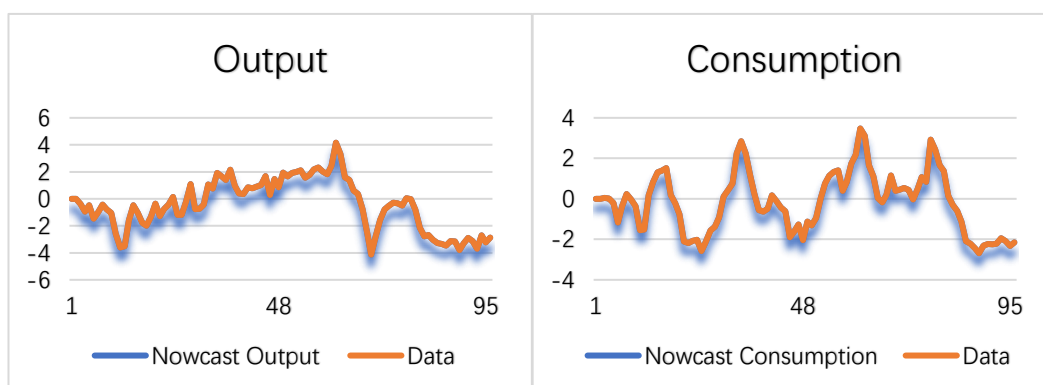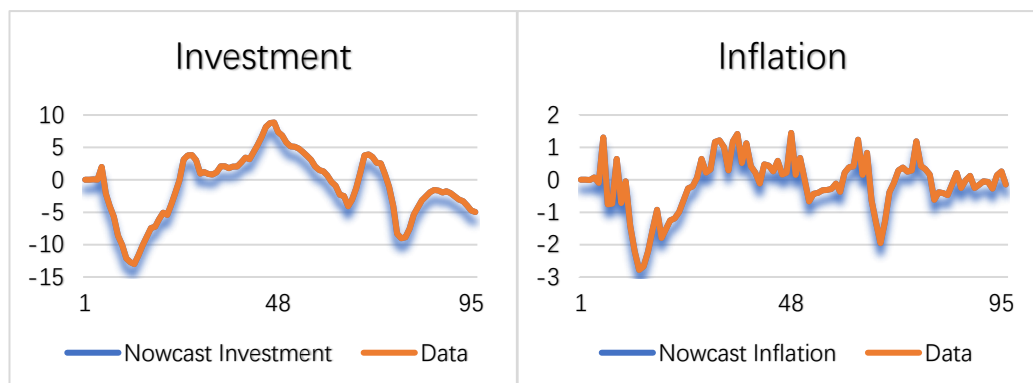
3.4.7 The Effectiveness of the Monetary Policy

Chinese GDP growth rate fell from 14 per cent in 2007 to 9.6 per cent in the fourth quarter of 2008 due to the latest financial crisis. To combat the pressure of economic downturn, the PBoC engineered a series of loose monetary policies, including lower interest rates by three times in 2009. During the same period, the central government announced a 'four-trillion' stimulation package that injected multitrillion RMBs into the Chinese market. In 2010, the economy bounced back to 10 per cent GDP growth rate.

To prevent the potentially overheated market, by the end of 2009, the PBoC persuaded contractionary monetary policy with the aim of tightening the credit supply. The standard transmission of monetary policy through interest rate mechanisms indicates a tighter monetary policy leading to a rise in real interest rates, which in turn increases the cost of borrowing, thus causing a decline in credit supply and capital investment and resulting in a fall in output. Since our model contains two types of producing sectors and SOEs' entrusted lending behaviour, the questions I want to find out are 1) which production sector is affected more by the tightened policy? 2) whether the

effectiveness of monetary policy is dampened due to the entrusted lending to SMEs.

Figure 3 shows the impulse responses of a temporary monetary policy shock. As can be seen, a tighter monetary policy exerts a more negative impact on SMEs' output (ysme) compared to that of SOEs (yspb). Private investment (i) decreases since higher interest rate increases the cost of borrowing in both sectors that cause the decline of credit supply. Fewer aggregate bank loans to the state sector decrease the output and the money flow into the private sector. Turning to private firms, besides the similar impact of reductions in the output level, it also triggers the 'financial accelerator' effect (Bernanke et al., 1999). Less credit causes a lower level of net worth in the credit-constrained companies, which means SMEs have less collateral for their loans and become riskier. Hence, to compensate a higher default probability, SOEs entrusted lenders charge a higher risk premium, which further discourages the borrowing and investment spending (ipoe) by the private firms. Total households' consumption (c) and inflation rate (pi) decrease due to the tighter monetary policy. Private capital input (ksme) decreases along with the decreasing in private investment (ipoe). Output in both sectors decreases cause firms to hire fewer labour inputs in total (n).

Comparing the IRFs of a monetary policy shock in Bernanke et al. (1999), my model exhibits similar patterns for output, investment and risk premium but with relatively more 'kinked' reactions. In my model, the two sectors react differently to tighter policy shocks. SMEs' output decreases by approximately 0.4% and goes back to the steady state gradually. However, the state sector reduces production at first and quickly

Figure 3 Contractionary Monetary Policy Shock
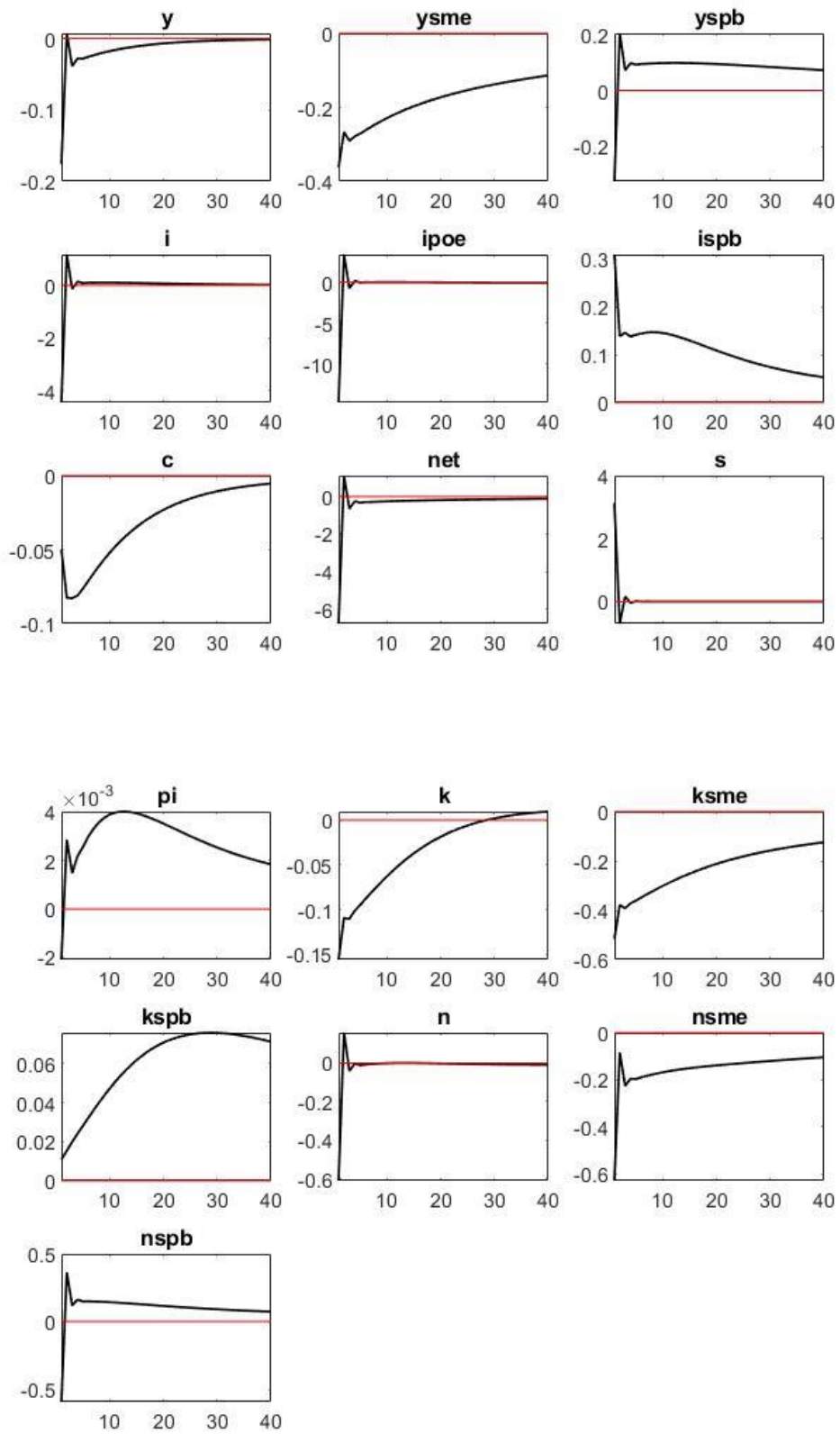
bounces back to the steady-state level. Bernanke et al. (1999) only illustrates the aggregate output reaction, which shows a smoother pattern compare to the IRFs in my model. Similarly, the output, private investment and risk premium exhibit a 'kinked' response to the shock, while it is smoother and more persistent in Bernanke et al. (1999).

To understand the effectiveness of the monetary policy, I impose the same monetary policy under two different scenarios, higher versus lower default probabilities of the private sector. Figure 4 shows that the effectiveness of the policy is dampened when the default probability is higher. The contractual rate of nonaffiliated loans is higher to compensate for the higher risk level; therefore, the return on the non-default loans increases. From the perspective of the SOE entrusted lenders who are risk-neutral, the higher return increases their incentive to engage in more non-affiliated loans to SMEs. The overall impact on SMEs' output is still negative, but the magnitude is smaller when the default risk is higher, indicating that the effectiveness of monetary policy is attenuated.

Figure 4 The effectiveness of the Monetary Policy

A **B**
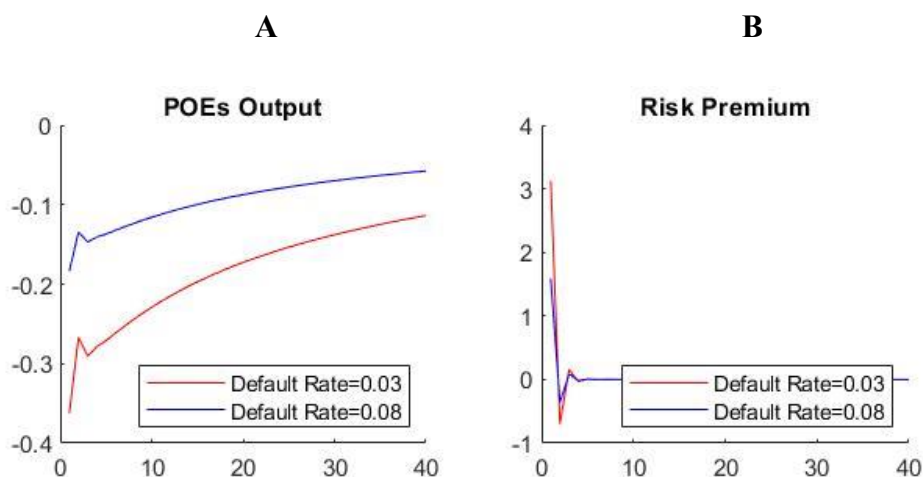
Panel A plots the output responses in the private sector under different default risks. The blue line indicates default risk equals 8 per cent, while the red line implies 3 per cent. The SMEs output responses with less magnitude and persistence when the default risk is higher. Risk premium increases only by 1.5 per cent when default risk is higher, compared to a 3 per cent increase when default risk is lower (panel B).

3.4.8 The Effect of the Fiscal Policy

To support the economic recovery in 2009 and 2010, the Chinese central government undertook a fiscal stimulus program worth four trillion RMB. It approximately equals 11 per cent of the annual GDP in that year (Bai et al., 2016). In a typical Ricardian-type closed economy, when the government conducts an expansionary fiscal policy, i.e., increases government spending, it may induce the 'crowding out effect'. Our model follows the same rule that private investment decreases after the expansionary policy (Figure 5, panel i). The temporary shock increases the output in aggregate level and in both sectors, which explains the economic recovery after the stimulus program. However, the less private investment in the economy decreases the net worth in the SMEs sector (net), which in turn triggers the 'financial accelerator' effect. The lower the net worth, the higher the risk premium (s) SMEs need to pay. Thus, a positive fiscal policy shock raises the cost of borrowing in the private sector, which may explain the economic slowdown after 2010[32]. The private sector contributes more than 60 per cent of China's GDP growth and providing over 70 per cent of employment (Elliot et al., 2015). Hence, SMEs are the backbone and play an essential role in the Chinese economy. If the 'stimulus' package leads to a lower level of private investment, it is not surprising to observe a fall in GDP growth rate. Since capital investments are

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[32] According to the World Bank, China's GDP growth rate has been decreased from 10.6 per cent in 2010 to 6.9 per cent in 2015.

Figure 5 Positive Government Spending Shock
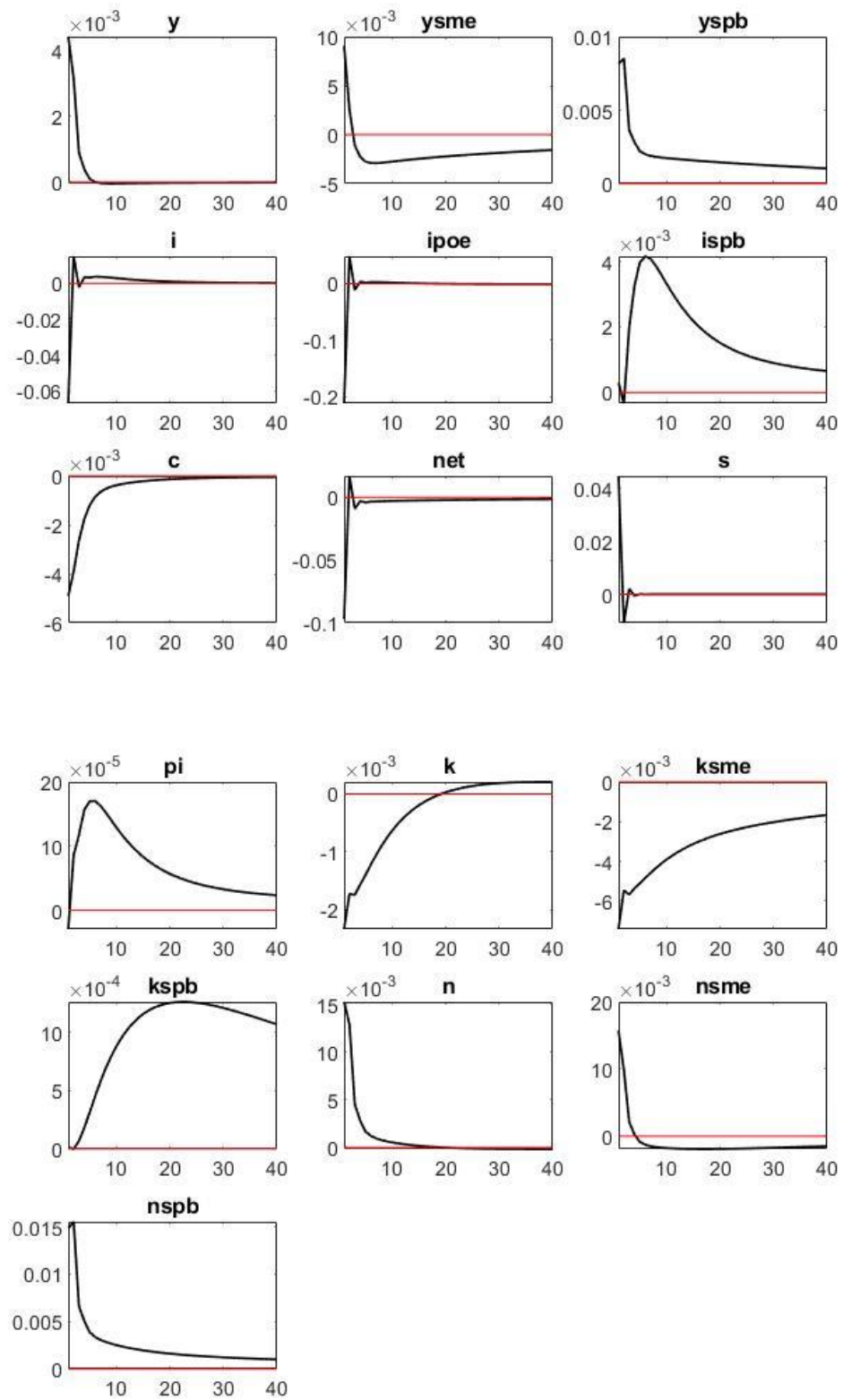
driven down by the positive government spending, which causes fewer capital inputs in the production sectors, the only way for firms to increase their output temporarily is to increase the other input, labour. Hence, labour inputs in both sectors (nsme and nspb) increase.

3.5 Conclusion

I build a dynamic stochastic general equilibrium (DSGE) framework of the entrusted lending market, which constitutes one of the main segments of China's shadow banking system. Credit misallocation has been an ongoing issue in China. Commercial banks strongly favour state-owned enterprises (SOEs) for loans because of government endorsement. By taking advantage of the privileged access to the formal banking system, state sectors obtain over 75 per cent of bank loans (Tsai, 2015). On the contrary, private-owned enterprises (SMEs) face severe financial constraints in accessing the bank credit, compelling them to rely on shadow banking for funds, mainly entrusted loans. In the meantime, SOEs have a long history of suffering in low productivity and inefficiency, which creates an incentive for them to engage in entrusted lending market to seek extra profit. The latest evidence shows that approximately 74 per cent of entrusted lenders is SOEs (Allen et al., 2019).

The research findings of this study can provide several policy implications. First, I find that a tighter bank credit regulation, particularly a higher reserve ratio, pushes SOEs to raise the proportion of risky loans to SMEs. SOEs' profit decreases due to the shortage of bank loans (higher reserve ratio). To compensate for the lost, SOEs are

willing to increase lending to SMEs, which provides higher return on loans. However, high return is always accompanied by high risk. Without controlling SOEs' risk lending activities, the default probability of entrusted loans may induce systemic risk may be a potential way to attenuate the expansion of SOEs' entrusted lending activities in the first place.

Second, I find that the effectiveness of the monetary policy is dampened since SOEs entrusted lenders (SELs) are free to adjust the credit allocation to SMEs regardless of the underlying risks. The credit-constrained (private) sectors have to bear a higher cost of borrowing when monetary policy becomes tighter. However, with the opportunities to borrow from the SOEs, SMEs can offer a higher return and offset their shortage of funds proportionally, which in turn makes the monetary policy less effective. According to this finding, I suggest that reforming the state sector by restricting the provision of government guarantees might be an effective method to curtail the risk behaviour of SOEs and enhance the efficacy of monetary policy.

