Essays on Financial Development, Innovation and Chinese Economy

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Contents

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Abstract

Motivated by a fundamental question, namely how the Chinese economy is or was working, this thesis studies two puzzles regarding Chinese economic growth and business cycles based on comparative perspectives.

Chapter One studies whether the finance-growth relationships in China contradict cross-country findings. This issue is empirically examined with particular emphasis on the role of innovation based on data from 30 Chinese provinces over 1991 to 2014. Our findings suggest that there is an innovation channel through which banking sector development promotes productivity and economic growth while stock market development impedes them. We further investigate if the effects of financial development differ in different development stages. Based on the sub-sample regressions, we show that the effects have dramatic difference across different periods, which is very likely due to multiple reforms. These findings also provide a reconciliation that the Chinese finance-growth nexus is not completely different from cross-country findings.

In chapter Two, we build and estimate a DSGE model with endogenous technology creation and extended financial markets to compare the contributing factors behind Chinese and the US profiles for economic activity. Our analysis is motivated by a puzzling contrast in business cycle behaviour between the two countries, which share similar profiles for the path of gross domestic product (GDP) yet contrasting profiles for total factor productivity (TFP). Our findings suggest that government policies through fiscal and investment interventions work well for output smoothing in China, but exacerbate the volatility of TFP. The addition of a stock market in the model reinforces this explanation; the option to switch into equities for US firms has a dampening effect on TFP, with the reverse case for China, meaning that China should develop equity markets, but proceed cautiously.

Dedication

To mum and dad

Declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

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Introduction

Forty years have passed since China opened up its markets to the global economy; over this period, and especially in recent years, significant economic progress has been achieved. Chinese gross domestic product (GDP) and its world share[1] rose from 368 billion RMB and 1.8% in 1978 respectively to 83 trillion RMB and 16% in 2017 (NBS[2]). At the same time, per capita GDP in China increased from 381 RMB to 60 thousand RMB (NBS). In addition, China has become the center of world manufacturing and the largest trading country. Furthermore, China has a stable economic environment especially in the recent two decades; there was no severe financial or economic crisis originating from Chinese domestic markets. Moreover, there was no significant recession even if China was strongly hit by external shocks like the Asian financial crisis and the global financial crisis.

With such economic achievements in China, it is intriguing and important to understand how the Chinese economy is, or was, working. An essential question is commonly asked: is Chinese economy a miraculous outlier? These questions have been extensively studied yet there is still no conclusive answer. China-based studies can be broadly classified into two areas: economic growth and business cycles. The bulk of literature (Aziz and Duenwald 2002, Boyreau-Debray 2003, Chen 2006, Hsieh and Klenow 2007, Naughton 2007, Guariglia and Poncet 2008, Chen et al. 2009, Hasan et al. 2009, Song et al. 2011, Fleisher et al. 2015, Zilibotti

[1] World shares are calculated based on exchange rate.
[2] National Bureau of Statistics of China

2017) focuses on the former area. They study what constitute engines of Chinese economic growth and compare China with other countries to draw similarities and differences. An early but common finding is that Chinese high and long-lasting growth is achieved despite the absence of a sound institutional environment, especially developed financial sectors. Such a finding motivates scholars to examine the finance-growth relationship in China from various aspects. Another strand of literature, which is under-developing, investigates Chinese business cycles (Le et al. 2014, Dai et al. 2015, Ma and Li 2015, Chang et al. 2016, Chen et al. 2018). They suggest that driving forces of Chinese business cycles are different compared with other countries including many developed and emerging economies. However, owing to the underdevelopment of the literature, these studies only partially cover topics in Chinese business cycles and some investigations remain superficial.

Motivated by the existing literature and the fundamental question how the Chinese economy was or is working, this thesis uses comparative perspectives to investigate two puzzles in terms of economic growth (Chapter One) and business cycles (Chapter Two) in China. We cover both economic growth and business cycles, the two sub areas of Macroeconomics, in order to have a broad examination of the Chinese economy.

In the first chapter, we study whether the Chinese finance-growth relationship is a true counter-example to the cross-country finding. In other words, is financial development non-conducive to economic growth in China? This question is not new but we add contributions in four aspects. Firstly, this study is the first one to directly address the finance-growth relationship in China through an innovation channel which has been paid limited attentions before. We focus on this channel because innovation becomes increasingly important for China to sustain its economic growth in the long run. Secondly, we use newly constructed stock market data to examine effects of stock market development on economic growth in China. Thirdly, different dimensions of financial development are differentiated for the Chinese case. Finally, we investigate if there are time-varying patterns in terms of the finance-growth nexus in China. This examination is helpful to understand why findings about the Chinese finance-growth relationships differ dramatically in different studies.

The first chapter sheds light on the aforementioned puzzle about the Chinese finance-growth relationship. We show that banking sector development promotes productivity and economic growth by encouraging more innovation, while stock market development does promote economic growth but this growth-enhancing effect is dampened by discouraging innovation. These two findings partially reconcile the unfavourable effect of financial development on growth and provide evidence that China is not a counter-example to cross-country findings in all aspects, although China is an exception in some ways. Moreover, this study further shows that the finance-growth relationships in China differ in different development stages and hence the exceptional aspects of China could be due to its phase of development.