Third, provisional positive government spending increases the output in both the private and the state sectors. However, it crowds out private investment, which reduces the net worth and increases the risk premium of the private sector. Consequently, SMEs must reduce external finance and slow down their production. Bai et al., (2016) document that, at the end of 2010, approximately 75 per cent of fiscal stimulus funds were spent on public infrastructure projects. Hence, most of the liquidity released by banks flows into government projects rather than into the real economy, which results

in a subsequent fall in the private investment. As mentioned earlier, SMEs are the engine of Chinese economic growth. Without sufficient funds flowing to the private sector, it is not surprised to observe an economic slowdown after 2010. Therefore, fiscal policy needs to be implemented with cautious as it may harm the real economy unless regulators can target the private sector for funds. Specifically, if the fiscal stimulus can provide more funding opportunities to the private firms rather than mainly focus on infrastructure projects, SMEs may not have to turn to the entrusted lending market, and the economy might be improved in the longer term.

Appendix 3A Log-linearised Equations

Goods Demand

$$\tilde{Y}_t = \frac{C}{Y} * \tilde{C}_t + \frac{I}{Y} * \tilde{I}_t + \frac{G}{Y} * \tilde{G}_t + \frac{\tau D}{Y} * \tilde{D}_t$$

$$\tilde{C}_t = \tilde{C}_{t+1} - \tilde{R}_t + E_t \tilde{\pi}_{t+1}$$

Goods Supply

$$\tilde{Y}_t = a * \left(\frac{Y^{SME}}{Y}\right)^{\rho} * \tilde{Y}_t^{POE} + (1-a) * \left(\frac{Y^{SOE}}{Y}\right)^{\rho} * \tilde{Y}_t^{SOE}$$

$$\tilde{Y}_t^{SME} = \tilde{A}_t^{SME} + \alpha_1 * \tilde{K}_t^{SME} + (1-\alpha_1) * \tilde{N}_t^{SME}$$

$$\tilde{Y}_t^{SOE} = \tilde{A}_t^{SOE} + \alpha_2 * \tilde{K}_t^{SOE} + (1-\alpha_2) * \tilde{N}_t^{SOE}$$

Labor Demand

$$\tilde{w}_t = \rho * \tilde{Y}_t^{SME} - \tilde{x}_t - (\rho - 1) * \tilde{Y}_t - \tilde{N}_t^{SME}$$

$$\tilde{w}_t = \rho * \tilde{Y}_t^{SOE} - \tilde{x}_t - (\rho - 1) * \tilde{Y}_t - \tilde{N}_t^{SOE}$$

$$\widetilde{N}_t = \frac{N^{SME}}{N} * \widetilde{N}_t^{POE} + \frac{N^{SOE}}{N} * \widetilde{N}_t^{SOE}$$

Labor Supply

$$\widetilde{w}_t = \tilde{C}_t + \iota * \widetilde{N}_t$$

Capital Demand

$$\tilde{R}_t^K = (1 - \epsilon_1) * \left[\rho * \tilde{Y}_t^{SME} - \widetilde{K}_t^{SME} - \tilde{x}_t - (\rho - 1) * \tilde{Y}_t\right] + \epsilon_1 * \tilde{Q}_t^{SME} - \tilde{Q}_{t-1}^{SME}$$

$$\tilde{R}_t^L = (1 - \epsilon_2) * \left[\rho * \tilde{Y}_t^{SOE} - \widetilde{K}_t^{SOE} - \tilde{x}_t - (\rho - 1) * \tilde{Y}_t\right] + \epsilon_2 * \tilde{Q}_t^{SOE} - \tilde{Q}_{t-1}^{SOE}$$

$$\tilde{Q}_t^{SME} = \phi_K^{SME} * \left(\tilde{I}_t^{SME} - \widetilde{K}_t^{SME}\right) - \left(1 - \phi_K^{SME}\right) * \tilde{e}_t^{SME}$$

$$\tilde{Q}_t^{SOE} = \phi_K^{SOE} * \left(\tilde{I}_t^{SOE} - \widetilde{K}_t^{SOE}\right) - \left(1 - \phi_K^{SOE}\right) * \tilde{e}_t^{SOE}$$

Capital Supply

$$\widetilde{K}_t^{SME} = \delta^{SME} * \tilde{I}_t^{SME} + (1 - \delta^{SME}) * \widetilde{K}_t^{SME} + \delta^{SME} * \tilde{e}_t^{iSME}$$

$$\widetilde{K}_t^{SOE} = \delta^{SOE} * \tilde{I}_t^{SOE} + (1 - \delta^{SOE}) * \widetilde{K}_t^{SOE} + \delta^{SOE} * \tilde{e}_t^{iSOE}$$

$$\widetilde{K}_t = \frac{K^{SME}}{K} * \widetilde{K}_t^{SME} + \frac{K^{SOE}}{K} * \widetilde{K}_t^{SOE}$$

$$\tilde{I}_t = \frac{I^{SME}}{I} * \tilde{I}_t^{SME} + \frac{I^{SOE}}{I} * \tilde{I}_t^{SOE}$$

Loan Market

$$E_t \tilde{R}_{t+1}^K - \tilde{R}_{t+1}^L = -\nu * \left(\widetilde{Net}_t - \tilde{Q}_t^{SME} - \widetilde{K}_t^{SME}\right) + \tilde{e}_t^S$$

$$\widetilde{Net}_{t+1} = \gamma * R^L * \frac{K^{SME}}{Net} * \left(\tilde{R}_t^K - \tilde{R}_t^L\right) + \tilde{R}_t^L + \widetilde{Net}_t$$

$$\tilde{s}_t = E_t \tilde{R}_{t+1}^K - \tilde{R}_{t+1}^L + \tilde{e}_t^S$$

$$\tilde{R}_{t+1}^L = \tilde{R}_{t+1}^D + \frac{\tau}{(1-\tau)} * \tilde{e}_t^\tau$$

Taylor Rule and Fisher Equation

$$\tilde{R}_t = \rho_D * \tilde{R}_{t-1} + (1 - \rho_D) * \left(a_\pi * \tilde{\pi}_t + a_y * \tilde{Y}_t\right) + \tilde{e}_t^m$$

$$\tilde{R}_t = \tilde{R}_t^D + E_t \tilde{\pi}_{t+1}$$

New Keynesian Philips Curve

$$\tilde{\pi}_t = \beta E_t \tilde{\pi}_{t+1} + \frac{(1 - \theta)(1 - \theta\beta)}{\theta}(-\tilde{x}_t)$$

AR (1) Shock Processes

$$\tilde{G}_t = \rho^G * \tilde{G}_{t-1} + \tilde{\varepsilon}_t^G$$

$$\tilde{A}_t^{SME} = \rho_A^{SME} * \tilde{A}_{t-1}^{SME} + \varepsilon_t^{aSME}$$

$$\tilde{A}_t^{SOE} = \rho_A^{SOE} * \tilde{A}_{t-1}^{SOE} + \tilde{\varepsilon}_t^{aSOE}$$

$$\tilde{e}_t^\tau = \rho_\tau * \tilde{e}_{t-1}^\tau + \tilde{\varepsilon}_t^\tau$$

$$\tilde{e}_t^{iSME} = \rho_k^{SME} * \tilde{e}_{t-1}^{iSME} + \tilde{\varepsilon}_t^{iSME}$$

$$\tilde{e}_t^{iSOE} = \rho_k^{SOE} * \tilde{e}_{t-1}^{iSOE} + \tilde{\varepsilon}_t^{iSOE}$$

$$\tilde{e}_t^S = \rho^s * \tilde{e}_{t-1}^S + \tilde{\varepsilon}_t^S$$

Appendix 3B List of F.O.Cs

Households

$$E_t \left[\beta \left(\frac{C_{l,t+1}}{C_{l,t}}\right)^{-1} \frac{1}{\pi_{t+1}} \right] R_t^D = 1$$

$$\frac{C_{l,t}}{1 - N_{l,t}} = w_{l,t}$$

Commercial Banks

$$B_t = \left(1 - \tau\varepsilon^{e_t^\tau}\right)D_t$$

SMEs

$$\Gamma'(\bar{\omega}_i) = \lambda_t^{SME}[\Gamma'(\bar{\omega}) - \mu G'(\bar{\omega})]$$

$$[1 - \Gamma(\bar{\omega}_i)]s_t + \lambda_t^{SME}[\Gamma(\bar{\omega}) - \mu G(\bar{\omega})]s_t = \lambda_t^{SME}$$

$$[\Gamma(\bar{\omega}) - \mu G(\bar{\omega})] \, s_t \, \aleph_t = \aleph_t - 1$$

$$s_t = E_t\left(\frac{R_{t+1}^K}{R_{t+1}^L}\right) = \frac{1 - Net_{i,t}/Q_t^{SME} K_{t+1}^{SME}}{\Gamma(\bar{\omega}) - \mu G(\bar{\omega})}$$

$$E_t(R_{t+1}^K) = \frac{\alpha_1 \dfrac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^W} \dfrac{Y_{i,t+1}^{SME}}{K_{i,t+1}^{SME}} + Q_{t+1}^{SME}(1 - \delta^{SME})}{Q_t^{SME}}$$

$$w_{t+1} = (1 - \alpha_1) \frac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^W} \frac{Y_{i,t+1}^{SME}}{N_{i,t+1}^{SME}}$$

SOEs

$$R_{t+1}^L = \frac{\alpha_2 \dfrac{P_{t+1}^{w,SOE}}{X_{t+1}P_{t+1}^W} \dfrac{Y_{j,t+1}^{SOE}}{K_{j,t+1}^{SOE}} + Q_{t+1}^{SOE}(1 - \delta^{SOE})}{Q_t^{SOE}}$$

$$w_{t+1} = (1 - \alpha_2) \frac{P_{t+1}^{w,SOE}}{X_{t+1}P_{t+1}^W} \frac{Y_{j,t+1}^{SOE}}{N_{j,t+1}^{SOE}}$$

Capital Goods Producers

$$\frac{1}{Q_t^{SOE}} = \left[1 - \phi_K^{SOE}\left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE}\right)\right] e_t^{ISOE}$$

$$\frac{1}{Q_t^{SME}} = \left[1 - \phi_K^{SME}\left(\frac{I_t^{SME}}{K_{t-1}^{SME}} - \delta^{SME}\right)\right] e_t^{ISOE}$$

Final Goods Producers

$$\sum_{k=0}^{\infty} \theta^k E_t\left\{\left[\Lambda_{t,k}\left(\frac{P_t^*}{P_{t+k}}\right)^\epsilon Y_{t+k}^W(z)\left[\frac{P_t^*}{P_{t+k}} - \left(\frac{\epsilon}{\epsilon - 1}\right)\frac{P_{t+k}^W}{P_{t+k}}\right]\right]\right\} = 0$$

$$P_t^* = \frac{\epsilon}{\epsilon - 1} \frac{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k} \left(P_{t+k}^W P_{t+k}^{-(1-\epsilon)} Y_{t+k} \right)}{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k} \left(P_{t+k}^{-(1-\epsilon)} Y_{t+k} \right)}$$

Appendix 3C Steady State Values From the Model

Variables	Steady State Values
C	0.0852
I	0.0073
G	0.0291
Y	0.2080
Y^{SME}	0.0914
Y^{SOE}	0.1371
I^{SME}	0.0023
I^{SOE}	0.0050
K	0.2092
K^{SME}	0.0661
K^{SOE}	0.1431
N	0.2448
Net	0.0300
N^{SME}	0.1135
N^{SOE}	0.1313
R^D	1.0101
R^K	1.2284
R^L	1.1884

Appendix 3D Data

Nominal GDP: Datastream (code: CHOEXP03A);

Nominal consumption: Datastream (code: CHCNPER.);

Inflation: Datastream (code: CHOCFCPIE);

Total employment: Datastream (CHXEMPT.P);

Output in SOEs: Total output multiplied by SOE output share.;

SOE output share: Total State-Owned Industrial Output over total Industrial

Output. (From Fudan University);

Total investment: From Fudan University or Quandl (GDP multiplied by

Investment to GDP ratio);

Risk premium: CEIC and city of Wenzhou;

Capital return in SMEs: Lending rate of the commercial bank plus the risk premium.

Raw Data Description (RMB)			
Variable	Minimum	Maximum	Mean
GDP (Billion)	795.30	19195.07	6862.9
Consumption (Billion)	291.57	6891.48	2351.8
Investment (Billion)	176.45	7656.95	2570.5
Inflation (Per cent)	-1.00	6.74	1.01
Employment (Billion)	5.83E-06	1.92E-05	1.34E-05
SOEs Output (Billion)	439.38	1219.04	718.906
Risk Premium (Per cent)	2.79	7.76	4.49
Capital Return (Per cent)	3.88	10.77	6.25
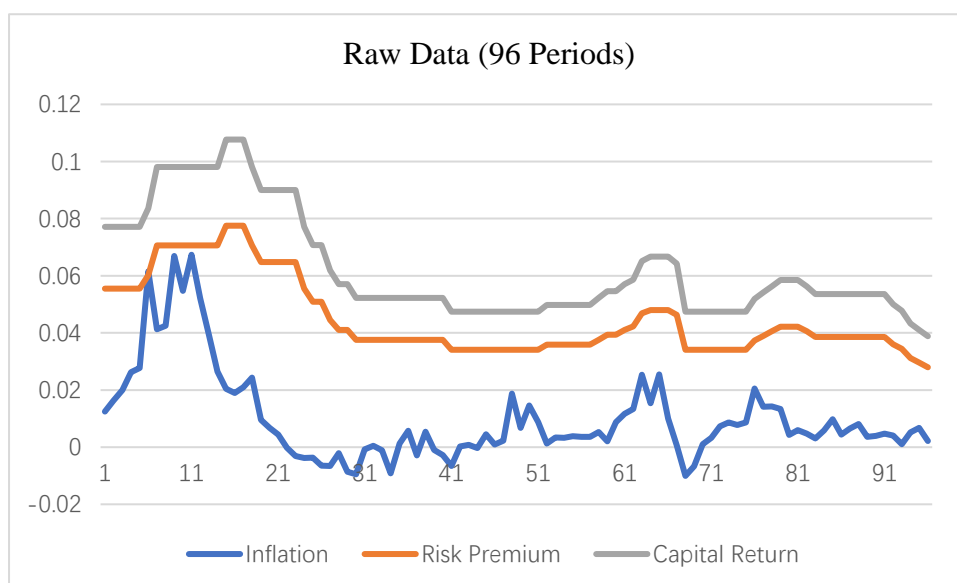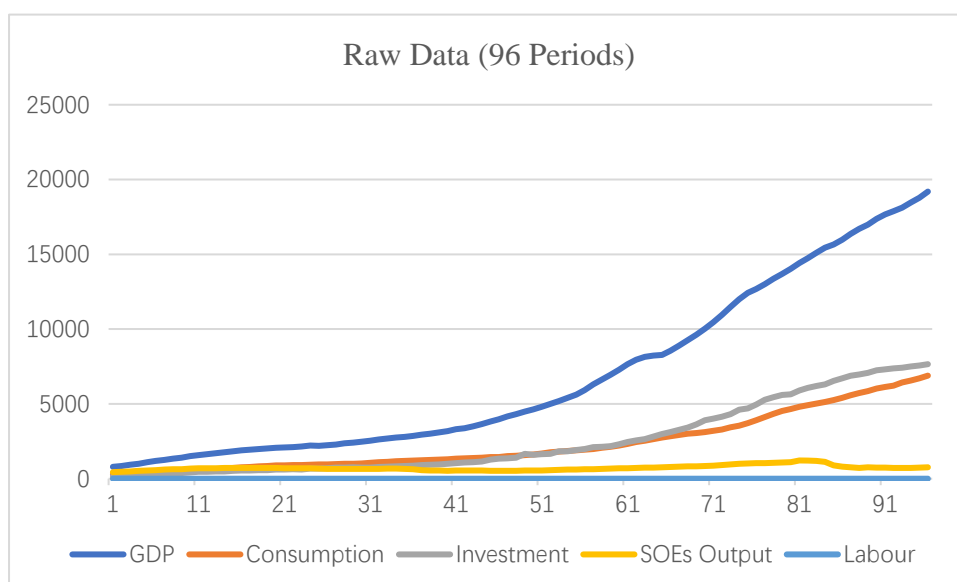
Chapter 4 Shadow Banking Activities in the Formal Banking Sector

4.1 Introduction

Many factors burgeon the development of shadow banking activities in China. In this chapter, I focus primarily on building a model of the shadow banking activities conducted by commercial banks. Since commercial banks in China sustain a better reputation and less credit failure in providing services and products to the financial market, they have preserved the dominant role in the entire Chinese financial system. Ehler et al. (2018) claim that shadow banking in China is the 'shadow of the banks', where commercial banks develop market-based deposit and lending rates outside the conventional system when credit amount and interest rate are strictly controlled by regulators and government.

One of the main shadow banking instruments, wealth management products (WMPs) results from the initial undertaking to bypass regulation on deposit rates ceiling (Wang and Zhao, 2016). WMPs are generally treated as high yield alternatives to bank deposits, being usually of short-term investment for a duration of less than six months. Separately, trust loans and entrusted loans are alternatives to bank loans, in which trust companies and client funds invest according to a pre-specified objective, purpose, amount, maturity, and interest rates (which is not subject to interest rate control). Meanwhile, cash-rich enterprises, such as SOEs, lend their extra funding to SMEs through entrusted lending platforms. WMPs are operated on the banks' off-balance-

sheet and offer attractive yields to individual investors, while trust loans and entrusted loans do not face interest rate restrictions, loan-to-deposit ratio requirement, or safe loan regulation; these parallel channels have grown enormously and supported economic growth. In essence, the increasing operation of commercial banks' off-the-balance sheet activities results in the rapid development of the Chinese shadow banking system, which distorts the formal financial system and the effectiveness of monetary and regulatory policies.

In the model section, the general equilibrium framework is altered by adding a risk lending channel in the banking sector, in which bankers offer both safe bank deposits and risk shadow banking products to households. The funds obtained from depositors are used to fund the risk-free SOEs, while the money from shadow banking products is used to finance risky SMEs.

This chapter is organised in the following way: Section 4.2 is the detailed institutional background knowledge and WMPs. Section 4.3 presents the second DSGE model framework in this research. In Section 4.4, I describe the data used in this model. Section 4.5 illustrates the indirect inference estimated results. Section 4.6 concludes.

4.2 Monetary Policy, Institutional Background and Wealth Management Products

4.2.1 Quantity-based Monetary Policy

Taylor-type interest rate rule, developed by Taylor (1993), has been tested as a good way to capture monetary policy for the advanced economy, such as the US and Europe for the period between the post-World War II and the latest financial crisis. During the same period, New Keynesian DSGE models have developed dramatically and become the mainstream economic frameworks for monetary policy analysis. The most common method to capture sophisticated monetary policy behaviour in DSGE models for developed nations is using Taylor-type interest rate rule, which uses the nominal interest rate as the intermediate target. However, whether interest rate type Taylor rule is suitable for the monetary policy in large developing countries, such as China where the monetary policy is not fully market-oriented, is still questionable.

US monetary authority uses the federal funds rate as the intermediate target to stabilise inflation and output (or employment). According to Chen et al. (2018), the intermediate target of Chinese monetary policy has been M2 growth since 2000. Unlike the US central bank, whose primary goal is inflation stability, the priority for PBoC is to achieve the annual GDP growth target. Money supply policy and interest rate policy are not fully decided by the PBoC as it has only limited operational independence from the State Council. The key decisions need to be approved by the

State Council[33]. Normally, by the end of each year, the Central Economic Work Conference, jointly organised by the State Council and the Central Committee of Communist Party of China (CPC), sets specific targets for GDP growth rate and M2 growth rate for the coming year. However, if the key indicators deviate from the targets after one season, the PBoC proposes policy plans with the aim of achieving quarterly targets. The plans cannot be implemented until the State Council reviews and approves the implementation (Huang et al., 2018). To meet the target M2 growth, which is the intermediate target of monetary policy, the PBoC uses various instruments, including open market operations and two important banking regulations, loan-to-deposit ratio and safe-loan regulation (detailed information is included in Section 4.2.3).

4.2.2 Chinese Banking System

The scale of the Chinese banking system has expanded substantially over the past two decades, and the size is relatively larger than the Chinese economy. Banking assets that include both domestic and foreign branches and subsidiaries were equivalent to approximately 200% of GDP in 2012 (Turner et al., 2012) and it surpassed the US banking system and all euro area banking systems put together, with $35 trillion (approximately 300% of China's annual GDP) in 2016 (Cerutti and Zhou, 2018). In addition to the People's Bank of China (PBoC), which is the central bank in China, there are principally four other types of banks, comprising state-owned policy banks,

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[33] See Article 2 of the General Rules in the PBoC Law.

six state-owned banks, national joint-equity commercial banks and urban and rural commercial banks.

The first (policy banks) type of banks includes EXIM Bank of China, China Development Bank and Agriculture Development Bank of China, whose goal is to issue policy lending only. The second category of the six state-owned banks includes the 'Big Five' and a leading large retail bank, Postal Savings Bank of China (PSBOC). 'Big Five' banks are Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Bank of China (BOC), Agricultural Bank of China (ABC) and the Bank of Communications (BCOM). The first four banks - ICBC, CCB, BOC and ABC - are known as the original 'Big Four' as their size constitutes the largest throughout the world. BCOM is one of the banks with the longest history (established in 1908) in China and the very first state-owned incorporated bank; therefore, it is consistently regarded as the fifth big bank. The 'Big Five' are majority-owned by the government but also have private shareholders since they are all publicly listed on the Hong Kong stock exchange. They are the predominant players in commercial loans and deposit market and jointly account for 35.5% of the total assets[34] in the industry in 2018. Most of the time, these banks are market-oriented but also support policy lending during extreme periods. For example, the stimulation package, 'four-trillion RMB', was largely financed by the big state-owned banks in order to prevent the spillover effect of the 2007-2009 financial crisis.

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[34] China banking sector's assets up 7.5%: http://www.chinadaily.com.cn/a/201808/27/WS5b83e160a310add14f38804c.html

The third type of banks comprises 12 national joint-equity commercial banks. Compared to the big state-owned banks, these banks are usually young, mid-sized with mixed ownership, and the size is approximately 10% of the average size of the 'Big Four' and jointly account for around 18% of Chinese banking sector assets in 2014. Joint-equity banks operate a similar type of commercial banking business by targeting SMEs loans at the same time. The fourth category of banks includes several types of small-size city and rural commercial banks, and small local banks, such as rural cooperative banks, rural credit cooperatives, as well as village and township banks. These banks are normally founded by the city or the provincial governments to carry out local government lending operations. The total assets of these banks reached approximately 10% at the end of 2014 (Fungáčová et al., 2018).

4.2.3 Regulations in the Banking System

PBoC and China Banking and Insurance Regulatory Commission (CBIRC) are the official authorities to supervise and monitor all commercial banks. PBoC[35] was consolidated by the Huabei Bank, the Beihai Bank and the Xibei Farmer Bank in 1948 and officially endowed with the function of a central bank by the State Council in 1983. The main responsible of PBoC is to carry out monetary policy and regulation of financial institutions in mainland China. CBIRC[36] was merged by China Banking Regulatory Commission (CBRC) and China Insurance Regulatory Commission

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[35] People's Bank of China Official Website: http://www.pbc.gov.cn/english/130712/index.html

[36] China Banking and Insurance Regulatory Commission http://www.cbrc.gov.cn/chinese/newIndex.html

(CIRC) in April 2018. CBRC, established in 2003, was an agency of the People's Republic of China (PRC) to regulate the banking sector excluding the special administrative regions, Hong Kong and Macau, while CIRC was an authority to regulate insurance product and services and manage the stable operation of the insurance industry.

In conjunction with the Basel III Accords, all banks in China are required to comply with minimum capital requirements. PBoC has frequently altered banks' reserve ratio to regulate the economy. The ratio was quite high during 2009 and 2012, and it has been decreasing since 2012 to spur the economy. The latest figure shows the ratio is 14.5% for large institutions and 12.5% for smaller banks[37]. PBoC has also tightly regulated interest rates. Before 2015, commercial banks adjusted their interest rates according to the base rate set by the central bank together with both upper and lower bounds. The upper bound of the deposit rates - up to 1.5 times of base rate – has been eliminated in recent years, which is helpful for banks to attract more deposits. In China's investment-driven model, these interest rate policies are part of the model to transfer savers, such as large industrial enterprises, to borrowers (Song et al., 2011). The lower bound of the rates has also been gradually liberalised, which gives banks stronger incentives to increase their lending to stimulate the economy. CBRC has been limiting the total amount of bank lending by setting capital ratio following the Basel Accord and loan-to-deposit ratio. Loan-to-deposit ratio restricts total lending below

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[37] China slashes banks' reserve requirements again as growth slows https://www.reuters.com/article/us-china-economy-rrr-cut/china-slashes-banks-reserve-requirements-again-as-growth-slows-idUSKCN1OY0RL

75% of their total deposits in each bank, which was first established in 1994 as a way to manage the quantity of bank loans. Nevertheless, this requirement is no longer binding following 2015.

In addition to controlling the quantity of bank loans, the PBoC uses another regulation to control the quality of bank loans, the so-called safe-loan regulation. Both Eliott et al. (2015) and Chen et al. (2018) document that banks are discouraged from lending to certain industries, such as coal miners, shipbuilders and real estate developers. Concerned with potential financial risks related to bank lending to certain risk industries, in 2006, the State Council issued a notice regarding the restructuring of these industries. In 2010, the CBRC restricted bank lending to those industries, and all the actions were reinforced in the 2013 Guidelines by the State Council.

Restricted regulations in the banking sector are the main reason for the growth of shadow banking in China. Banks can either increase capital by issuing new equity and bonds to meet the capital ratio requirements, or they can develop more off-balance sheet activities which do not increase assets on the balance sheet; for example, the issuance of WMPs, which has become the most important off-balance-sheet activity. Banks can surpass the loan-to-deposit ratio set by CBRC and deposit rate ceiling set by PBoC through attracting more depositors since WMPs normally offer a higher yield and conduct less on-balance lending.

4.2.4 Wealth Management Products

The size of WMPs has surpassed entrusted loans since 2014 and become the largest component in China's shadow banking system (Allen et al., 2019). It is mainly offered by commercial banks, but can also be offered by non-bank financial institutions, such as Alibaba. The most famous WMPs with money market fund issued by Alibaba is called Yu'e'Bao, which grew very rapidly from RMB 200 million in May 2013 to RMB 700 billion in April 2014 and reached RMB 1.58 trillion at the end of 2017[38]. Another important component contributing to the stature of WMPs is trust loans, which provides a channel for banks to lend out their money that raised from WMPs to risky firms, such as SMEs, who do not have access to bank credit. Private credit agencies have also engaged in lending money to small firms that cannot borrow from banks (Allen et al., 2005).

China's financial market has become a 'dual-track' system with the growth of the shadow banking sector. On the one hand, interest rates control, capital requirements and loan-to-deposit rate make bank deposit less attractive and more difficult to access bank loans. On the other hand, the shadow banking sector has been largely unregulated compared to the formal banking system, creating an impetus for shifting business into more shadowy methods to circumvent tight regulations. Therefore, both commercial and non-bank institutions are willing to benefit from off-balance sheet funding. However, the rapid growth of shadow banking, especially WMPs, has acquired

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[38] Investment limits tightened on $233 bn Yuebao https://fundselectorasia.com/investment-limits-tightened-233bn-yuebao/

increasing attention from the regulation sector, CBRC. In fact, CBRC has been trying to restrict this shadow banking instrument, but banks persistently find a way to bypass monitoring.

The early version of WMPs is produced through cooperation between banks and trust companies. Initially, trust companies purchase loan assets from banks and package them into trust plans. Then banks invest in these trust plans by using the money raised from WMPs. In this way, borrowers can borrow money that they cannot originally, and both banks and trust companies are paid by the interests of the trust plan without increasing banks' on-balance sheet loan balance. Increasing apprehension about the effectiveness of monetary policy prompted the CBRC in July 2009 to forbid banks from investing their money raised from WMPs into their own banks' loan assets. However, they failed to work. The trick here is that providing banks do not invest money into their own loan assets, and the policy is not binding. For example, bank A can sell its loan assets to trust companies and form a trust plan; bank B now purchases the trust plan by using the money raised from bank B's WMPs. Similarly, bank A can initially purchase trust plan from bank B's loan assets. By this means, borrowers can secure finance, both banks A and B and the trust companies can obtain payment by the interests from trust plans.

It is difficult for CBRC to forbid this type of cooperation completely, while in turn, the regulator has tried to limit this amount of activity. In August 2010, CBRC required that the maximum amount of WMPs targeting loan assets is 30% of all bank-trust

cooperation MWPs (Acharya et al., 2019). Again, banks can circumvent the rule by investing money raised from WMPs into loan assets that do not belong to any bank. Specifically, trust companies first make loans to borrowers and form trust plans. Then, banks issue WMPs and delegate the money to investment banks. In this way, banks claim that they allow investment banks to manage the money. In fact, banks ask investment banks to invest money into the specific trust plan. CBRC cannot now criticise banks since banks' WMPs are not targeted to banks' loan assets.

Once the situation was realised, CBRC passed a new policy in late March 2013[39]. WMPs target any form of non-standard financial assets, including all trust assets that exceed 4% of total bank assets or 35% of all WMPs. To bypass this regulation, banks need to invest most of their WMPs money into standard financial assets, which can still generate a higher yield to WMPs investors higher than normal deposit account. In short, bank A places WMP money into bank B's special contracted deposit account, which offers higher 'deposit rate' than a regular interest rate. Bank B then invests its own money into trust plans or delegates it to investment banks to purchase those trust plans issued by trust companies. The contracted deposits in bank B's balance sheet acts as a guarantee for the trust plans and the return from the trust plans is substituted to the contracted deposit, which is higher than normal risk-free bank deposit rate. WMPs investors still earn a higher interest rate; bank A does not invest WMP money into any trust assets. Bank B does invest money to trust plans directly or indirectly but

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does not use WMP money. Finally, the borrower is financed. All participants obey the CBRC rule, but the rule is completely ineffective.

Banks can always find more complicated ways and cooperate with trust companies, directly or indirectly, to avoid CBRC's rules; thus, the complicated interactions among banks make it difficult to prevent WMPs from channeling trust plans. The ongoing game between regulator and banks may reflect the inefficiency of the banking industry as these complicated channels make the transaction less transparency and increase agency problems. In fact, more inefficiency in the banking system may arise when the CBRC cannot-do list becomes longer. Apart from policy ineffectiveness, the underlying risk cannot be neglected. Risks can be swiftly accumulated due to maturity mismatch. Most loans to risky borrowers are long-term; however, all WMP investors want liquid assets. In addition, counterpart banks in the market also prefer short-term as they do not want to take long-term risks. In fact, the banks that issue the WMPs want short duration, as WMP money can transfer to deposit accounts to assist in meeting the loan-to-deposit ratio at the end of each year. In other words, all parties on the lender side of the market are impatient, but no one is willing to abandon the opportunities to make a profit. Therefore, banks can either issue new WMPs to refinance the loans or go to the interbank market for temporary liquidity. These activities will not only increase potential rollover risks but can also spread risks to the entire financial system as banks are closely connected to each other.

4.3 Model Framework

4.3.1 Households

In the model developed in the previous chapter, there is no role for money. Economics with that characteristic is illustrated as cashless economies. Since M2 serves as the intermediate target in the Chinese monetary policy, it is useful to incorporate a role for money other than that of a unit of account and how it can generate demand for money. The introduction of money in the utility function requires modifying the household's problem in two ways. First, the representative infinitely lived household's preferences are now given by,

$$\max E_0 \sum_{t=0}^{\infty} \beta_H^t [ln C_t^H + ln(M_t)] \tag{64}$$

Where $\beta_H < 1$ is the discount factor, C_t^H denotes households' consumption in each period, and M_t is the real balances of money holding in period t. Note that I exclude the disutility from the labour supply for two reasons, first, it makes the model less complicated since I include one more element (money) in the model and release, to some extent, computation burden; second, all other variables can be treated as 'per capita', for example, consumption in this model can be interpreted as consumption per capita. Therefore, it does not affect the model by excluding labour. The second modification is the flow budget constraint incorporates monetary holdings explicitly, taking the form,

$$C_t^H + D_t + SB_t + M_t = \frac{R_{t-1}^D}{\pi_t} D_{t-1} + [1 - F(\overline{w}_t)] \frac{R_{t-1}^{SB}}{\pi_t} SB_{t-1} + Div_t + \frac{M_{t-1}}{\pi_t} \tag{65}$$

The left-hand side of the equation (65) represents the expenditure of the households. Banks offer two 'products', which are risk-free deposits D_t, and risky products, SB_t; therefore, the household chooses how much to consume, how much money they are willing to deposit, and how much they are willing to invest in the shadow banking products in period t. Recalling the entrusted loans, firms with extra cash[40] can use commercial banks as the servicing agents to lend out their money and earn interests. The flow of funds has a similar feature with WMPs, which is operated on the bank's off-the-balance sheet. The source of funds of WMPs is households, while the source is the entrepreneurs in entrusted loans. Therefore, for simplicity but without losing generality, we define all the funds as shadow banking products[41] (including WMPs from regular households and lenders of entrusted loans), denoted as 'SB', which is the quantity of one-period nominally risky discount shadow banking products purchased in period t and maturing in period $t+1$ with the interest rate R_t^{SB}. The last item on the expenditure side is the real money demand.

The right-hand side implies the overall earnings, including earning from deposits, interest-earning from shadow banking products that subject to a default probability $F(\overline{w}_t)$. The supply of the funds is from households who invest in WMPs and entrepreneurs who have extra credit, the demand of the funds is the SMEs who can not obtain bank loans, while banks only act as the channelling platform in between the demand and the supply. Thus we assume commercial banks do not bear the risk but

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[40] The source of their extra cash can be varied, we do not specify it in our model.

[41] In other words, we define the entreprenuers who have extra cash to lend out also as a type of household.

transfer the risk from the demand side to the supply side. Therefore, aggregately, households can only get a proportion of their money back from investing the shadow banking products. Since the shadow banking activities are not restricted by the banking regulations, we assume, the default probability of the shadow banking products from the bank directly link to the idiosyncratic shock, w_t, of the SMEs' capital investment. While $\bar{w}_t$ implies the threshold of the risky investment, if $w_t > \bar{w}_t$, SMEs are able to pay back the loans to commercial banks, and in turn payback to the supply side of the funds; however, if $w_t < \bar{w}_t$, SMEs default, the household will lose the entire money in their shadow banking account. The idiosyncratic risk follows a log-normal distribution with the mean value $E(w) = 1$.

$$logw_t \sim N\left(-\frac{\sigma_w^2}{2}, \sigma_w^2\right) \tag{66}$$

Where $F(\bar{w}_t)$ is a CDF function of the idiosyncratic risk. The last two terms in equation (65) are the dividend from retailers and real money balance they hold from the previous period. Household maximizes the lifetime utility (64) subject to the constraint (65) whose Lagrangian multipliers is denoted as λ_t^H

$$L = E_0 \sum_{t=0}^{\infty} \beta_H^t \left\{ lnC_t^H + ln(M_t) \right.$$
$$+ \lambda_t^H \left[\frac{R_{t-1}^D}{\pi_t} D_{t-1} + [1 - F(\bar{w}_t)] \frac{R_{t-1}^{SB}}{\pi_t} SB_{t-1} + Div_t + \frac{M_{t-1}}{\pi_t} \right.$$
$$\left. \left. - M_t - C_t^H - D_t - SB_t \right] \right\} \tag{67}$$

The F.O.Cs are,

$$\partial C_t^H: \quad \frac{1}{C_t^H} = \lambda_t^H \tag{68}$$

$$\partial M_t: \quad \frac{1}{M_t} + \beta_H \lambda_{t+1}^H \frac{1}{\pi_{t+1}} = \lambda_t^H \tag{69}$$

$$\partial D_t: \quad \beta_H \frac{R_t^D}{\pi_{t+1}} \lambda_{t+1}^H = \lambda_t^H \tag{70}$$

$$\partial SB_t: \quad \beta_H [1 - F(\bar{w}_t)] \frac{R_t^{SB}}{\pi_{t+1}} \lambda_{t+1}^H = \lambda_t^H \tag{71}$$

$$\partial \lambda_t^H: \frac{R_{t-1}^D}{\pi_t} D_{t-1} + [1 - F(\bar{w}_t)] \frac{R_{t-1}^{SB}}{\pi_t} SB_{t-1} + Div_t + \frac{M_{t-1}}{\pi_t} - M_t - C_t^H - D_t - SB_t \tag{72}$$
$$= 0$$

Combining equations (67) with (68), (69) and (70) respectively, we obtain,

$$\frac{1}{M_t} + \beta_H \frac{1}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H} \tag{73}$$

$$\beta_H \frac{R_t^D}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H} \tag{74}$$

$$\beta_H [1 - F(\bar{w}_t)] \frac{R_t^{SB}}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H} \tag{75}$$

Equation (72) indicates the demand for money, in which higher current consumption associated with higher money demand. Equations (73) and (74) are Euler equations. A rise in either R_t^D or R_t^{SB} reduces the next periods' cost of consumption, relative to current consumption; hence, households have motivations to increase future consumption in relation to present consumption. Nevertheless, in equation (74), a rise in the default probability, $F(\bar{w}_t)$, would discourage households to consume in the future as the risk of losing money from the investment of risky shadow banking products is higher.