In the second chapter, we carry on comparative perspectives to study a puzzling contrast regarding business cycles; that output is smooth in both China and US but Chinese TFP is more volatile. In this chapter, we focus on China and compare it with the US, where the latter often serves as a benchmark in the business cycle literature. To the best of our knowledge, we are the first to discover this puzzling contrast, which is worthy of study for the following three reasons. Firstly, such a pattern is special in China and in answering the puzzle has potential to update our understanding about Macroeconomics. Secondly, the distinct volatility in output and TFP may mislead our judgement about whether the nature of macroeconomic environment in China is volatile or not. Thirdly, high TFP volatility can exacerbate mis-allocation of capital which overshadows long-run growth prospects in China. With such importance, it is necessary to study what factors lead to the puzzle. Furthermore, we study whether TFP volatility can be smoothed by a developed technology-based stock market like that in the US. This further investigation is motivated by the Chinese ongoing deleveraging reforms which aim to reduce macroeconomic fluctuation in China.

The second chapter contributes to three strands of literature. Firstly, we bridge a gap in Chinese business cycles regarding how Chinese TFP fluctuates and how multiple shocks affect output through a technology creation channel. A critical finding is that the heavy use of government policies significantly reduces output volatility but increases TFP volatility through technology creation in China. In addition to the main finding, we stress importance of technology creation in driving TFP and business cycle fluctuation in China. Furthermore, we make two general contributions which are not limited to the Chinese scenario. By incorporating extended financial markets into a Dynamic Stochastic General Equilibrium (DSGE) model, we show transmission mechanisms of financial shocks through an innovation channel. This contributes to the finance-innovation-TFP nexus within the business cycle literature, particularly in terms of role of financial risks. Moreover, we apply the finance-innovation-TFP nexus to address a debate whether stock market development reduces macroeconomic volatility and a reconciliation is provided. Specifically, the stock market could act as a cushion from financial shocks given that the stock market itself is not too risky and volatile. The last finding provides policy implications to financial reform for not only China but also other emerging economies with the similar financial structure.

Chapter 1

Financial Development, Innovation and Growth: Evidence from China

1.1 Introduction

The last four decades have witnessed impressive economic performance of China along with its rapid expansion in financial intermediation. It has become the second largest economy in 2010 and the largest trading country in 2012.[1] Its average growth rate was 9.8% between 1979 and 2012, contributing to 25% of the world's growth in 2015 (NBS). What's more interesting is that China doesn't seem to follow a standard path of advanced economies (Fu 2015). As a result, the roles of innovation and financial sector were not adequately addressed in the literature as being among the drivers[2] of China's steep economic growth.

Cross-country studies suggest a positive effect of financial development on economic growth (McKinnon 1973, King and Levine 1993*a*,*b*, Levine and Zervos 1998, Levine et al. 2002, Beck et al. 2000, Calderón and Liu 2003) and this nexus

[1]White, Garry (10 February 2013). "China trade now bigger than US". Daily Telegraph. London. Retrieved 15 February 2013. Calculations are based on exchange rate.

[2]Fleisher et al. (2015), Chen et al. (2009), Hsieh and Klenow (2007), Song et al. (2011), Naughton (2007) summarize that they are high rate of saving, improvement in the efficiency of agriculture and industry, reallocation of labour from farming- to the non-farm- and from rural- to the urban sectors, adopting and adapting modern technology, and reform of state-owned enterprises (SOEs).

is run through innovation (Beck et al. 2000) and capital accumulation (Rioja and Valev 2004*b*). In recent literature, a non-monotonic relationship between finance and economic growth is identified for both advanced and middle-income countries (Cecchetti and Kharroubi 2012, Law and Singh 2014, Pagano et al. 2012, Aizenman et al. 2015, Arcand et al. 2015), yet the finance-growth nexus within the Chinese framework is far from being well-studied. The existing Chinese case studies mainly focus on banking intermediation with less attention on financial markets. Indeed, most of them (Aziz and Duenwald 2002, Boyreau-Debray 2003, Chen 2006, Hasan et al. 2009, Guariglia and Poncet 2008) conclude that bank loans are not a favourable source of growth. Moreover, there has been little or no systemic study on the role of innovation in the Chinese finance-growth nexus. It is believed that domestic innovation was not an essential determinant for China's growth up to recent stage[3] but is critical for further transition.

A number of researchers (Rioja and Valev 2004*a*, Kassimatis and Spyrou 2001, Demetriades and Hussein 1996) argue that finance-growth nexus is not a 'one-size-fits-all' issue and hence analysis based on a single country can provide additional information. For this reason, a provincial level study of China can exploit the considerable difference among Chinese provinces in terms of both economic and financial development (Chen 2006, Boyreau-Debray and Wei 2005). Boyreau-Debray and Wei (2005) further argue that the regional barrier of fund mobility enables such a study to mimic cross-country one. In addition, such a study can provide clearer results as the issue of data comparability is avoided (Hasan et al. 2009).