4.3.2 Bankers

Unlike the banking system in the previous chapter, where the role is transferring money from households to entrepreneurs only, in this model, I introduce a representative banker[42] who solves the following problem:

$$max \, E_0 \sum_{t=0}^{\infty} \beta_B^t ln C_t^B \tag{76}$$

Where β_B denotes bankers discount factor. The key difference between the first model and this one is the behaviour of the banker. I incorporate both on-the-balance and off-the-balance sheet activities in the Chinese commercial banking system. The banks' regular business is to accepting deposits and make loans. However, as we mentioned earlier, the burdensome bank regulation makes POEs, especially SMEs very difficult to get access to bank credit; while SOEs can easily get financed from the formal banking system. Thus, the creation of WMPs is used to circumvent the regulation and expand credit to the risky borrowers, i.e. SMEs. The funds from bank deposits are used to finance the risk-free state-owned sector, while the money from risky shadow banking assets is used to finance risky sector through banks' off-the-balance sheet. The main difference of these two channels is loans on the banks' balance sheet is heavily restricted by the regulation, including reserve requirement, loan-to-deposit ratio and low-risk loan regulation, while off-the-balance sheet activities have no restrictions. The bankers' flow of budget is constructed as,

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[42] Note that maximizing bankers' utility can be treated as equivalent to maximizing a function of dividends in the banking system, discounted at rate β_B.

$$C_t^B + R_t^D D_{t-1} + [1 - F(\overline{w}_t)]R_t^{SB} SB_{t-1} + L_t^{SOE} + L_t^{SME} = D_t + SB_t$$

$$+ R_t^L L_{t-1}^{SOE} + [1 - F(\overline{w}_t)]R_t^{SB} L_{t-1}^{SME} + (1 - \mu)\int_0^{\overline{w}_t} w_t dF(w) R_t^K Q_{t-1}^{SME} K_t^{SME} \tag{77}$$

In each period, banker decides how much to consume and the allocation of loans to both SOEs and SMEs. The left-hand side of the budget constraint implies the total expenditure, while the right-hand side is the total revenue. C_t^B is bankers' private consumption, D_t denotes household deposits and SB_t indicates the holding of household shadow banking assets. Loans to both sectors are L_t^{SOE} and L_t^{SME} respectively. The banker needs to pay back to households with an underlying interest rate, R_t^D for deposits and R_t^{SB} for risky products, in the meantime, the banker also receive interests from the previous loans to firms with the risk-free rate to SOEs, R_t^L, and the risky rate to SMEs, R_t^{SB}, subject to the default probability. The last two items on the right-hand side indicate the expected return on the loans to SMEs. with non-default probability, $1 - F(\overline{w}_t)$, the banker can get back their money; while if the SMEs default on their borrowing, banker needs to pay extra monitoring cost μ, to find out how much assets left in the SMEs' account and collect them back to compensate proportionally the lost.

In addition, bank loans to SOEs subject to the banking regulation, while loans to SMEs through shadow banking channel do not. For simplicity, we assume that the pooled funds from each individual household on the bank's off-the-balance sheet are used to on-lend to private entrepreneurs who cannot get access to bank loans initially. The risk from the SMEs is thus transferred to households via commercial bank's shadow

banking activities. More concretely, bank loans are restricted by both reserve ratio

requirement, v, and the loan-to-deposit ratio, h, which is 75% constantly,

$$L_t^{SOE} \leq (1 - ve^{\varepsilon_t^v})hD_t \tag{78}$$

While there is no restriction on shadow banking loans, banks can lend out all funds

from shadow banking funds.

$$L_t^{SME} \leq SB_t \tag{79}$$

To compensate for the potential loss from the loans to SMEs, commercial banks need

to charge extra risk premium. To formulate the risk premium, I follow the financial

accelerator model (Bernanke et al., 1999), the total return from the SMEs' loans must

equal to the opportunity costs of loans at the risk-free rate in the equilibrium, therefore,

$$[1 - F(\overline{w}_t)]R_t^{SB}L_{t-1}^{SME} + (1 - \mu) \int_0^{\overline{w}_t} w_t dF(w) \, R_t^K Q_{t-1}^{SME} K_t^{SME} = R_t^L L_{t-1}^{SME} \tag{80}$$

Maximising the bankers' utility function (76) subject to the budget constraint (77), (78)

and (79), the Lagrangian can be written as,

$$
\begin{aligned}
\mathcal{L} = \ E_0 \sum_{t=0}^{\infty} \beta_B^t \Big\{ & lnC_t^B + \lambda_t^B [D_t + R_t^L (1 - ve^{\varepsilon_{t-1}^v})hD_{t-1} \\
& + (1 - \mu) \int_0^{\overline{w}_t} w_t dF(w) \, R_t^K Q_{t-1}^{POE} K_t^{POE} - C_t^B - R_t^D D_{t-1} \\
& - (1 - ve^{\varepsilon_t^v})hD_t] \Big\}
\end{aligned}
\tag{81}
$$

In principle, the banker can lend out all the funds from the shadow banking assets

through the off-the-balance sheet. Therefore, the loan amount to SMEs is not

determined by the bankers' maximisation problem. Hence, we take F.O.Cs with

respect to consumption, C_t^B, and L_t^{SOE} (or D_t) to work out the loan amount to SOEs and

the risk-free lending rate,

$$\partial C_t^B: \frac{1}{C_t^B} = \lambda_t^B \tag{82}$$

$$\partial D_t: \lambda_t^B[1 - (1 - ve^{\varepsilon_t^v})h] + \beta_B \lambda_{t+1}^B[R_{t+1}^L(1 - ve^{\varepsilon_t^v})h - R_{t+1}^D] = 0 \tag{83}$$

Combining the two equations above, we obtain the spread between the deposit rate

and risk-free lending rate in the banking sector,

$$\frac{C_{t+1}^B}{\beta_B C_t^B} = \frac{[R_{t+1}^D - R_{t+1}^L(1 - ve^{\varepsilon_t^v})h]}{[1 - (1 - ve^{\varepsilon_t^v})h]} \tag{84}$$

There is no literature on the value of the bankers' discount factor; therefore, I use data

to back it out. The quarterly steady-state value of the deposit rate, R^D, and lending

rate, R^L, are approximately 1.0135 and 1.0211, respectively. The steady-state reserve

ratio, v, set by the central bank is 0.15. Hence, combining with the loan-to-deposit

ratio, $h = 0.75$, the bankers' discount factor β_B is calculated as 0.9999. The value is

higher than the households' discount factor, which implies banker is more patient than

households in this case. The reason is that banker does not bear the risk from the risk

lending to SMEs. The risk is eventually transferred to the households' sector, as stated

in the households' budget constraint (64). In the case of SMEs default, as can be seen

from the bankers' budget constraint (77), the banker can still collect the assets left in

the SMEs' account after paying the monitoring cost.

Equation (80) is used to determine the risk premium on SMEs loans. Following the

financial accelerator model (Bernanke et al., 1999), the total return form the SMEs'

loans must equal to the opportunity costs of loans at the risk-free rate in the equilibrium.

SMEs need to borrow from banks based on how much capital they need to purchase

and how much retained earnings or net worth, N_t, they have accumulated; thus, the

loan amount is determined as,

$$L_t^{SME} = Q_t^{SME} K_{t+1}^{SME} - N_t \tag{85}$$

In addition, SMEs are allowed to keep the rest of the value from the capital investment

once they repay the loans, which implies they only need to pay back the value up to

the threshold of the idiosyncratic shock, $\bar{w}$, hence,

$$R_t^{SB} L_{t-1}^{SME} = \bar{w} R_t^K Q_{t-1}^{SME} K_t^{SME} \tag{86}$$

Combining equations (80), (85) and (86), we can derive the following equation,

$$\frac{R_t^K}{R_t^L} = \frac{1 - N_{t-1}/Q_{t-1}^{SME} K_t^{SME}}{\Gamma(\bar{w}) - \mu G(\bar{w})} \tag{87}$$

Where $\Gamma(\bar{w}) - \mu G(\bar{w})$ implies the share of the net return goes to the bank, $1 - N_{t-1}/Q_{t-1}^{SME} K_t^{SME}$ is the leverage ratio in SMEs,

Where $\Gamma(\bar{w}) - \mu G(\bar{w})$ implies the share of the net return goes to the bank, $1 - N_{t-1}/Q_{t-1}^{SME} K_t^{SME}$ is the leverage ratio in SMEs,

$$G(\bar{w}) = \left[\int_0^{\bar{w}} w dF(w) \right] \quad \& \quad \Gamma(\bar{w}) = \left[\int_{\bar{w}}^{\infty} \bar{w} dF(w) \right] + \left[\int_0^{\bar{w}} w dF(w) \right] \tag{88}$$

We then define the wedge between the expected capital return and risk-free lending

rate in period $t + 1$, as the risk premium, s_t,

$$s_t = E_t \left(\frac{R_{t+1}^K}{R_{t+1}^L} \right) \tag{89}$$

Which is negatively related to the net worth, indicating that SMEs would have a lower leverage ratio and pay less risk premium if they have more retained earnings.

4.3.3 Government Sector and Quantity-based Monetary Policy

Different from the government sector from the first model, we specify that government spending is financed by the money supply in this framework.

$$G_t = \frac{M_{t-1} - M_t}{P_t} \tag{90}$$

Since the PBoC explicit states that Chinese monetary policy uses M2 growth as the intermediate target, therefore, in this chapter, we incorporate a quantity-based monetary policy where the log-linearised form is,

$$g_{m,t} = \rho_m g_{m,t-1} + (1 - \rho_m)(a_\pi \pi_t + a_y y_t) + e_{m,t} \tag{91}$$

$g_{m,t}$ is the money supply growth rate, which implies,

$$g_{m,t} = \ln \frac{M_t}{M_{t-1}} \tag{92}$$

Therefore, Chinese monetary policy uses money growth to stabilise both inflation and output target.

4.3.4 The Rest of the Model

The rest of the model includes SMEs and SOEs production sectors, capital goods producers and final goods producers, which solve the same problem with the first

model in Chapter 3. Therefore, I briefly recall the relevant equations in this section.

Capital demand is determined by solving the SMEs and SOEs profit maximisation problems, which result in two equations,

$$E_t(R_{t+1}^K) = \frac{MPK_{i,t+1}^{SME} + Q_{t+1}^{SME}(1 - \delta^{SME})}{Q_t^{SME}} \tag{93}$$

Where $MPK_{i,t+1}^{SME}$ represents the marginal product of capital in the SMEs' sector, which is equal to $\alpha_1 \frac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^{w}} \frac{Y_{i,t+1}^{SME}}{K_{i,t+1}^{SME}}$. δ^{SME} is the capital depreciation rate. Equation (93) states the expected gross return to holding a unit of capital from period t to $t + 1$. R_{t+1}^K is the return on capital investment.

$$R_{t+1}^L = \frac{MPK_{j,t+1}^{SOE} + Q_{t+1}^{SOE}(1 - \delta^{SOE})}{Q_t^{SOE}} \tag{94}$$

Equation (94) implies the gross return to holding a unit of capital in the SOEs, which equal to the risk-free lending rate from the commercial banks. δ^{SOE} is the depreciation rate and $MPK_{j,t+1}^{SOE}$ is the marginal product of capital in SOE's sector, which takes the form as $\alpha_2 \frac{P_{t+1}^{w,SOE}}{X_{t+1}P_{t+1}^{w}} \frac{Y_{j,t+1}^{SOE}}{K_{j,t+1}^{SOE}}$.

There is a representative capital goods producer who purchases final output as materials inputs, I_t^{SOE} and I_t^{SME}, and produce new capital goods for both SOEs and SMEs. the new capital goods are sold at the price Q_t^{SOE} and Q_t^{SME}. Capital accumulation with adjustment costs in both sectors are,

$$K_t^{SME} = (1 - \delta^{SME})K_{t-1}^{SME} + e_t^{ISME}\left[I_t^{SME} - \frac{\phi_K^{SME}}{2}\left(\frac{I_t^{SME}}{K_{t-1}^{SME}} - \delta^{SME}\right)^2 K_{t-1}^{SME}\right] \tag{95}$$

And

$$K_t^{SOE} = (1 - \delta^{SOE})K_{t-1}^{SOE} + e_t^{ISOE}\left[I_t^{SOE} - \frac{\phi_K^{SOE}}{2}\left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE}\right)^2 K_{t-1}^{SOE}\right] \tag{96}$$

Tobin's Q equations are,

$$\frac{1}{Q_t^{SME}} = \left[1 - \phi_K^{SME}\left(\frac{I_t^{SME}}{K_{t-1}^{SME}} - \delta^{SME}\right)\right] e_t^{ISOE} \tag{97}$$

And

$$\frac{1}{Q_t^{SOE}} = \left[1 - \phi_K^{SOE}\left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE}\right)\right] e_t^{ISOE} \tag{98}$$

A unit mass of monopolistic competitive retailers is included to incorporate sticky prices. They purchase intermediate wholesale goods from SMEs and SOEs at aggregate wholesale price P_t^W, then bundle them into the homogeneous final products. This is identical to the final goods producer sector from Chapter 3, which yields the same New Keynesian Phillips curve,

$$\tilde{\pi}_t = \beta E_t \tilde{\pi}_{t+1} + \frac{(1-\theta)(1-\theta\beta)}{\theta}(-\tilde{x}_t) \tag{99}$$

Where $\tilde{x}_t = \widetilde{p_t - p_t^w}$ implies the relative price between the aggregate wholesale price and retail price.

4.4 Data

Bayesian estimation from Chapter 3 requires eight macroeconomic time series data, which are: GDP, consumption, investment, labour, inflation, risk premium, capital investment return in SMEs' sector, and SOEs output. In this chapter, we exclude labour input in the Cobb-Douglas function; therefore, we do not require data for labour. As we use M2 as the intermediate target in the monetary policy rule, we include M2 (M_t) in our data sample. In addition, to conduct indirect inference estimation, we require capital inputs (K_t^{SOE} and K_t^{SME}) and capital investments (I_t^{SOE} and I_t^{SME}) in both SOEs and SMEs' sectors, SMEs output (Y_t^{SOE}). Sample periods are reduced to 84 periods due

to the data availability of capital investments in both sectors, which is between 1995Q1

and 2015Q4. It is noted that all data are per capita in real term, and the source of the

data is in the appendix.

4.5 Calibrated Parameters

There are two discount factors in this model, one is in the household sector, and the

other is in the banker sector. Household's discount factor β_H is set to be 0.9867, which

can be used to pin down the steady-state quarterly real deposit rate of 0.0135 or four

per cent expressed at an annual frequency. The steady-state rate for shadow banking

products R^{SB} can be pinned down as 1.0419 by the household discount factor and the

steady-state default rate, $F(\overline{w})$, is 0.0273. The steady-state reserve ratio, v is still set

to be 0.15, and the steady-state loan-to-deposit ratio, h is 0.75, which is the average

value of the ratio between 1992 and 2015. The banker's discount factor can be

calculated by using equation (83) at the steady-state, which is 0.9999. Bankers are

computed to be more patient than households since they offer both risk-free and risky

products but do not bear any risks. The risk from the shadow banking loans is

transferred to the households' sector. The remaining calibrated parameters are identical

to the first model in Chapter 3.

4.6 Indirect Inference Estimation

The DSGE framework in this chapter captures both the largest component in the

Chinese shadow banking system, WMPs, and the commercial bank shadow banking

activities[43]. Therefore, this model can be treated as a more general case to represent the shadow banking sector. It is meaningful to discover whether this model that is closer to reality can find the optimal estimated parameters that can pass the indirect inference.

The VAR auxiliary model is used in the evaluation estimate, and the choice of the auxiliary model includes output, inflation and money supply. The output is important in the auxiliary model because explaining output behaviour is essential in any macro model. Furthermore, quantity-based money supply uses money supply growth as the intermediate target to eventually stabilise both inflation and output. Therefore, including inflation, output and money supply in the auxiliary model are reasonable choices. As explained in the data section 4.4, the data employed in the estimated model is filtered by using one-sided HP filter.

Figure 6 Filtered Data for the Auxiliary Model

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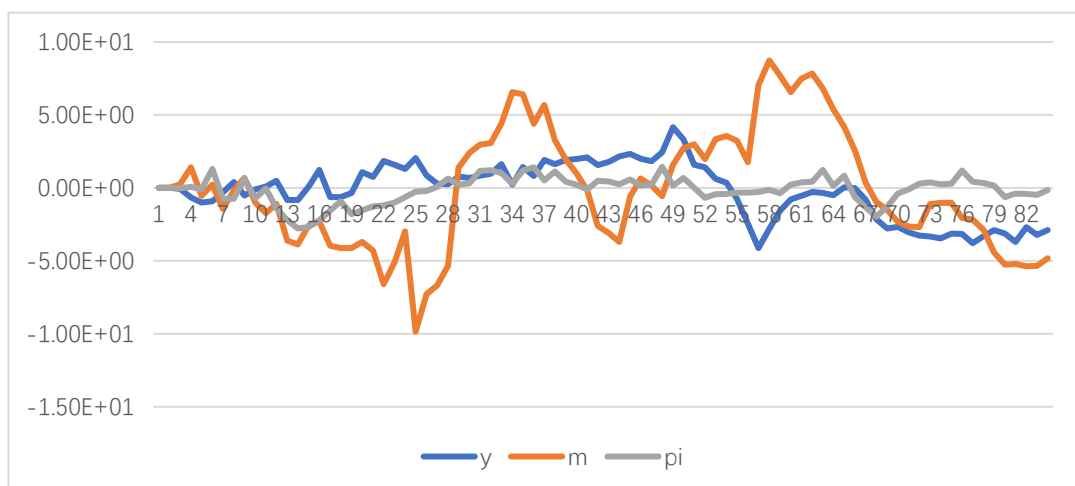
[43] Noting that in the first model, the lending channel between SOEs and SMEs still use commercial bank as the intermediary in reality; hence, the commercial bank shadow banking activities in this model also capture the function of entrusted loans.

As can be seen in figure 6, money growth is more volatile than GDP and inflation rate. The mean value of the money supply is -0.13 with standard deviation 4.05; the mean value of output is -0.23 with standard deviation 1.92, and the mean value of inflation rate is -0.14 with standard deviation 0.92.

The simulated annealing algorithm is used when conducting indirect inference estimation in order to find the best combination of estimated parameters that can possibly pass the test. I use the calibrated values as the starting point to estimate the model; this includes the capital share in both SMEs and SOEs sectors, α_1 and α_2, and the starting values are 0.4 and 0.5. Again, the higher value of the capital share in SOEs reflects a higher level of capital intensity. The parameter determines nominal price rigidity, θ, is set to be 0.75, which is consistent with Bernanke et al. (1999). In addition, the starting values for the investment adjustment costs in both sectors are set to be 0.25, which is consistent with the model in Chapter 3. For the monetary policy rule, the parameters ρ_m, a_π, a_y are set to be 0.9, 1.5 and 0.5. Finally, all the coefficients in the AR (1) shock processes are calibrated to be 0.9.

To determine whether any set of estimated parameters can pass the indirect inference test at the 95% confidence level, I use Transformed Wald statistics[44] where the critical value is 1.645. If the Transformed Wald statistics is less than the critical value, then the model can be treated as passing the test, or in other words, the model is not rejected

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[44] Transformed Wald statistics (TW) is calculated by the following formula, $TW = 1.648(\frac{\sqrt{2w^\alpha}-\sqrt{2k-1}}{\sqrt{2w^{0.95}}-\sqrt{2k-1}})$, where is the Wald statistics for the actual data and is the Wald statistics for the 95th percentile of the simulated data.

by the actual data. Hence, in the first procedure, I specify the auxiliary model; second, I start with the calibrated parameters and iterate the indirect inference test 10000 times by using simulation annealing searching algorithm; finally, I need to search whether any set of parameters from the 10000 results can pass the test. If there is at least one combination of parameters that can provide a Transformed Wald statistic value less than 1.645, then I conclude the model is not rejected by the actual data. If there is no statistic smaller than 1.645, then the model is rejected by the data.