[3]According to classifications from World Competitiveness report, there are three development stages including factor-driven, efficiency driven and innovation-driven. China is in the efficiency driven stage.

This study empirically examines the impact of the banking sector and stock market development on productivity and economic growth by distinguishing the innovation channel against others. We make contribution to the existing literature in the following ways. As far as we know, this study is the first one to 1) directly examine the Chinese finance-innovation-growth relationship, 2) investigate the nonlinear effect of financial development (including banking and stock markets) on Chinese productivity and economic growth and 3) differentiate two dimensions (depth and function or efficiency) of financial development for China. Moreover, this study complements two strands of literature. On one hand, we reconcile distinct findings from Chinese finance-growth literature based on different periods. On the other hand, we complement cross-country studies by showing the Chinese finance-growth nexus is not a counter-example in all aspects.

Our findings suggest that a) Innovation measured by invention patent boosts total factor productivity (TFP) and economic growth; b) the unfavourable role of banking sector development, as suggested by existing literature, is reconciled as it promotes TFP and economic growth by encouraging more innovation; c) stock market development promotes economic growth but this growth-enhancing effect is dampened by discouraging innovation; d) the finance-growth relationship differs in different development stages. Finally, a new dataset related to Chinese stock market, human capital and TFP growth at the provincial level is produced.

The structure of this chapter is as follows. Section 1.2 summarizes relevant literature and proposes the hypotheses to be tested. Section 1.3 describes data and methodology. Section 1.4 presents long-run finance-growth nexus as well as discussions. Section 1.5 checks the robustness of long-run results. Section 1.6

discusses finance-growth nexus in different development stages and section 1.7 concludes.

1.2 Literature Review and Hypotheses

1.2.1 Banking Sector Development and Growth

The finance-growth nexus in China is examined particularly with respect to the banking sector. Based on provincial level data in 1980s and 1990s, a bulk of literature found that the various indicators of banking sector development have either negative (Boyreau-Debray 2003, Chen 2006, Guariglia and Poncet 2008) or insignificant effect (Aziz and Duenwald 2002, Hasan et al. 2009) on GDP growth in China. That is because the majority of credits are supplied from state-owned commercial banks (SOCBs) to stated-owned enterprises (SOEs) (Chen 2006) but little to more productive private-owned firms (POEs), which leads to fund misallocation and waste of resources (ownership-structure issue[4]). In addition to this widely-mentioned reason, there is also a size-structure issue, argued by Lin et al. (2015). They have analysed industry-province data and find that the over-concentrated banking structure[5] in China further exacerbates misallocation of funds.

However, the channels through which bank-growth nexus fails are far from well understood. There is very limited literature investigating links between banking

[4]Lin et al. (2015) document that SOEs are inefficient in utilization of funds and are subject to administrative order.

[5]It refers to the fact that too large share of financial services are provided by the Big Four banks (the Bank of China, the China Construction Bank, the Agricultural Bank of China, and the Industrial and Commercial Bank of China), which does not meet demands of small and medium firms (Lin et al. 2015).

sector development and two sources of growth, namely TFP growth and accumulation of capital. To the best of our knowledge, Guariglia and Poncet (2008) is the first one to bridge this gap. They find that various indicators of banking sector development have negative effect on not only capital accumulation but also per capita TFP growth[6] over 1989 to 2003 for 30 Chinese provinces.

Although many studies[7] demonstrate adverse bank-growth nexus based on pre-2000s data, a few recent studies challenge findings from aforementioned literature by focusing on data in 2000s. For example, Zhang et al. (2012) find that economic growth is positively associated with financial development, using city-level data over 2001 to 2006. Moverover, based on data from 2400 Chinese firms in three consecutive years from 2000, Cull and Xu (2005) and Ayyagari et al. (2010)[8] show that access to formal finance[9] is associated with higher productivity growth while informal finance is not. In addition, Cull and Xu (2005) and Ayyagari et al. (2010) show that the type of ownership does not make any difference in the association between access to finance and productivity growth. Furthermore, based on approximately 600 thousand firms from 1998 to 2009, Li et al. (2018) show that bank credits supply significantly promotes productivity growth for both POEs and SOEs despite the effect on SOEs being quantitatively smaller. Since many reforms have taken place in 2000s, these recent studies together imply that the effect of banking sector development in China may have

[6] In their study, estimated TFP growth is equal to per capita GDP growth minus capital share times capital growth. One issue is that they use provincial labour income share only in 1997, which is not reliable for a long-run analysis. We do find that labour income share for majority Chinese provinces has significant variation in 1990s. Another issue is that they assume a province-invariant capital depreciation which is proved to have substantial variation across provinces by later studies (see Wu (2008*a*) as an example).

[7] As far as we know, majority of these recent studies does not establish causality.

[8] Cull and Xu (2005) only use data in 2002.

[9] They define bank credit as formal finance while other types of funding as informal finance.

changed recently.

According to the banking-growth relationship found in the existing literature, we hypothesize:

(i): direct effect[10] of banking sector development on economic growth is negative or insignificant in China.

(ii): direct effect of banking sector development on TFP growth is negative or insignificant in China. However, we will not be surprised if our hypotheses are rejected. Majority of commonly-used measures of banking sector development for China have inefficient elements. For example, the credit to GDP ratio includes loans to SOEs, which are less efficient than POEs. If measures that are less subject to inefficiency are used, it is possible to obtain positive effect of banking sector development on economic and TFP growth.

(iii): direct effects of banking sector development on TFP and economic growth differ in different development stages.

1.2.2 Capital Market Development and Growth

While substantial evidence regarding Chinese finance-growth nexus is provided (Aziz and Duenwald 2002, Boyreau-Debray 2003, Chen 2006, Guariglia and Poncet 2008, Hasan et al. 2009), less attention is paid to the role of the capital market[11] in economic growth especially at the provincial level. The reasons are of twofold: 1) lack of available data and 2) relative unimportance and small size of capital market in early period. As far as we know, Hasan et al. (2009) is the

[10] "Direct effect" refers to the effect unconditional on other variables. This definition applies to the whole study.

[11] For Chinese scenario, capital market refers to stock market and enterprise bond market. Since bond market has been relatively small compared with stock market in the past three decades, we concentrate only on stock market.

first one providing evidence on how capital market development affects economic growth at Chinese provincial level. Using data for 31 provinces over the period from 1986 to 2002 they find that the issuance of equity and enterprise bonds has positive impact on economic growth[12]. However, this study has omitted two important dimensions of China's capital markets: depth and efficiency. Focusing on the latter two dimensions, several studies document two critical issues in the Chinese stock market. Pistor and Xu (2005) suggest that Chinese stock prices might be deviated from their true values and hence market capitalization may not be informative. In addition, Yao and Yueh (2009) suggest that Chinese stock market has excessive liquidity which is a typical signal of active speculation rather than efficiency (Allen et al. 2005). Rousseau and Xiao (2007) empirically examine stock market-growth relationship for China using national level data between 1995 and 2005. They find Chinese stock market-growth relationship is insignificant. In spite of this finding, Rousseau and Xiao (2007) point out that a positive effect of stock market development might appear later with economic development.

Considering the issues summarized above, we hypothesize:

(iv): direct effect of stock market development on economic growth is negative or insignificant in China.

(v): direct effect of stock market development on TFP growth is negative or insignificant in China.

(vi): direct effects of stock market development on economic and TFP growth differ in different development stages.

[12]Although Hasan et al. (2009) find growth-enhancing effect of equity and bond issuance, we want to point out that Chinese government has intervened in initial public offering (IPO) process in 1990s and IPO prices are often devalued.

1.2.3 Innovation, Financial Development and Growth

Cross-country studies suggest that both banking sector and stock market development can promote economic growth by stimulating innovation (e.g Rajan and Zingales (1998)). Some recent studies (Brown et al. 2009, 2013, Hsu et al. 2014) further evaluate the effectiveness of debt and equity in stimulating innovation and find that stock market is more able to support innovation than banks. That is because banks may not favour innovative investments as they are risky and hard to evaluate, while lacking the collateral value and being subject to severe information asymmetry.

With regard to Chinese finance-innovation-growth relationship, there is a lack of direct study. Thus, we resort to innovation-growth and finance-innovation relationships separately to indirectly understand potential finance-innovation-growth relationships and draw hypotheses.

Some scholars suspect the quality of Chinese innovation and doubt on the effectiveness of innovation-growth relationship in China. Applying meta analysis, Ljungwall and Tingvall (2015) find very weak growth-enhancing effect of total R&D. Similar conclusion can be found in Fu (2008) who uses overall patent count to proxy innovation at provincial level over 1998 to 2004. On the contrary, some firm-level studies (Hu and Jefferson 2004, Fu and Gong 2011) identify productivity- or growth-enhancing effect of Chinese enterprise R&D in both 1990s and 2000s. They further show that R&D performed by SOEs and POEs both significantly improve efficiency and technology and hence increase TFP growth. To sum up, the existing literature uses various measures of innovation and find contradictory results for China. Those who find weak innovation-growth relationship are more likely to use inefficient measures of innovation such as total R&D and overall patent. The inefficiency comes from low quality of measured innovation. Total R&D includes public R&D whose effect on growth is ambiguous. Overall patent includes not only invention but also utility model and design. The latter two are only minor innovation. It is likely that a better measure of innovation may reveal its true effects.

In terms of finance-innovation relationship, there is a lack of study at aggregate level. To the best of our knowledge, there is only limited evidence at the firm level. (Girma et al. 2008, Cull et al. 2015, Howell 2016) find that bank loans stimulate enterprise innovation. For example, Girma et al. (2008) find that access to bank loan is conducive to product innovation based on about 240 thousand Chinese manufacture firms over 1999 to 2005. In addition, Girma et al. (2008) show that this relationship is not conditional on ownership status.