The estimated results are shown in Table 6. On the firm side, the estimated value of α_1 is 0.47, which implies SMEs rely less on capital inputs in their production phase. Meanwhile, SOEs have more capital intensity with the estimated parameter, α_2 equals 0.54. The estimated value of price stickiness, θ, is 0.70, which is slightly smaller than the calibrated value. This indicates prices are adjusted around every three quarters in China. The investment-specific parameters in SOEs are estimated to be much higher than in the SMEs sector, 1.16 and 0.26 respectively. This strongly indicates a higher capital adjustment cost in SOEs capital investment. The last three estimated parameters are monetary policy-related, which are money growth smoothing parameter, inflation reaction parameter and output reaction parameter in the Quantity-based monetary policy rule. The inflation reaction parameter, a_π is estimated to be 1.04, which is smaller than the calibrated value, 1.5. This indicates that Chinese monetary policy matters less on inflation stabilisation.

Table 6 Indirect Inference Estimation

Estimated Parameters			
Definition	**Parameter**	**Calibration**	**Estimation**
Capital Elasticity in SMEs	α_1	0.40	0.47
Capital Elasticity in SOEs	α_2	0.50	0.54
Price Rigidity	θ	0.75	0.70
Investment Specific in SMEs	ϕ_K^{SME}	0.25	0.26
Investment Specific in SOEs	ϕ_K^{SOE}	0.25	1.16
Inflation Reaction in Taylor Rule	a_π	1.5	1.04
Output Reaction in Taylor Rule	a_y	0.5	1.22
Money Growth Smoothing	ρ_m	0.9	0.70
Transformed Wald statistics			23.91

However, the authority focuses more on output stabilisation since the estimated value is 1.22 (a_y), compared to the calibrated value, 0.5. The smoothing parameter, ρ_m, is smaller in the estimated result, which implies the monetary policy is less persistent than the initial guess. The estimated results are relatively consistent with the Bayesian estimation results in Chapter 3 apart from the price stickiness level, capital adjustment costs in SOEs, and output reaction in Taylor rule. The level of price stickiness is estimated to be higher in Bayesian approach (0.8256); capital adjustment cost is higher in Bayesian, but with a much lower level (0.2030) compared to the indirect inference results. Both estimation methods exhibit a higher level of output reaction in the Chinese economy, but the result is 0.5283 in Bayesian, while Indirect Inference reports 1.22. Further to the estimated results, the main aim of this exercise is to test whether

the model can pass the indirect inference test. Unfortunately, the Transformed Wald statistic is 23.91, which is much higher than the critical value 1.645, and this concludes that my model fails to pass the test against the actual data.

Compared to the calibrated parameters; the estimated parameters are mostly in line with the calibrated values. Estimated capital elasticity in the SMEs sector is 0.07 higher than the calibrated value, while estimated capital elasticity in the state sector is 0.04 higher. The estimated level of price stickiness is 0.05 lower than the calibrated parameter. Investment specific in SMEs is very close between calibration and estimation. However, it is much higher in SOEs sector with 1.16 estimated value compare to the 0.25 calibrated value. This implies a much higher adjustment costs for the state sector regarding the capital investment. In terms of the monetary policy reaction, the output indicates a more substantial effect (1.22 estimated parameter compare to 0.5 calibrated value), while inflation reaction has a smaller response (1.04 estimated parameter compare to 1.5 calibrated value). If we compare the estimated results between the first model and the one in this chapter, capital elasticity in both sectors are similar, SMEs are less capital intensity (0.42 in the first model and 0.47 in the second), while in the state sector, it is more capital intensity (0.45 and 0.54). Price rigidity is higher in the first model (0.82) compare to this model (0.70), which indicates that if commercial banks directly involved in the shadow banking activities, the model illustrates a lower level of stickiness. The output reaction in the monetary policy is much more significant if the model incorporates a quantity-based policy rule (1.22), while in the conventional rule, the estimated output reaction is only 0.52 even though

it is already higher than the calibrated value. Therefore, this second model indicates that the priority of the central bank monetary policy is to stabilise output rather than inflation.

4.7 Impulse Response Functions and the Properties of the Estimated Model

Figure 7 shows the estimated IRFs for a contractionary monetary policy shock. Similar to the previous scenario, the tighter monetary policy further restricts the source of financing for the private sector; therefore, the private investment (inv) drops, which causes the decreasing in the private net worth (n). SMEs have less net worth, which implies they have less collateral to borrow money from the banks; as a result, they must pay a higher level of risk premium (rp). Under a quantitative-based monetary policy, the model behaves with a lagged reaction of output (y, ysoe and ypoe), the tighter policy reduces outputs in both sectors but after the first period rather than a prompt response.

Figure 8 shows the estimated IRFs with a positive fiscal policy. Unlike the previous case that the positive fiscal policy shock increases the output, in the second model, output in both sectors decreases dramatically after the first period of the occurrence of the shock. Consistent with the previous model, expansionary fiscal policy crowds out the private investment (ipoe) and household's consumption (ch). It increases the net worth temporarily because of the stimulation package; however, it quickly drops the net worth (n) and increases the risk premium (rp) in the private sector since the public investment worsens the financial situation of the private sector.

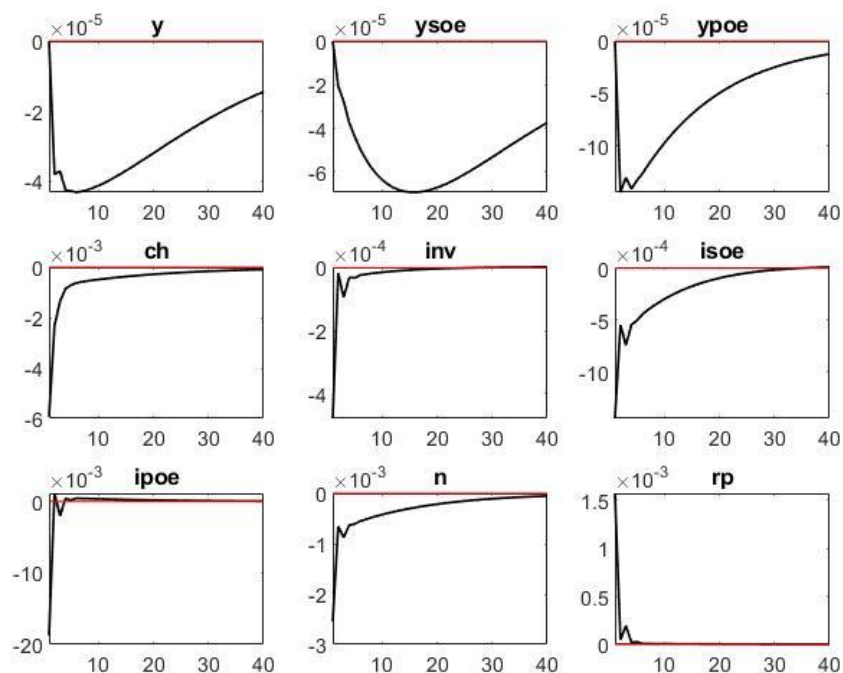Figure 7 Contractionary Monetary Policy Shock

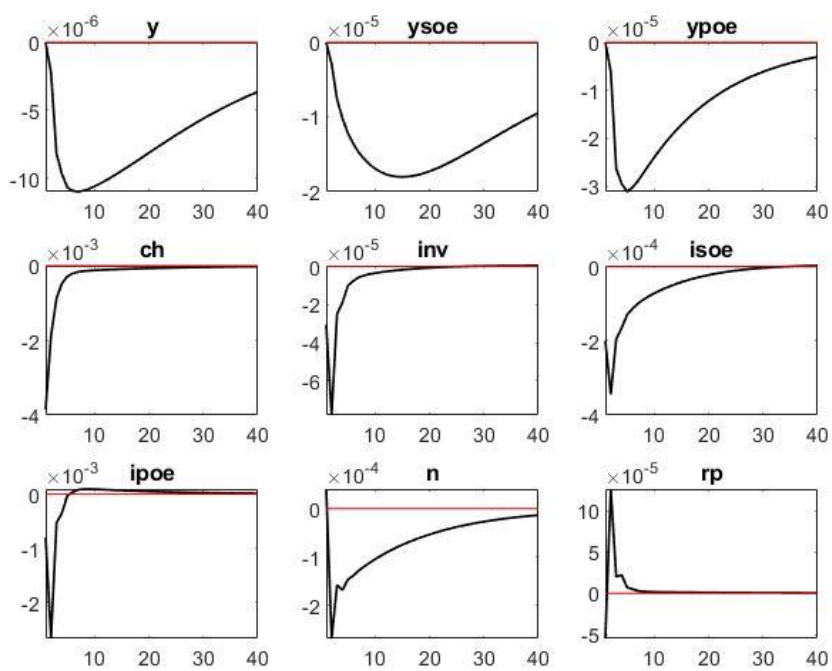Figure 8 Positive Fiscal Policy Shock

Table 7 shows the property of the estimated model, specifically, the forecast error variance decomposition of GDP, money supply and inflation rate. Productivity shocks in both sectors (35.58 per cent and 14.43 per cent) play dominant roles in determining the forecast error of the output, and the risk premium shock has the second-largest impact on forecasting error of GDP (20.51 per cent). Besides, investment-specific shock in the private sector accounts for 10 per cent of forecasting error on output. Monetary policy shock and SME investment-specific shock play a significant role in forecasting future money supply with the value of 30.44 per cent and 32.96 per cent, respectively. Reserve ratio shock ranks third place in influencing the forecast error (6.10 per cent). The model shows the risk premium shock has the most significant impact on forecasting inflation rate in the future period with 45.11 per cent and investment-specific shock in the private sector plays the second-highest impact (40.96 per cent). Monetary policy shock ranks the third but only accounts for 5.44 per cent.

Table 7 Variance Decomposition

	e_t^M	e_t^{aSOE}	e_t^{aSME}	e_t^{ISOE}	e_t^{ISME}	e_t^{τ}	e_t^S	e_t^G
Y_t	0.11	35.58	14.43	0.99	10.80	0.22	20.51	0.01
M_t	30.44	1.31	0.54	0.10	32.96	6.10	34.38	0.26
π_t	5.44	1.26	0.53	0.14	40.96	7.34	45.11	0.32

4.8 Conclusion

In this chapter, I incorporate WMPs and commercial bank shadow banking activity in a DSGE framework. Compared with the model in Chapter 3, this model is closer to

reality as it considers both the largest shadow banking instrument and banks' off-balance-sheet lending behaviour. Specifically, commercial banks offer both deposit account and shadow banking products to households. Households are free to choose which products they want to invest, and the differences are that deposit is risk-free but with lower interest payment, while shadow banking products (WMPs) are risky but with a higher return. Commercial banks make a profit from lending out the funds they obtain from households. However, due to safe-loan regulation, on the commercial banks' on-balance sheet, commercial banks are assumed to lend out the money obtained from deposits only to SOEs who are treated as risk-free borrowers. Banks have the incentive to circumvent the burdensome regulations; therefore, they create off-balance-sheet lending channels by cooperating with trust companies. Basically, trust companies issue WMPs, and banks sell it to households. The transactions then do not appear on the banks' balance sheet. These funds are not subject to the banking regulation and can be lent to risky firms, such as SMEs.

The aim of developing this model is that I want to test whether this model can be rejected or not rejected by the actual data. Bayesian estimation does not test the model against the actual data; hence, indirect inference estimation is applied to fulfil the purpose. Output, inflation and money supply are adopted in the VAR auxiliary model. The idea is using both actual data and simulated data of output, inflation and money supply in the same VAR model to work out the moments that represent the properties of the real data and the model; then, to compute the Transformed Wald statistics to search whether the estimated parameters can pass the indirect inference test. The

results in Section 4.6 show that, unfortunately, the estimated results fail to pass the

test, and the model is rejected by the actual data; it cannot mimic the data. This may

indicate the model possibly misses some important information from the data; hence,

in the next chapter, an essential feature of the Chinese economy, the housing market,

is incorporated into the model to see whether the performance can be improved.

Appendix 4A Log-linearised Equations

The main difference of this model is the money market and the banking sector; the rest

of the model is the same as the first model in Chapter 3.

Money Demand

$$\tilde{C}_t^H = \frac{C^H}{M} \tilde{M}_t + \beta^H \tilde{C}_{t+1}^H$$

Money Supply

$$\tilde{g}_{m,t} = \rho_m \tilde{g}_{m,t-1} + (1 - \rho_m)(a_\pi \tilde{\pi}_t + a_y \tilde{y}_t) + \tilde{e}_{m,t}$$

$$\tilde{g}_{m,t} = \tilde{M}_t - \tilde{M}_{t-1}$$

Banker

$$\tilde{R}_{t+1}^L = \frac{R^D}{(1-v)hR^L} \tilde{R}_{t+1}^D - (\frac{R^D}{(1-v)hR^L} - 1)(\tilde{C}_{t+1}^B - \tilde{C}_t^B) + \frac{v(R^L - 1/\beta^B)}{(1-v)R^L} \tilde{e}^{\varepsilon_t^v}$$

Appendix 4B List of F.O.Cs

Households

$$\frac{1}{M_t} + \beta_H \frac{1}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H}$$

$$\beta_H \frac{R_t^D}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H}$$

$$\beta_H[1 - F(\bar{w}_t)] \frac{R_t^{SB}}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H}$$

Banker

$$\frac{C^B_{t+1}}{\beta_B C^B_t} = \frac{[R^D_{t+1} - R^L_{t+1}(1 - ve^{\varepsilon^v_t})h]}{[1 - (1 - ve^{\varepsilon^v_t})h]}$$

SMEs (Note that N in Chapter 4 implies net worth)

$$s_t = E_t\left(\frac{R^K_{t+1}}{R^L_{t+1}}\right) = \frac{1 - N_{i,t}/Q^{SME}_t K^{SME}_{t+1}}{\Gamma(\bar{\omega}) - \mu G(\bar{\omega})}$$

$$E_t(R^K_{t+1}) = \frac{\alpha_1 \frac{P^{w,SME}_{t+1}}{X_{t+1}P^W_{t+1}} \frac{Y^{SME}_{i,t+1}}{K^{SME}_{i,t+1}} + Q^{SME}_{t+1}(1 - \delta^{SME})}{Q^{SME}_t}$$

SOEs

$$R^L_{t+1} = \frac{\alpha_2 \frac{P^{w,SOE}_{t+1}}{X_{t+1}P^W_{t+1}} \frac{Y^{SOE}_{j,t+1}}{K^{SOE}_{j,t+1}} + Q^{SOE}_{t+1}(1 - \delta^{SOE})}{Q^{SOE}_t}$$

Capital Goods Producers

$$\frac{1}{Q^{SOE}_t} = \left[1 - \phi^{SOE}_K\left(\frac{I^{SOE}_t}{K^{SOE}_{t-1}} - \delta^{SOE}\right)\right] e^{ISOE}_t$$

$$\frac{1}{Q^{SME}_t} = \left[1 - \phi^{SME}_K\left(\frac{I^{SME}_t}{K^{SME}_{t-1}} - \delta^{SME}\right)\right] e^{ISOE}_t$$

Final Goods Producers

$$\sum_{k=0}^{\infty} \theta^k E_t\left\{\left[\Lambda_{t,k}\left(\frac{P^*_t}{P_{t+k}}\right)^{\epsilon} Y^W_{t+k}(z)\left[\frac{P^*_t}{P_{t+k}} - \left(\frac{\epsilon}{\epsilon - 1}\right)\frac{P^W_{t+k}}{P_{t+k}}\right]\right]\right\} = 0$$

$$P^*_t = \frac{\epsilon}{\epsilon - 1} \frac{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k}\left(P^W_{t+k}P^{-(1-\epsilon)}_{t+k} Y_{t+k}\right)}{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k}\left(P^{-(1-\epsilon)}_{t+k} Y_{t+k}\right)}$$

Appendix 4C Steady State Values From the Model

| Variables	Steady State Values
C^H	2.2634
C^B	0.7520
C^E	0.1151
I	0.6778
G	0.6602
M	170.1806
Y	4.7154

Y^{SME}	1.8862
Y^{SOE}	2.8293
I^{SME}	0.1710
I^{SOE}	0.5067
K	19.3644
K^{SME}	4.8860
K^{SOE}	14.4785
N	2.1987
R^D	1.0101
R^K	1.0713
R^L	1.0211
R^{SB}	1.0419

Appendix 4D Data

The source of quarterly data of M2, capital investment in SOEs and SMEs is from

Chen et al. (2016). The time series of M2 is derived and seasonally adjusted from the

year-over-year growth rates published by the PBoC. Capital investment in SOEs is

named as 'NominalSOEGFCF (gross fixed capital formation: SOEs)'; and capital

investment in SMEs is 'NominalPrivGFCF (gross fixed capital formation: private

sector—excluding government, households, SOEs, and other non-SOEs, for example,

joint ventures)'. Capital inputs (K_t^{SOE} and K_t^{SME}) are constructed according to the

capital accumulation functions in each sector. Finally, SMEs output (Y_t^{SOE}) is obtained

from total output subtract the output in SOEs.