As far as we know, there is no study that empirically examined the interaction between stock market development and innovation for the case of China. The reason might be that Chinese stock market did not provide sufficient support for innovative firms, especially before establishment of Small and Medium Enterprise Board[13]. Even after 2004, hi-tech firms only account for small share in terms of stock market capitalization and value of share trade.

Based on documented finance-innovation and innovation-growth relationships together, we formulate the following hypotheses.

(vii): innovation based on appropriate measure promotes TFP and economic growth.

[13]Small and Medium Enterprise (SME) Board is designed to allow SMEs to get listed in China stock market in 2004

(viii): banking sector development has productivity- and growth-enhancing effect through innovation.

(ix): Since data suggest that innovative sector does not get much financial support from stock market, there is probably no significant positive effect from stock market development through innovation.

1.3 Data and Methodology

1.3.1 Data

Our data[14] comes from 30 provinces[15] over 1991 to 2014. Tibet is excluded due to lack of data availability. We intend to investigate the direct effect of financial development and its indirect effect through innovation on real per capita GDP growth and TFP growth simultaneously in both the long run and the short run. For our main analysis, TFP growth is constructed using growth accounting. The details of construction of TFP growth is shown in Appendix B. In terms of long-run analysis, five-year averages[16] are adopted to eliminate the effect of short term shock (Levine et al. 2002). This helps us to understand finance-growth relationship in the whole sample period and we can compare Chinese case with cross-country studies. In terms of short-run analysis, annual data based on sub-samples are adopted. This helps us to understand finance-growth relationship in different development stages[17] and we can compare our results with other Chinese

[14]The detailed definitions and sources of all variables are provided in Appendix C.

[15]There are 22 provinces, 5 autonomous regions and 4 municipal cities in China's mainland. We refer them all as provinces or regions interchangeably.

[16]Whole sample is divided into 5 periods, namely 1991-1995, 1996-2000, 2001-2005, 2006-2010 and 2011-2014.

[17]More details about sample split will be discussed in section 6.

case studies based on different periods.

Measures of Financial Development

Our measures of financial development are mainly traditional ones adopted in existing literature though these measures embody negative factors in Chinese financial system. We do not try to remove these negative factors due to three reasons. As far as we know, there is no more desirable measures free from these negative factors. Secondly, one of our essential aims is to identify potential positive effects which are hidden from overall inefficient financial system in China. Hence, if the measures that include the negative factors can generate positive effects, that will indicate much stronger positive effects of financial development. Thirdly, we investigate if the effect of financial development becomes more favourable or less unfavourable in recent development stages. Hence, the traditional measures serve our purpose well and should be used.

The measures of financial development (expressed as FD) are divided into two categories including banking sector and stock market in this study. In addition, each sector is measured by two dimensions, basically *depth* and *function* or *efficiency*. *Depth* is a quantitative measure capturing relative size and importance of a financial sector to the whole economy (Levine 2005), while *function* or *efficiency* is a qualitative measure capturing functions or operational efficiency of a financial sector.

The first set of indicators measure banking sector development. The ratio of total bank loans to GDP (*Loan*[18]) is used to measure the banking sector

[18]Information related to private credit is not available at firm- or provincial or national level and hence private credit to GDP ratio cannot be used.

depth. This is the most commonly-used indicators in Chinese case studies so far (Boyreau-Debray 2003, Chen 2006, Guariglia and Poncet 2008, Aziz and Duenwald 2002, Hasan et al. 2009). The ratio of total bank loans to deposit (*LTD*[19]) is used to measure the banking sector *function*. This indicator generally captures the function through which banks can mobilise saving into credit. Higher *LTD* means banks can spend less resources on intermediation process and are more productive in supplying financial services (Fries and Taci 2005). In this sense, the higher *LTD*, the more cost efficiency of banking sector[20]. We want to make a clarification that *LTD* seems to mainly capture efficient operation of banking sector development and hence it will not be surprising if we find the effect of *LTD* going against our hypotheses (i) and (ii).

The second set of indicators measure stock market development. The ratio of overall market capitalisation to GDP (*Stockdepth*) measures stock market *depth*. Another measure is the turnover ratio (*Turnover*) which measures the stock market *function* and reflect liquidity of stock market. As suggested by Beck et al. (2009), a small market with high volume of trading activities is active and liquid. In addition, Levine (2005) points out that *Turnover* inversely reflects trading frictions and captures the function that active trading in the stock market can signal information to investors. Most of the above data are not available[21] at provincial level[22]. In order to complete the dataset, we collect firm-level data and

[19]Excessively high *LTD* is interpreted as liquidity alert of banks and is potential to damage the economy. However, due to strict regulation and support from People's Republic Bank of China, *LTD* was hardly beyond 80% and there was no severe liquidity problem as in the western world. Hence, interpretation of *LTD* is free from liquidity concern of banks.

[20]Net loan to asset ratio maybe another good measure of banking efficiency. However, neither net loan nor bank asset is available at provincial level.

[21]Only stock market capitalisation is available officially since 2004.

[22]The concept of provincial stock market is not exactly the same as it is in the cross-country study. In China, there are only two stock exchanges. However, stock funding raised from them are distributed to listed firms in all provinces. In this sense, *Stockdepth* and *Turnover* reflect

summarise them according to their registered provinces at the end of each year to generate the provincial level data[23].

Measures of Innovation

The measure of innovation (expressed as *inno*) is the number of invention patents[24] granted per ten thousand people. Moreover, we use number granted rather than application. That is because the amount of application is largely affected by patent subsidy programs (Hu and Jefferson 2009) but amount granted is not significantly affected (Dang and Motohashi 2015). Furthermore, existing literature suggests that enterprise R&D[25] seems to be another sensible measure of innovation. We do not use it for three reasons. Firstly, provincial enterprise R&D is not available before 2003 and as a result it cannot cover our full sample periods. Secondly, official statistics about enterprise R&D only cover large and medium enterprises and this coverage has several breaks since 2004. Thirdly, enterprise R&D expenditure is only an input to innovation while patents are outcome of innovation and hence the latter is better at capturing innovation.

With regards to quality of innovation, there are other potential measures in addition to invention patents. One possibility is citation number of patents

relative size and liquidity of stocks owned by listed firms within a province.

[23]A fact to be noted is that a Chinese listed firm can change its location of registration easily. There are a number of reasons, mainly due to changing primary business, merger or acquisition, backdoor listing, so on and so forth. We have checked that information for each listed firm. Details of aggregation are shown in Appendix A.

[24]There are three types of patents according to China's Patent System which are invention patent, utility model and external design. Invention refers to new technical solution relating to a product, a process and improvement thereof. Utility model refers to new technical solution relating to a product's shape, structure, or a combination thereof. Design refers to new design of a product's shape, pattern or a combination thereof. Among the three categories of patent, invention is the most sophisticated and innovative one while the other two are minor improvement.

[25]We do not use overall R&D as existing literature demonstrate that it is not a good proxy of innovation.

which, however, is unavailable at provincial level. Another option is survival patents or patents in force which exclude un-renewed patents. The latter are often of low quality and their holders do not have incentives to new them. In this sense, patents in force can be regarded as both quantitative as well as qualitative measure of innovation. However, patents in force are only available since 2006 and hence it cannot cover our full sample periods.

Control Variables

We use control variables used in the standard growth literature that follows Barro (1991). They are as follows: initial GDP per capita (*Y0*) controls for convergence, openness (*open*) is the the ratio of export and import to GDP, government consumption (*gov*) is the ratio of government consumption to GDP, investment (*inv*) is the ratio of capital formation to GDP, inflation (*inf*) is the change of Consumer Price Index (CPI), human capital (*hc*) is the average years of schooling. All control variables are expressed as natural logarithm. In addition to Barro's specification, two more variables, non-SOE assets ratio (*priva*) and foreign direct investment (*fdi*), are added as they are documented as important sources of Chinese economic growth. Non-stated assets ratio refers to the percentage of total assets owned by non-stated sector[26]. In addition, we add period dummies to account for any period-specific effect that may arise from any national policy changes or reforms and any external shock.

[26]This variable basically captures the effect of SOE reforms.

1.3.2 Methodology

Econometric Analysis

We include our major dependent variables in standard growth regressions setup such as (Barro 1991). The econometric analyses involve three models. We start from examining the direct effects of financial development (FD) using equation (1.1).

$$Growth_{it} = \alpha_i + \beta^{'} FD_{it} + \gamma^{'} Z_{it} + \theta^{'} D_t + \mu_{it} \tag{1.1}$$

where $Growth_{it}$ is either $per\,capita\ \ GDP\,Growth$ or $TFPgrowth$[27], FD is a vector containing two dimensions of development of a sub financial sector and Z_{it} is a vector of control variables. The $\beta^{'}$ captures overall effects of financial development through multiple channels such as capital accumulation and innovation. Then we examine the effects of financial development, captured by $\beta_2^{'}$, after controlling innovation using equation (1.2).

$$Growth_{it} = \alpha_i + \beta_1 Inno_{it} + \beta_2^{'} FD_{it} + \gamma^{'} Z_{it} + \theta^{'} D_t + \mu_{it} \tag{1.2}$$

where $Inno$ is innovation. Finally we examine the interaction effect between FD and $inno$ controlling both innovation and financial development using equation (1.3).

$$Growth_{it} = \alpha_i + \beta_1 Inno_{it} + \beta_2^{'} FD_{it} + \beta_3^{'} FD_{it} Inno_{it} + \gamma^{'} Z_{it} + \theta^{'} D_t + \mu_{it} \tag{1.3}$$

[27] All regressions are run relative to $per\,capita\ \ GDP\,Growth$ and $TFPgrowth$ separately.