Raw Data Description (RMB)			
Variable	Minimum	Maximum	Mean
M2 (Billion)	5241.57	139738.42	448423.00
SOEs Capital Inputs (Billion)	1201.66	6229.26	2394.21
SMEs Capital Inputs (Billion)	565.47	2092.24	967.39
SOEs Capital Investment (Billion)	217.77	1453.82	661.85
SMEs Capital Investment (Billion)	73.23	2248.20	666.08

Raw Data (84 Periods)
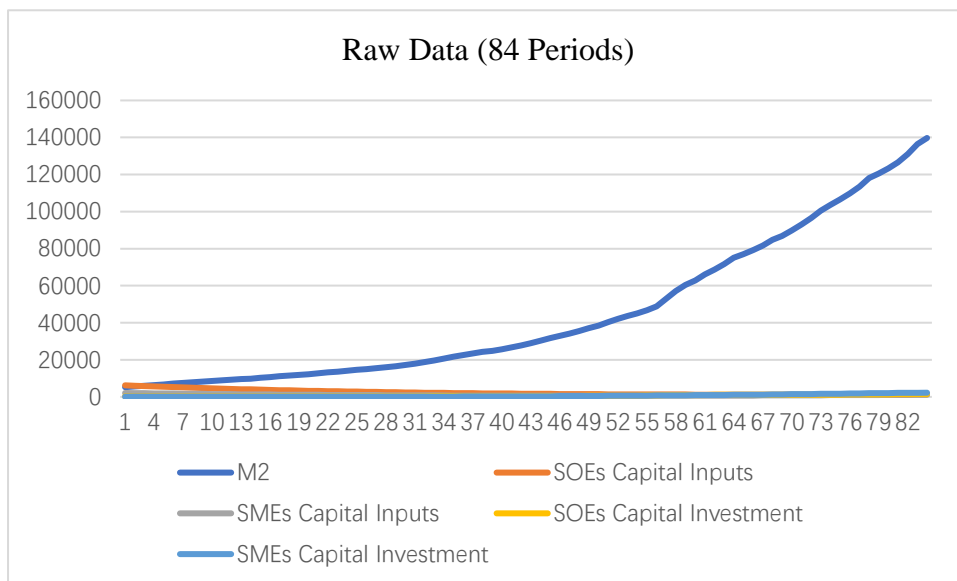
Chapter 5 Chinese Shadow Banking with the Housing Market

5.1 Introduction

Due to restrictive capital controls in China, households and firms cannot freely invest their money abroad, therefore, they must seek investment opportunities domestically, for example, bank deposits, stock market and housing market. Figure 9 shows the national inflation rate with nominal bank deposit rate from 2003 to 2013. As can be seen that inflation rate fluctuates dramatically between 2% and 8%, while bank deposit rate stays in a narrow range between 2% and 4%. This is because the deposit rate is regulated by the central bank in China. Due to this reason, national inflation rate surpasses the deposit rate in 2004, 2008-2009, and 2011-2012, resulting in the negative

Figure 9 Bank Deposit and Inflation Rate
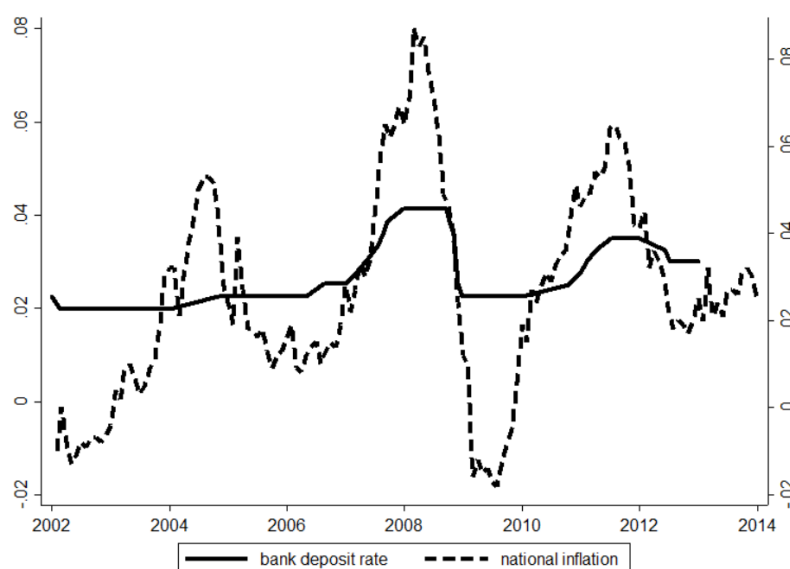
Source: Cited from Fang et al (2015)

real deposit rate. In addition, the average real deposit rate in 2003-2013 is 0.01%. Consequently, the low real return on bank deposit motivate households to seek for alternative investment vehicles in the recent decade.

Households can also invest in the stock market inside China. However, compared to the US market, the stock market is still underdeveloped and small by size. China has two stock markets that established in the early 1990s, Shanghai and Shenzhen stock markets. Figure 10 depicts the Shanghai Stock Market Index for 2003-2013. There is substantial stock market boom at the beginning of 2006 from 1200 to the peak of 6092 in October 2007. However, in conjunction with the global financial crisis in 2008, it

Figure 10 Shanghai Stock Market Index

Source: Cited from Fang et al (2015)

experiences a bust in October 2008. Since then, the Shanghai Stock Market Index fluctuate between 2000 and 2003. During this period, the annual return is 7.3% but with 51.5% volatility. Hence, the large volatility in the underdeveloped stock market

prevent households and firms to invest too much in the stock market.

During the same period, the annual returns of the housing among all cities are much higher than any other investment vehicles in China and with relatively small volatility. Table 8 summarises the annual returns in all first, second, and third-tier cities. The average return is 15.7% annually and the volatility is only 15.4% in tier 1 cities. Second tier cities offer an average 13.4% annual return with volatility of 9.9%. Tier 3 cities provide lowest return of 11% but also with the smallest volatility of 7.5%.

Table 8 Housing Return and Volatilities

Full Sample (2003-2013)			
	Mean	Std. Dev.	Skewness
First-Tier Index	.157	.154	-.674
Second-Tier Index	.135	.0989	.564
Third-Tier Index	.110	.075	.092

Source: Cited from Fang et al (2015)

Considering the effect of the financial crisis in 2007-2009, the volatility of housing return has been remarkably low with much attractive return compare to the other types of investment opportunities. Therefore, housing investment becomes the most attractive investment vehicle than bank deposits and the stock market in China.

The stable return in the housing market leads to further housing booms in China, and the booming always associated with credit expansion. Figure 11 shows the ratio of real estate mortgage loans to total bank loans in the period of 2010-2017. It clearly shows that the ratio remains very high level during the sample period, which increases from 51.7% in 2010 to 75.9% in 2017.

Figure 11 Mortgage Loans Over Total Bank Loans
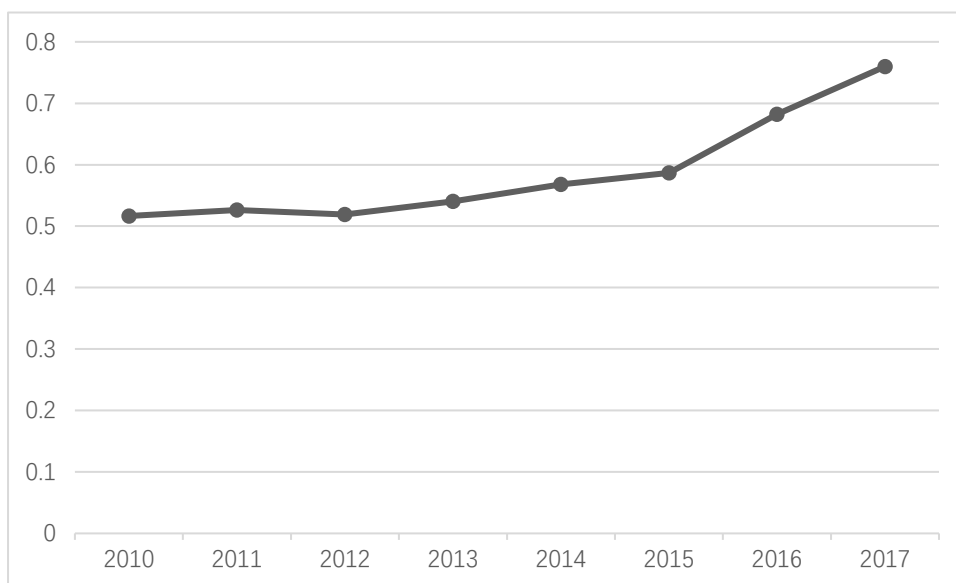
Source: CEIC

The financial system in China is highly regulated by the government. Credit policies have been used to either stimulate or prevent the housing market from potentially overheating. To guard against the global financial crisis in late 2008, the central government encouraged housing market by implementing administrative measures and guidelines, such as lowering minimum down payment ratio to 20% (Bian and Gete, 2015), and even introducing the first pilot securitisation programs (Koss and Shi, 2018). Moreover, commercial banks have been using financial innovations or shadow banking activities; for example, WMPs to circumvent heavy bank regulation, as mentioned in Chapter 4.

Fontevecchia (2015) claims that the credit surge by the government has provided channels for weak borrowers, who are normally rejected by commercial banks, and encouraged them to increase expenditure in real estate market. This credit expansion

is similar to expansion in the US housing market before the 2007-2009 financial crisis, as explained by Favilukis et al. (2017). Allen et al. (2019) show that a large proportion of nonaffiliated loans (nonaffiliated entrusted loans) to SMEs have eventually flowed into the real estate industry, probably causing problematic performance. Table 9 summarises the statistics from Allen et al (2019) for both the affiliated and nonaffiliated loans received by the real estate and construction sector within the sample period of 2004-2013. The sum of the entrusted loans accounts for 58.3% of total entrusted loans, which clearly shows most of the funds in entrusted lending market flows into the real estate and construction sectors during the sample period.

Table 9 Entrusted Loans to Real Estate and Construction Sectors (Billion)

	Loan Amount	Proportion to the Total Entrusted Loans
Affiliated Entrusted Loans	77.8	12.2%
Nonaffiliated Entrusted Loans	294.3	46.1%

Source: Cited from Allen et al. (2019)

There has been growing concern about the Chinese housing market boom. The main concern is whether meltdown of the housing market may damage the Chinese economy, possibly resulting in similar following footsteps to Japan in the early 1990s and suffering economic downturn for many decades. The economic loss in China could further generate contagious effects on the rest of the world. Given the importance of housing market in the Chinese economy and credit expansion in the shadow banking sector, this exercise aims to add the housing market into the DSGE framework that developed from the two previous chapters and test whether this model

can present a higher chance of passing the indirect inference test. Section 5.2 briefly reviews the Chinese housing market. Section 5.3 describes the additional part of the model related to the housing market. Section 5.4 provides the estimated results, and section 5.5 concludes.

5.2 Related Background

The real estate market is a key component in the financial system of China. Housing sales in China reached 13.37 trillion RMB, which was approximately equivalent to 16.4% of China's GDP in 2017. The housing market is closely connected to the financial system through several channels. First, due to a lack of other quality investment opportunities for both households and firms and underdeveloped capital market, housing holdings have been the largest aspect of asset portfolios. More than 70% of households' wealth is in the housing market (Xie and Jin, 2015). Second, local governments rely heavily on land[45] sale to generate fiscal income following the 'tax reform' in 1994 (Shu-ki and Yuk-shing, 1994). Local authorities can also use future land sale as collateral to borrow money through 'Local Government Finance Vehicles' (LGFVs). Third, since the global financial crisis in 2007, firms, especially well-capitalised firms, rely on real estate assets as collateral to access bank credit. Finally, banks have accumulated real estate risks through lending to households, real estate developers, local governments, and firms backed by real estate assets. Property-related bank loans totalled 55 trillion RMB in the third quarter of 2016, which account for 25%

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[45] In China, all buildable land is belonged and supplied by the government.

of banking assets in China, in which loans to housing developers and firms backed by

real estate assets accounted for 37 trillion RMB (Liu and Xiong, 2018).

According to Federal Housing Finance Agency data[46], between 1996 and 2006,

housing index maintained 5% annual growth rate but turned to averagely 6.4%

negative growth rate during 2007 and 2012. Annual construction exceeded more than

1.9 billion new housing units during 2005 and 2006 but decreased to only 0.7 million

units per year averagely between 2009 and 2013. Although the change in the US

housing market appears dramatic after the financial crisis, compared to the Chinese

real estate boom, it still appears relatively stable. Fang et al. (2015) show that the

growth rate of real housing prices in China from 2003 to 2013 was 13.1% annually,

which is persistently faster than per capita disposable income growth. The greatest

cost for housing developers is land; between 2004 and 2015, real land prices increased

five times in 35 large cities (Wu et al., 2015). More than 100 billion square feet of

floor space, or 74 square feet for each person, was added by Chinese housing

developers from 2003 to 2014 (Chivakul et al., 2015).

The mainstream explanations for rapidly increasing housing prices in China at national

level include economic development, government intervention in land supply, and

irrational investment (Wang and Zhang, 2014; Hui and Wang, 2014; Liu et al., 2016).

However, housing prices increase largely unevenly across China's cities. Cities in

China are typically classified as four levels: tier 1, tier 2, tier 3 and tier 4. Basically,

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[46]   FEDERAL HOUSING FINANCE AGENCY https://www.fhfa.gov/AboutUs/Reports/ReportDocuments/HPI_2019Q2.pdf

GDP in tier 1 cities are over two trillion RMB; in tier 2 cities, GDP is over 70 billion RMB in mainly large, industrialised areas with relatively strong, well-established economies. Tier 3 cities are less wealthy but still relatively large by western standard with GDP over 20 billion, while tier 4 cities are the most underdeveloped areas with GDP less than 20 billion RMB.

Tier 1 cities only include four most developed areas: Beijing, Shanghai, Guangzhou and Shenzhen. Housing prices have badly experienced high hikes over time in the first-tier cities. Figure 12 depicts the monthly housing price indices in all four tier 1 cities with two measures of households' purchasing power, per capita Gross Regional Product (GRP)[47] and urban disposable income[48]. As can be seen, in Panel A, Beijing experienced a dramatic housing price rise since January 2003, which has increased 660% within 10 years. Noticing that there are two price drops, one starts from May 2008, and continued to around March 2009; another is between May 2011 and June 2012. The first price drop represents a 13% drop in housing price which is coincided with the global financial crisis. The housing price index fluctuates between the vertical interval of 5.99 and 6.67 in the second episode of downward movement. In addition, both measurements of households' purchasing power share similar growth from 2003 to 2013, which substantially smaller than the housing price appreciation in Beijing.

Panel B shows the overall housing price in Shanghai. It is more modest than that in

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[47] The per capita value of output in the whole city.

[48] The per capita income received by urban residents of the city.

Beijing, which is increased from index 1 in 2003 to 4.43 in 2013. However, Shanghai started faster than Beijing, housing price is doubled by April 2005, while Beijing does not double until August 2006. There are two other price adjustments after 2005. Housing price pricks up from March 2007 and reaches an index level of 2.72 in August 2008, and slightly drops down to 2.41 by the end of 2008. The second episode of rising starts from June 2011 with index 4.27 to 4.43 by March 2013. The growth of households' disposable income is also smaller than the house price but is much closer than that in Beijing. GRP per capita is doubled in the sample period but still exhibits more modest growth in Shanghai.

Guangzhou and Shenzhen experience similar path of the housing price movements. Between 2003 and 2013, the index increases from 1 to 5.1 in Guangzhou, while in Shenzhen, it increases from 1 to 3.65. The most severe price drop in both cities start from October 2007 and January 2009, index drops from 2.97 to 1.82 in Shenzhen, which represents for a 39% price correction. While index drop from 3.08 to 2.38 in Shenzhen, which indicates a 23% price correction. The reason of the dramatic drop in the housing market is because of the global crisis since both cities are the world's largest manufacturing export center. Disposable income grows differently in both cities, it increases approximately three times in Guangzhou, while it only rises 68% in Shenzhen during the same period.

Figure 12 Housing Prices in Tier 1 Cities
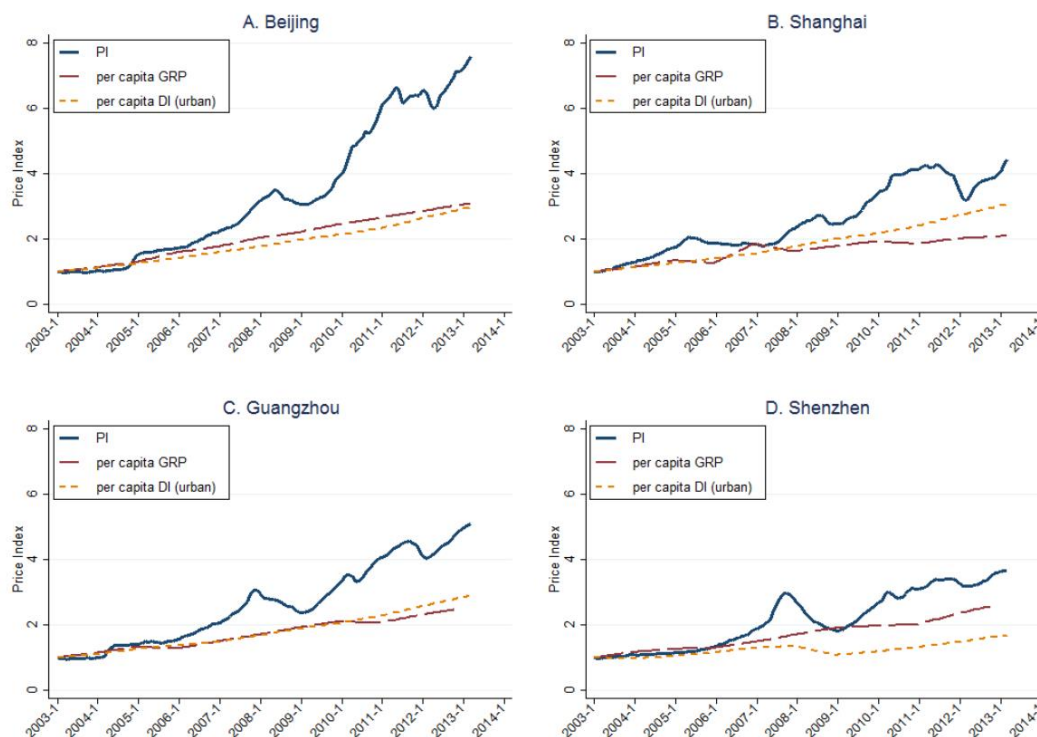
Source: Cited from Fang et al (2015)

One of the reasons for this high price in the first-tier cities is the high proportion of non-local residents. Foreign migrants are too scarce to influence the domestic housing market in China, but the migration from lower-tier cities to first-tier cities is massive. The proportion of non-local residents was more than 40% in most tier cities and, in Shenzhen, the rate even exceeded 80% (Wang et al., 2017).

There are 35 tier 2 cities, and these can be treated as the second choice for migration with higher income and more working opportunities compared to tier 3 and 4 cities. Figure 13 shows the housing price indices for second and third tier cities, which also depicts the monthly housing price indices with the two measures of households' purchasing power. Although the magnitude of the housing price appreciation in

second-tier cities is smaller than the first-tier cities, the appreciation is 292%, which

is still substantial by any standard. This is even larger than the housing price

appreciations in both US and Japan housing crisis. However, Panel A shows a

remarkable growth in measures of purchasing power, which may imply the

fundamental reason of appreciation is income growth, or GRP growth.

Figure 13 Housing Prices in Tier 2&3 Cities
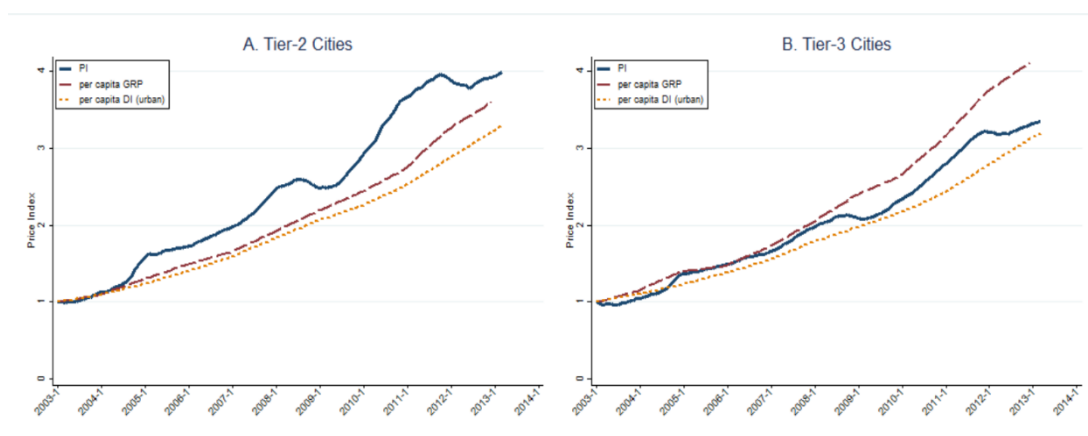
Source: Cited from Fang et al (2015)

Apart from migration at city level, central policies also have considerable influence

on housing prices. The four-trillion stimulation plan immediately after the 2007-2009

global crisis prompted a rapid surge in development of the real estate industry. Bai et

al. (2016) document that most stimulus planning was implemented by local

government through LGFVs. Moreover, large amounts of fund flowed unnecessarily

into real estate developers and other infrastructure projects (Ueda and Gomi, 2013).