Regarding interpretation of β_3', we have two major options as suggested by finance theories[28]: the effect on growth running from either financial development through an innovation channel[29] or (financial) innovation through a financial development channel. We choose the former way of interpretation based on suggestions from innovation data, namely number of granted invention patent by industries. That number for financial industries[30] is 1622 on average over 2008 to 2012[31] while total granted invention patent is 149305[32] on average in this period (SIPO 2013). This finding suggests that financial innovation only account for a tiny share (1.1%) and hence the effect running from innovation through finance channel is unlikely, while interpreting β_3'[33].

In terms of the regression technique, we depart from the traditional fixed-effect or random effect methods and exploit General Method of Movement (GMM) proposed by Arellano and Bond (1991) mainly due to the issue of model dynamics and endogenity. As well documented in the existing literature, endogenity can be result from heterogeneity and potential feedback effect from economic or productivity growth to innovation and financial development. Owing to the reason raised above, FE estimator will be biased.

Generally, there are two types of GMM estimators, difference-GMM and

[28] We want to acknowledge that the coefficient generally captures marginal effect of $Inno_{it}$ or FD_{it} conditional on the other.

[29] Another way of investigating the channel is to regress $Inno_{it}$ against FD_{it}, which has been addressed in firm level studies, see Ayyagari et al. (2010) among others. Their findings could be supports for our results.

[30] According to Chinese Industries Classification, financial industries include Monetary and Financial Services (J66), Capital Market Services (J67), Insurance (J68) and Other Financial Industries (J69).

[31] We do not have information for early periods.

[32] Both numbers are at national level.

[33] In order to fully purge out financial innovation, it maybe better to remove invention patent granted from $Inno_{it}$. However, we do not have invention patent information for financial industries at provincial level.

system-GMM. Specifically, system GMM estimator is applied in this study. Compared with difference-GMM, system-GMM estimation can exploit information of variables in both level and difference. In addition, system-GMM is free from weak instrument problem and more efficient given mean-stationary initial conditions[34] (Hayakawa and Nagata 2016). Moreover, we apply the one-step rather than two-step system-GMM estimation. Although the two-step GMM estimator is consistent, it is shown to have biased standard error when the sample size is small (Windmeijer 2005). Considering this argument, one-step system-GMM is applied in this study as the sample is small especially for long-run analysis.

It should be noted that there are four issues related to the validation of instruments. Firstly, error term is assumed to be not serially correlated. The AR(2) test is employed to detect autocorrelation in levels. Secondly, the number of instruments should not be too large. As a rule of thumb, it should not exceed the number of groups (provinces in this study). Otherwise, there could be significant finite sample bias. In order to correct the problem of too many instruments in a small panel, a collapsed matrix of instruments is used (Roodman 2006, 2009), which "creates one instrument for each variable and lag distance, rather than one for each time period, variable, and lag distance." Furthermore, the Sargan-Hansen test (J-test) of over-identifying restriction[35] is applied to validate the use of instruments. Finally, the difference-in-Sargan test (C-test) is employed to examine validity of level instruments. By testing this, we are able to know whether initial conditions satisfy the mean-stationary assumption which is critical to the

[34]We use the difference-in-Sargan test (C-test) to examine if mean-stationary assumptions are held.

[35]There are two statistics, Sargan statistic and Hansen statistic, related to validation of instruments. When heteroscedasticity is presented, Sargan statistic is not distributed as Chi-Square as it should be but Hansen statistic is. Then it is possible that Sargan wrongly rejects the null hypothesis and hence Hansen test is favoured.

consistency of estimation results.

Treatment of Outliers

As suggested by Poncet et al. (2010), accounting deficiency is a serious issue in developing economies, which results in missing values and outlier observations. In the light of this statement, the issue of outlier can not be ignored. To remove outliers, we first run one-step GMM estimation of the model and then apply the Hampel Identifier (HI) as suggested in Wilcox (2012) to the regression residuals stacked over time and individual countries (R_i) and treat any observation as an outlier for which the following is true:

$$HI = \frac{|R_i - M|}{MAD/0.6745} > c$$

where M is the median of observations $R_1, R_2, ..., R_n$, MAD is the median of the centred absolute values $|R_i - M|$, 0.6745 is the 75th quantile of the standard normal distribution and $c = 2.24$ is the critical value or cut-off. $MAD/0.6745$ is a consistent estimator for standard deviation.[36] Any observation with HI greater than cut-off will be treated as outlier and will be dropped.

1.3.3 Summary Statistics

Table 1.7 and 1.8 in appendix C report summary statistics and Pearson correlation between main variables separately. Notice that correlation between *loan* and *LTD* and that between *stock* and *turnover* are both very small. This suggests that two dimensions of banking sector or stock market development are independent and

[36] MAD is a more robust statistic compared with mean and hence is more resilient to outliers.

it is valid to add two dimensions in one regression.