To tighten the potentially overheated real estate industry, the Chinese government

introduced a series of policies to restrict the market. This has included new national

10 article[49] in 2010 and new national 8 article[50] in 2011. During the same period, monetary policy became tighter to restrict the overall bank credit for firm financing. The housing market began to cool down rapidly after the regulations, which even caused the central government to worry that the policies might be too tight (Koss and Shi, 2018). Hence, several relaxation measures were introduced to stabilise the cooling market and ensure the prices rose back to the steady value in 2012. Since then, housing prices in several tier 1 and tier 2 cities bounced back. Beginning in 2013, property prices started to deviate largely across a different notch of cities. Tier 1 and tier 2 cities experienced a large boom in real estate market, while tier 3 and tier 4 remained steady. Response from the central government has been to introduce different policies in different areas, and the related policy is known as national 5 article[51].

Although national 5 was designed to slow down the overheated market, the central policy of encouraging sale and reduction of housing inventories, has, to some extent, conflicted with the article. Therefore, the influence of the policies varies among different municipal levels, and largely depends on land supply. For the tier 1 and heated tier 2 cities with a higher level of urbanisation but restricted land supply, housing price has continued to increase at a steady acceleration since demand outweighed supply in the housing market. On the other hand, ghost town[52] in lower-

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[49] Stop providing mortgage for purchasing the third house; restrict purchasing from non-local speculators http://house.people.com.cn/GB/11400758.html

[50] Down payment for purchasing second house increased to 60% http://finance.sina.com.cn/focus/gbt_2011/

[51] In tier 1 and tier 2 cities, down payments increased to 30% for first home and 70% for second home. http://www.gov.cn/zwgk/2013-03/01/content_2342885.htm

[52] Newly constructed but mostly empty urban districts, usually in areas far away from traditional city centres.

tier areas has become more common. From 2014 to 2018, housing market has experienced very different regulation, including both stimulating and tightening processes. Starting from June 2014, a large number of non-tier 1 and heated tier 2 cities have cancelled house purchase quota policy[53] sequentially. However, market reaction was still very poor.

In September 2014, the central government recommenced the loosening policy, mainly relaxing the loan limit on purchasing a second house[54]. In March 2015, housing regulation continued relaxing, down payment for a second house decreased to 40%, and further decreased to 25% and without house purchase quota policy in September, since housing vacant rate remained very high. In the following period, down payment for the first house purchase decreased to 20% and 30% for a second house. Housing price began to recover in tier 3 and tier 4 cities due to the policy of rebuilding shanty areas in 2016 (Li et al., 2018). The new round of regulatory measures was introduced again by the central government in 2017 to curb rapid price rises. However, Koss and Shi (2018) argue that the policies were trying to freeze the market to avoid both dramatic increase and decrease in the market rather than changing the fundamentals of the housing market, particularly speculative activities.

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[53] One of the policies in the National 10 article: each family can only purchase one new commercial house.

[54] Summary of housing regulations between 2012 and 2017 https://www.tuliu.com/read-66385.html

5.3 Model Framework

The model in this chapter is constructed based on the second model in Chapter 4. The only difference is the housing market. However, the housing market is different from the Iacoviello (2005) type, in which impatient households borrow money from patient households and invest in housing. The Iacoviello-type financial friction incorporates two types of households and embeds only residential property in the conceptual framework. However, in China, households are not allowed to use property as collateral to borrow, on the contrary, firms, primarily private firms, can use housing as collateral to enhance their ability to get access to the credit. Thus, it is essential to include the housing sector in the production sector rather than just the household's sector.

Based on the above facts, one representative household remains in my model and can freely choose to save money in the deposit account or the shadow banking products. Bankers obtain money from households and lend out money to SOEs through on-balance-sheet channel and to SMEs through off-balance-sheet channel. As mentioned in section 5.2, property-related loans to entrepreneurs reached 37 trillion RMB out of a total 55 trillion RMB. Thus, in my model, I assume SMEs invest in both capital and housing and use both as inputs to produce. The rest of the model is the same as the model in Chapter 4.

5.3.1 Off-balance-sheet Lending Contract

The representative banker maximises the utility function,

$$max\, E_0 \sum_{t=0}^{\infty} \beta_B^t \ln C_t^B \tag{90}$$

Subject to the bankers' flow of budget,

$$
\begin{aligned}
C_t^B + R_{t-1}^D D_{t-1} &+ [1 - F(\overline{w}_t)]R_{t-1}^{SB} SB_{t-1} + L_t^{SOE} + L_t^{SME} \\
&= D_t + SB_t + R_{t-1}^L L_{t-1}^{SOE} + [1 - F(\overline{w}_{t-1})]R_{t-1}^{SB} L_{t-1}^{SME} \\
&+ (1 - \mu) \int_0^{\overline{w}} w dF(w)\,(R_t^K Q_{t-1}^{SME} K_t^{SME} + R_t^H Q_{t-1}^H H_t)
\end{aligned}
\tag{91}
$$

The only difference in the budget constraint from the previous model is the no arbitrary

condition, in period $t + 1$, the condition can be written as,

$$
\begin{aligned}
[1 - F(\overline{w})]R_{t+1}^{SB} L_{t+1}^{SME} &+ (1 - \mu) \int_0^{\overline{w}} w dF(w)\,(R_{t+1}^K Q_t^{SME} K_{t+1}^{SME} + R_{t+1}^H Q_t^H H_{t+1}) \\
&= R_{t+1}^L L_{t+1}^{SME}
\end{aligned}
\tag{92}
$$

Where

$$R_{t+1}^{SB} L_{t+1}^{SME} = \overline{w}(R_{t+1}^K Q_t^{SME} K_{t+1}^{SME} + R_{t+1}^H Q_t^H H_{t+1}) \tag{93}$$

The contractual return of the loans to SMEs, $R_{t+1}^{SB} L_{t+1}^{SME}$, equals the sum of capital and

housing return times the threshold. The rate of the housing return is R_{t+1}^H, and house

price is Q_t^H. The amount of housing inputs is H_{t+1}.

The amount of loans to SMEs is,

$$L_{t+1}^{SME} = \varphi\left(Q_t^{SME} K_{t+1}^{SME} + Q_t^H H_{t+1}\right) - N_{t+1} \tag{94}$$

the amount of loans is determined by how much money SMEs need to purchase capital

and housing subject to the loan-to-value ratio[55], φ, and the net worth, N_{t+1}. Combining

equations (3), (4) and (5), the risk premium can be derived as,

$$\frac{R_{t+1}^K R_{t+1}^H}{R_{t+1}^L} = \frac{[\varphi(Q_t^{SME} K_{t+1}^{SME} + Q_t^H H_{t+1}) - N_{t+1}]/\left(\frac{Q_t^{SME} K_{t+1}^{SME}}{R_{t+1}^H} + \frac{Q_t^H H_{t+1}}{R_{t+1}^K}\right)}{\left[[1 - F(\overline{w})]\overline{w} + (1 - \mu)\int_0^{\overline{w}} w dF(w)\right]} \tag{95}$$

And the net worth evolution in the SMEs sector is modified as,

$$N_{t+1} = \gamma R_t^K Q_{t-1}^{SME} K_t^{SME} + R_t^H Q_{t-1}^H H_t - \left(R_t^L + \frac{\mu \int_0^{\overline{w}} w dF(w) \; (R_t^K Q_{t-1}^{SME} K_t^{SME} + R_t^H Q_{t-1}^H H_t)}{\varphi(Q_{t-1}^{SME} K_t^{SME} + Q_{t-1}^H H_t) - N_t}\right) \tag{96}$$
$$[\varphi(Q_{t-1}^{SME} K_t^{SME} + Q_{t-1}^H H_t) - N_t]$$

recalling that all equations are similar to the previous chapter with only one

modification, the housing investment.

5.3.2 Small-and-medium Sized Enterprises

SMEs use both capital and housing as inputs to produce intermediate output, and the

profit function can be constructed as,

$$\pi_{t+1}^{SME} = \frac{P_{t+1}^{w,SME}}{X_{t+1} P_{t+1}^w} Y_{t+1}^{SME} - R_{t+1}^K Q_t^{SME} K_{t+1}^{SME} - R_{t+1}^H Q_t^H H_{t+1}$$
$$+ Q_{t+1}^{SME}(1 - \delta_K^{SME}) K_{t+1}^{SME} + Q_{t+1}^H (1 - \delta_H^{SME}) H_{t+1} \tag{97}$$

In each period, SMEs first invest in capital and housing and use them to produce goods.

By the end of the period, SMEs sell back undepreciated capital and housing back to

capital goods producer and housing goods producer respectively, in which the housing

depreciation rate is denoted as, δ_H^{SME}. The production function is,

$$Y_{t+1}^{SME} = A_{t+1}^{SME} (K_{t+1}^{SME})^{\alpha_1} (H_{t+1})^{\beta} \tag{98}$$

Solving the profit maximisation problem with respect to capital demand and housing

---

[55] The maximum loan-to-value ratio has been 80% in China.

demand yields,

$$R_{t+1}^K = \frac{\alpha_1 \frac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^w} \frac{Y_{t+1}^{SME}}{K_{t+1}^{SME}} + Q_{t+1}^{SME}(1 - \delta_K^{SME})}{Q_t^{SME}}$$

(99)

And

$$R_{t+1}^H = \frac{\beta \frac{P_{t+1}^{w,SME}}{X_{t+1}P_{t+1}^w} \frac{Y_{t+1}^{SME}}{H_{t+1}} + Q_{t+1}^H(1 - \delta_H^{SME})}{Q_t^H}$$

(100)

Equation (10) determines the capital return, and equation (11) determines the housing return.

5.3.3 Housing Goods Producers

The representative housing goods producer maximises profit by following the following profit function,

$$\pi_t^H = Q_t^H H_t - I_t^H$$

(101)

And the housing accumulation function is,

$$H_t = (1 - \delta_H^{SME})H_{t-1} + e_t^H \left[I_t^H - \frac{\phi_H}{2} \left(\frac{I_t^H}{H_{t-1}} - \delta_H^{SME} \right)^2 H_{t-1} \right]$$

(102)

which is similar to the capital accumulation technique with the housing investment-specific shock, e_t^H. After solving the profit maximisation problem, we obtain the Tobin's Q equation for housing, which is formed as,

$$\frac{1}{Q_t^H} = \left[1 - \phi_H \left(\frac{I_t^H}{H_{t-1}} - \delta_H^{SME} \right) \right] e_t^H$$

(103)

5.4 Indirect Inference Estimation

The choice of the VAR auxiliary model is slightly different from the previous one due to the existence of the housing market. The CPI inflation rate is replaced by the

housing price inflation as I want to test whether adding a housing market in the model can improve the model performance. The source of housing price is the National Bureau of Statistics of China. The sample period starts from 1995Q1 to 2015Q4 as in the previous chapters. Apart from the loan-to-value ratio ($\varphi = 0.80$) in this model, the rest of the calibrated parameters are identical as before. The Indirect Inference estimation results after 5000 iterations are shown below,

Table 10 Indirect Inference Estimation

Estimated Parameters			
Definition	**Parameter**	**Second Model**	**This Model**
Capital Elasticity in SMEs	α_1	0.47	0.48
Housing Elasticity in SMEs	β	--	0.28
Capital Elasticity in SOEs	α_2	0.54	0.58
Price Rigidity	θ	0.70	0.98
Investment Specific in SMEs	ϕ_K^{SME}	0.26	1.06
Housing Specific in SMEs	ϕ_H	--	1.61
Investment Specific in SOEs	ϕ_K^{SOE}	1.16	1.86
Inflation Reaction in Taylor Rule	a_π	1.04	4.17
Output Reaction in Taylor Rule	a_y	1.22	3.43
Money Growth Smoothing	ρ_m	0.70	0.78
Transformed Wald statistics		23.91	7.87

The estimated results show similar results on capital elasticity both in SMEs and SOEs sectors (0.48 and 0.58). The housing elasticity in SMEs is estimated as 0.28. The level of price stickiness jumped to 0.98, which shows a much higher rigid in adjusting the

retail price in this model. Although the capital adjustment cost in SMEs is estimated

to be much higher than the previous model (1.06 versus 0.26), it remains relatively

smaller than the SOEs sector (1.86). The greatest change is in the monetary policy;

both inflation reaction and output reaction exhibit much higher levels (4.17 and 3.43)

compared to the model without housing market (1.04 and 1.22). However, the

smoothing parameter, ρ_m, remains at a similar persistence level (0.78). As can be seen

from Table 10, the performance of this model has a significant improvement with the

Transformed Wald statistic 7.87, compared to the previous model, 23.91. This implies

that adding housing market in the framework brings the model closer to reality.

Unfortunately, the results are still not sufficiently good to pass the Indirect Inference

test, as the critical value is 1.645.

5.5 The Property of the Estimated Model and the Impulse Response Functions

Table 11 Variance Decomposition

	e_t^M	e_t^{aSOE}	e_t^{aSME}	e_t^{ISOE}	e_t^{ISME}	e_t^{τ}	e_t^S	e_t^G	e_t^H
Y_t	1.93	1.50	16.55	47.75	18.66	0.00	0.00	0.01	13.60
C_t^H	0.32	1.40	18.48	58.24	18.48	0.00	0.00	0.00	3.08
I_t	1.12	2.38	3.3	55.89	23.05	0.04	0.76	0.03	13.43
π_t	2.19	2.04	26.15	25.54	25.04	0.00	0.01	0.01	19.02
I_t^H	0.86	2.27	0.24	53.59	4.54	0.04	0.89	0.03	37.54

Table 11 gives variance decomposition of output, consumption, total capital

investment, inflation and housing investment based on the estimated results reported

in Table 10. This indicates the percentage contribution of different shocks on the

forecast error of selected variables. As can be seen from the table, all variables are

primarily driven by the exogenous shock of investment-specific shocks, especially from the SOE sector, e_t^{ISOE}. The housing shock e_t^H contributes 19.02% on the inflation rate, 37.54% on housing investment and provides more than 10% on other variables except for households' consumption (only 3.08%). Productivity shock in the SME sector, e_t^{aSME}, contributes 26.15% on inflation which ranks the first among all other shocks, but only contributes 3.3% of total capital investment. Both monetary policy, e_t^M and productivity shock in the SOE sector, e_t^{aSOE} have a smaller impact on the forecast error of all variables. Finally, reserve ratio shock, risk premium shock and government spending shock (e_t^τ, e_t^S and e_t^G) are all relatively trivial to the selected in the long run. To sum up, shocks in the SME sector, including productivity shock, investment-specific shock and housing investment shock jointly contribute approximately half of the impact of forecast error on all variables, and the other important part is the capital investment in SOE sector.

Figure 14 shows a positive fiscal policy. Similar to the second model in my thesis. Outputs in both sectors (ypoe and ysoe) exhibit lagged reaction on the shocks. However, the differences are the private investment in capital and housing investment are crowded out by government spending. Net worth decreases due to the crowding-out effect. The IRFs illustrate an apparent cyclical behaviour, which might signal some computational error in my model. This clearly needs some further investigation to understand better the current limitations in the framework.
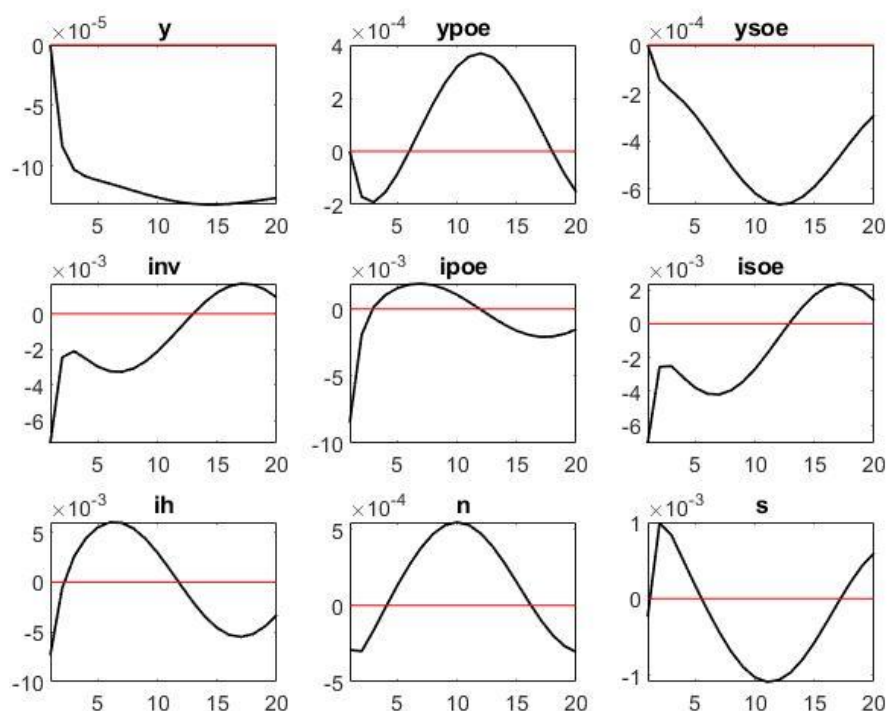
Figure 14 Positive Government Spending Shock

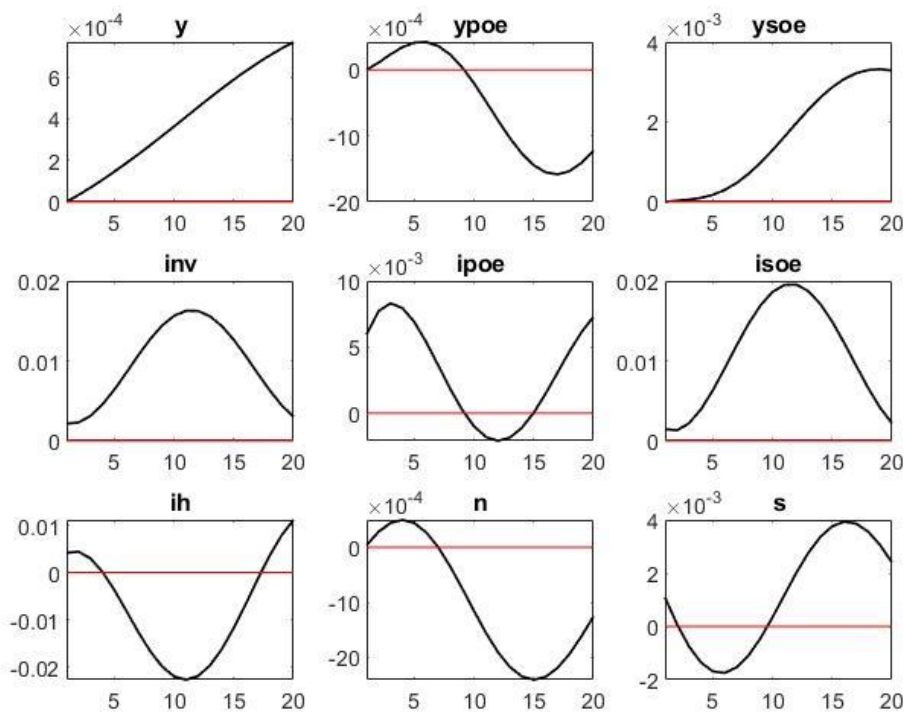Figure 15 Contractionary Monetary Policy Shock

Figure 15 illustrates the IRFs of the contractionary monetary policy. The tighter policy again fails to cool down the economy since commercial banks are able to circumvent the heavy regulation and increase risk lending behaviour through off-balance-sheet shadow channel. This can be shown by the increasing level of private investment in both capital and housing (ipoe and ih respectively). However, the same issue of the cyclical behaviour will require further investigation of my model.

5.6 Conclusion

In this chapter, housing market is incorporated into the model developed from Chapter 4. Housing market cannot be neglected since it is closely connected to the financial system through both conventional channels, for example, bank loans, and unconventional channel, i.e. shadow banking sector. The methodological purpose of adding the housing market into the framework is to investigate whether this modification can bring the model closer to the data or reality. The performance of the model in the previous chapter is not as good as I expect, which clearly indicates that the model is far from the reality. By adding the housing variable in the model, the performance dramatically improves; specifically, the Transformed Wald statistic decreases from 23.91 to 7.87, which is much closer to the critical value, 1.645. However, even though most of the estimated results are relatively robust compared to the model in Chapter 4, the results are still not good enough to pass the test. One possible reason might be that the model still lacks some important aspects of Chinese economy with shadow banking sector, or it could be because the model itself is too

complicated to pass the test. Although the model does not pass the test, the variance

decomposition analysis shows the importance of shocks in SME sector and the

influence of housing shocks on the forecast error of GDP, consumption, both capital

housing investment and inflation rate.

Appendix 5A Log-linearised Equations

Risk Premium

$$\frac{R^K K^{SME}}{R^L}\tilde{R}_{t+1}^K + \frac{R^H H}{R^L}\tilde{R}_{t+1}^H + \frac{R^K K^{SME} + R^H H}{R^L}\tilde{R}_{t+1}^L$$

$$= (\frac{\varphi}{\Gamma(\overline{\omega}) - \mu G(\overline{\omega})} - \frac{R^K}{R^L})K^{SME}(\tilde{Q}_t^{SME} + \tilde{K}_{t+1}^{SME}) + (\frac{\varphi}{\Gamma(\overline{\omega}) - \mu G(\overline{\omega})}$$

$$- \frac{R^H}{R^L})H(\tilde{Q}_t^H + \tilde{H}_{t+1}) - \frac{N}{\Gamma(\overline{\omega}) - \mu G(\overline{\omega})}\tilde{N}_{t+1} + \frac{\varphi(K^{SME} + H)}{\Gamma(\overline{\omega}) - \mu G(\overline{\omega})}\tilde{e}_t^s$$

Net Worth Accumulation

$$\tilde{N}_{t+1} = \frac{\gamma K^{SME}(R^K - R^L\varphi)}{N}(\tilde{Q}_{t-1}^{SME} + \tilde{K}_t^{SME}) + \frac{\gamma R^H H(R^H - R^L\varphi)}{N}(\tilde{Q}_{t-1}^H + \tilde{H}_t)$$

$$+ \frac{\gamma R^K K^{SME}}{N}\tilde{R}_t^K + \frac{\gamma R^H H}{N}\tilde{R}_t^H - \frac{\gamma R^L[\varphi(K^{SME} + H) - N]}{N}\tilde{R}_t^L + \gamma R^L \tilde{N}_t$$

SMEs Production Function

$$\tilde{Y}_{t+1}^{SME} = \tilde{A}_{t+1}^{SME} + \alpha_1\tilde{K}_{t+1}^{SME} + \beta\tilde{H}_{t+1}$$

Housing Return

$$\tilde{R}_{t+1}^H = (1 - \frac{1 - \delta_H}{R^H})[\rho\tilde{Y}_{t+1}^{SME} + (1 - \rho)\tilde{Y}_{t+1} - \tilde{X}_{t+1} - \tilde{H}_{t+1}] + \frac{1 - \delta_H}{R^H}\tilde{Q}_{t+1}^H - \tilde{Q}_t^H$$

Housing Accumulation and Tobin's Q Equation

$$\tilde{H}_t = (1 - \delta_H)\tilde{H}_{t-1} + \delta_H\tilde{I}_t^H + \delta_H\tilde{e}_t^H$$

$$\tilde{Q}_t^H = \phi_H^{SME} \delta_H (\tilde{I}_t^H - \tilde{H}_{t-1}) - \tilde{e}_t^H$$

Appendix 5B List of F.O.Cs

Households

$$\frac{1}{M_t} + \beta_H \frac{1}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H}$$

$$\beta_H \frac{R_t^D}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H}$$

$$\beta_H [1 - F(\bar{w}_t)] \frac{R_t^{SB}}{\pi_{t+1}} = \frac{C_{t+1}^H}{C_t^H}$$

Bankers

$$\frac{C_{t+1}^B}{\beta_B C_t^B} = \frac{[R_{t+1}^D - R_{t+1}^L (1 - v e^{\varepsilon_t^v}) h]}{[1 - (1 - v e^{\varepsilon_t^v}) h]}$$

SMEs

$$\frac{R_{t+1}^K R_{t+1}^H}{R_{t+1}^L} = \frac{[\varphi(Q_t^{SME} K_{t+1}^{SME} + Q_t^H H_{t+1}) - N_{t+1}] / \left(\frac{Q_t^{SME} K_{t+1}^{SME}}{R_{t+1}^H} + \frac{Q_t^H H_{t+1}}{R_{t+1}^K} \right)}{\left[[1 - F(\bar{w})] \bar{w} + (1 - \mu) \int_0^{\bar{w}} w \, dF(w) \right]}$$

$$E_t(R_{t+1}^K) = \frac{\alpha_1 \frac{P_{t+1}^{w,SME}}{X_{t+1} P_{t+1}^W} \frac{Y_{i,t+1}^{SME}}{K_{i,t+1}^{SME}} + Q_{t+1}^{SME} (1 - \delta^{SME})}{Q_t^{SME}}$$

$$R_{t+1}^H = \frac{\beta \frac{P_{t+1}^{w,SME}}{X_{t+1} P_{t+1}^W} \frac{Y_{t+1}^{SME}}{H_{t+1}} + Q_{t+1}^H (1 - \delta_H^{SME})}{Q_t^H}$$

SOEs

$$R_{t+1}^L = \frac{\alpha_2 \frac{P_{t+1}^{w,SOE}}{X_{t+1} P_{t+1}^W} \frac{Y_{j,t+1}^{SOE}}{K_{j,t+1}^{SOE}} + Q_{t+1}^{SOE} (1 - \delta^{SOE})}{Q_t^{SOE}}$$

Capital Goods Producers

$$\frac{1}{Q_t^{SOE}} = \left[1 - \phi_K^{SOE}\left(\frac{I_t^{SOE}}{K_{t-1}^{SOE}} - \delta^{SOE}\right)\right] e_t^{ISOE}$$

$$\frac{1}{Q_t^{SME}} = \left[1 - \phi_K^{SME}\left(\frac{I_t^{SME}}{K_{t-1}^{SME}} - \delta^{SME}\right)\right] e_t^{ISOE}$$

Housing Goods Producers

$$\frac{1}{Q_t^H} = \left[1 - \phi_H\left(\frac{I_t^H}{H_{t-1}} - \delta_H^{SME}\right)\right] e_t^H$$

Final Goods Producers

$$\sum_{k=0}^{\infty} \theta^k E_t\left\{\left[\Lambda_{t,k}\left(\frac{P_t^*}{P_{t+k}}\right)^{\epsilon} Y_{t+k}^W(z)\left[\frac{P_t^*}{P_{t+k}} - \left(\frac{\epsilon}{\epsilon-1}\right)\frac{P_{t+k}^W}{P_{t+k}}\right]\right]\right\} = 0$$

$$P_t^* = \frac{\epsilon}{\epsilon-1}\frac{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k}\left(P_{t+k}^W P_{t+k}^{-(1-\epsilon)} Y_{t+k}\right)}{E_t \sum_{k=0}^{\infty} \theta^k \Lambda_{t,k}\left(P_{t+k}^{-(1-\epsilon)} Y_{t+k}\right)}$$

Appendix 5C Steady State Values From the Model

Variables	Steady State Values
C^H	1.6564
C^B	0.4515
C^E	0.1600
I	0.4991
G	0.5656
M	138.0328
Y	4.0400
Y^{SME}	1.6160
Y^{SOE}	2.4240
I^{SME}	0.1162
I^{SOE}	0.3829
K	14.2589
K^{SME}	3.3197
K^{SOE}	10.9392
N	3.1405
R^D	1.0101
R^K	1.0620
R^L	1.0180
R^{SB}	1.0419
R^H	1.0190

Appendix 5D Data

Raw Data Description			
Variable	Minimum	Maximum	Mean
Housing Price (RMB Per Square Meter)	1007.25	6918.48	3770.57
Housing Price Inflation (Per cent)	-36.45	58.42	2.33
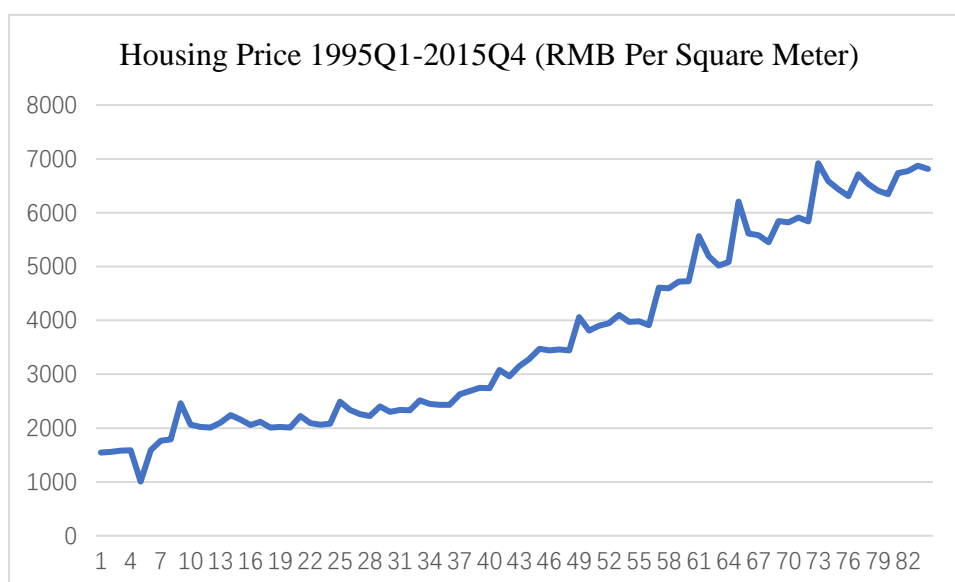
Source: NBS

Chapter 6 Conclusion

In summary, this thesis aims to investigate: 1) why I study shadow banking, in particular, Chinese shadow banking system; 2) what are the similarities and differences between the Chinese and US shadow banking sectors; 3) why I use dynamic stochastic general equilibrium framework to undertake my research; 4) why both Bayesian and Indirect Inference estimations are applied in my research; 5) what are the research findings and implications from these exercises; particularly, how shadow banking system affects the policy implementations and effectiveness; what are the transmission mechanisms of different policies with the existence of two production sectors, i.e. small-and-medium-sized entrepreneurs and state-owned enterprises; and whether the dynamic stochastic general equilibrium models with Chinese shadow banking system and housing market can or cannot be rejected by the actual data.

6.1 Why I study Chinese Shadow Banking System

There are two reasons to investigate the Chinese shadow banking system. Firstly, the 2007-2009 global financial crisis teaches the world a lesson about how badly an unregulated shadow banking can damage the economy. Chinese shadow banking sector has been growing dramatically since the four trillion stimulation package in 2009, and it plays an essential role in the Chinese economy. The benefits are to satisfy the demand of SMEs financing and fuel economic growth; otherwise, it is difficult for SMEs to contribute more than 60% of the GDP if the private sector is excluded from

official credit. However, less restriction in the shadow banking sector also comes with substantial economic costs, which may cause financial instability. Secondly, I am a research member of the three-year project 'Shadow Banking and the Chinese Economy – A Micro to Macro Modelling Framework', which is funded by the Economic Social Research Council (UK) and the National Natural Science Foundation (China).

6.2 The Similarities and Differences between Chinese and US Shadow Banking

Shadow banking system is the largest in the US compared to other countries, while the system is the fastest growing in China in the recent decade. Development of the shadow banking sectors shares some common factors in both countries, but at the same time, there are considerable differences since both countries retain different economic structures. The main similarity in the development of the shadow banking sector in the two countries is regulatory arbitrage. The traditional banking sector has been heavily regulated in US; most importantly, the regulatory capital requirements restrict their leverage (first introduced in the Basel I officially and modified in Basel II and Basel III). Similarly, due to heavy bank regulations in the Chinese conventional banking sector, small-and-medium-sized enterprises (the real backbones of Chinese economy) find it difficult to gain access to bank credit. In the meantime, commercial banks also have incentive to circumvent the central bank regulations and extend credit to risky sectors via shadow banking channels.

However, since the economic structures remain substantially different in China and the US, the shadow banking system operates very differently. With the developed capital market, the structure and operation of shadow banking system in the US is more complicated, compared to China, and relies more on indirect shadow banking activities, i.e. securitisation. By comparison, the structure in China is simpler, and most of the shadow banking activities are direct borrowing and lending between shadow banking lenders and borrowers.

6.3 Why I Use Dynamic Stochastic General Equilibrium Models

The reason for using dynamic stochastic general equilibrium framework is that this type of model arguably remains the mainstream in the macroeconomic school of thought and has been widely used by researchers in both academic research and policy institutions, especially in central banks. Since one of the research objectives of my thesis is to discover policy impacts with the existence of shadow banking system in China, it is useful to adopt dynamic stochastic general equilibrium model to examine a variety of macroeconomic phenomena and conduct counterfactual policy experiments. In addition, it is not difficult to imagine that innumerable criticisms would immediately arise if central banks or any policy institution claim that they want to build a model that relies on static, rather than dynamic, deterministic, rather than stochastic, and partial, rather than general, equilibrium.

6.4 Why Both Bayesian and Indirect Inference Estimation Are Applied

In terms of the methodological issue of adopting Bayesian and Indirect Inference estimations, I first use Bayesian technique to estimate the first model in my thesis. The reason is that Bayes can incorporate background knowledge into the estimation and allow for updating the previous understanding after analysing with the new data. Another advantage of Bayesian statistics is that it does not require testing the same null hypothesis repeatedly. One can locate the theory from prior literature and conduct further analysis. In addition to theoretical advantages, one practical advantage of using Bayesian methods is that it can deal with small sample size, which is not based on the central limit theorem as in the frequentist approach. However, Bayesian approach does not test the model framework with the actual data; instead, it normally concludes which model is more likely to be better than another, but the better model does not mean that it can mimic the real data. Indirect Inference provides a classical statistical inferential framework for judging whether the model is rejected or not rejected by the actual data. Thus, although it is convenient to apply Bayesian approach nowadays, it is still prudent to test the model before providing policy implications.

6.5 Research Findings, Implications and Future Research

The first model (Chapter 3) is a framework of one of the two largest shadow banking instruments, entrusted loans, and the risk-neutral state-owned enterprises lending behaviour. Commercial banks strongly favour state-owned enterprises for loans because of government endorsement. By taking advantage of the privileged access to

the formal banking system, state sectors obtain over 75% of bank loans (Tsai, 2015). By contrast, small-and-medium-sized enterprises face severe financial constraints in accessing bank credit, compelling them to rely on shadow banking for funds, mainly entrusted loans. In the meantime, SOEs have a long history of suffering from low productivity and inefficiency, which creates an incentive for them to engage in the entrusted lending market to seek additional profit.

Using Bayesian estimation for the period 1992Q1-2015Q4, the research finding of this model is, first, that a tighter bank credit regulation, particularly a higher reserve ratio, pushes SOEs to raise the proportion of risky loans to SMEs. SOEs' profit decreases due to the shortage of bank loans (higher reserve ratio). To compensate for the loss, SOEs are willing to increase lending to SMEs, which provides a higher return on loans. Second, the effectiveness of the monetary policy is dampened since SOEs' entrusted lenders (SELs) are free to adjust the credit allocation to SMEs regardless of the underlying risks. The credit-constrained (private) sectors need to bear a higher cost of borrowing when monetary policy becomes tighter. However, with opportunities to borrow from the SOEs, SMEs can offer a higher return and offset their shortage of funds proportionally, which in turn renders the monetary policy less effective. Third, provisional positive government spending increases the output in both the private and state sectors. However, this crowds out private investment, which reduces the net worth and increases the risk premium of the private sector. Consequently, SMEs must reduce external finance and slow down their production. As mentioned earlier, SMEs are the engine of Chinese economic growth. Therefore, fiscal policy needs to be

implemented with caution as it may harm the real economy unless regulators can target the private sector for funds.

The second model and third model are more sophisticated than the first model. The model framework in Chapter 4 includes both wealth management products, the other largest shadow banking instruments, and commercial banks' shadow banking activities, which fit the feature of the overall status of Chinese shadow banking sector, i.e. the shadow of the banks. The final model in Chapter 5 is built upon the second model by adding a housing market in the framework since real estate industry is closely connected to the financial system through both conventional banking system and unconventional channel, i.e. shadow banking sector. Both models are estimated and tested by Indirect Inference technique to answer the methodological research question – whether such shadow banking models can or cannot be rejected by the actual data. I find that, although adding housing market brings the model closer to reality, both models are difficult to pass the test, which implies the models are rejected by Chinese time series macroeconomic data. Indirect Inference is a powerful test that might be even stronger than likelihood ratio tests. It is not surprising that such complicated dynamic stochastic general equilibrium models are rejected by the test. Nevertheless, one should be cautious when applying policy implications from a complex model that does not pass the appropriate empirical tests; for example, Indirect Inference approach.

This study is a halfway house between the large structural models of Keynesian type

and simple models of the monetarist type. The aim of my research is not modelling everything in the Chinese economy that correlated to the shadow banking system, but the most relevant and important features. In the meantime, I do not want to neglect anything that might have a significant impact on my results. Therefore, although I have already developed three models, this research is still incomplete. None of my models passed the Indirect Inference test, which might be due to the models being still too complicated, or there being some important features hidden in the data that are not captured by my models.

One direction of modifying my model is to allow the two sectors, both state and private sectors, to have a different degree of price rigidities. Compared with the state-owned sector, the private sector might react more flexible regarding the price. Hence, instead of incorporating the sticky price in the final good producers, a flexible price regime can be embedded into the private sector, while price stickiness can be included in the state sector. In the philosophy of scientific method, as Karl Popper (2005) states 'the complex theories were the less probable ones', which implies that the less complex the structure, the greater the likelihood of non-rejection. Therefore, in the future, I plan to begin with a partial equilibrium framework which would investigate the distortion impacts of a particular regulation and test with the Indirect Inference approach. Once the model passes the test, then I would gradually add components to the framework and develop a simple general framework (even simpler than my first model) that can still pass the test. Otherwise, the policy implications concluded by a rejected model are unconvincing.

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