1.4 Long-Run Results

1.4.1 Long-Run Finance-Growth Nexus

We start from examining Chinese finance-growth relationships in the long run based on five-year averaged data[37]. Results are reported in Table 1.1. Before concentrating on financial development, we firstly show the effect of innovation. Table 1.1 shows that innovation has a significant positive effect on both TFP growth and per capita GDP growth. Hence, it is valid to examine if finance-growth nexus runs through innovation channel. Furthermore, our results imply that invention patent is a good proxy for innovation in China in the sense that invention patent is effective to generate growth-enhancing effect.

Column (1) of Table 1.1 shows that the direct effect of *Loan* on per capita GDP growth is negative while that of *LTD* is positive. The former finding is consistent with existing literature and further implies that unfavourable factor like lending bias is embodied in depth dimension. The latter suggests that Chinese bank sector development does produce growth-enhancing effect which is captured by function or efficiency dimension. With higher LTD ratio, a sign of cost-efficiency in operation of banking, banks are more able to supply financial services and hence stimulate economic growth. Concentrating on *LTD*, we further investigate channels through which banking sector development positively affects per capita GDP growth in China. Column (2) shows that the coefficient of *LTD* becomes

[37]Priva is dropped as it is insignificant in majority of specifications though the coefficient is positive.

Table 1.1: Long-run Finance-Growth Relationships

	Per capita GDP growth			TFP growth				Per capita GDP growth			TFP growth		
	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0129*	0.0109**		0.0377**	0.0398**	Inno		0.0152*	0.0238***		0.0163*	0.0322**
		(0.007)	(0.005)		(0.016)	(0.019)			(0.008)	(0.008)		(0.009)	(0.015)
Loan	-0.0510**	-0.0623**	-0.0275*	-0.0034	-0.0341	-0.0336	Stock	-0.0091	-0.0007	0.0062	0.0198	-0.0017	0.0088
	(0.019)	(0.023)	(0.015)	(0.009)	(0.035)	(0.032)		(0.015)	(0.011)	(0.013)	(0.016)	(0.010)	(0.013)
Inno*Loan			0.0035			0.0062	Inno*Stock			-0.0046**			-0.0103***
			(0.003)			(0.010)				(0.002)			(0.003)
LTD	0.0438*	0.0293	0.0024	0.0371*	0.0465	-0.0098	Turnover	-0.0047	-0.0046	0.0157	0.0301	0.0143	-0.0625*
	(0.025)	(0.033)	(0.019)	(0.019)	(0.041)	(0.082)		(0.017)	(0.025)	(0.018)	(0.019)	(0.016)	(0.034)
Inno*LTD			0.0126*			0.0554**	Inno*Turnover			-0.0081*			0.0003
			(0.007)			(0.027)				(0.004)			(0.006)
Y0	-0.0442***	-0.0509***	-0.0403***	-0.0221***	-0.0584***	-0.0457**	Y0	-0.0613***	-0.0730***	-0.0565***	-0.0217**	-0.0374***	-0.0435***
	(0.011)	(0.012)	(0.011)	(0.006)	(0.017)	(0.021)		(0.019)	(0.018)	(0.013)	(0.009)	(0.009)	(0.014)
inv	0.0339***	0.0423***	0.0372***	-0.0266***	-0.0073	-0.0375**	inv	0.0440***	0.0499***	0.0263**	-0.0188***	-0.0256**	-0.0483***
	(0.008)	(0.012)	(0.008)	(0.007)	(0.015)	(0.014)		(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.017)
inf	0.0086**	0.0088*	0.0029	0.0125***	0.0086	-0.0031	inf	0.0134***	0.0050	0.0138*	0.0103**	0.0120***	0.0065
	(0.004)	(0.005)	(0.005)	(0.004)	(0.007)	(0.014)		(0.004)	(0.005)	(0.008)	(0.005)	(0.004)	(0.007)
gov	-0.0116	-0.0332***	-0.0179**	0.0081	0.0048	0.0242	gov	-0.0329**	-0.0503***	-0.0475***	-0.0171	-0.0021	0.0073
	(0.010)	(0.008)	(0.008)	(0.006)	(0.016)	(0.020)		(0.014)	(0.012)	(0.013)	(0.019)	(0.012)	(0.018)
open	0.0115*	0.0019	0.0020	0.0020	-0.0016	-0.0022	open	0.0111	0.0070	0.0034	-0.0045	-0.0037	0.0092
	(0.006)	(0.005)	(0.004)	(0.004)	(0.007)	(0.010)		(0.009)	(0.006)	(0.004)	(0.004)	(0.006)	(0.006)
hc	0.0721***	0.0089	0.0336	0.0614**	-0.0414	0.0122	hc	0.0653	-0.0126	0.0215	0.0354	-0.0023	0.0511
	(0.026)	(0.020)	(0.021)	(0.023)	(0.047)	(0.077)		(0.042)	(0.026)	(0.024)	(0.023)	(0.032)	(0.032)
fdi	0.0024***	0.0028***	0.0019**	0.0029***	0.0032***	0.0019	fdi	0.0027***	0.0021***	0.0016	0.0018***	0.0034***	0.0000
	(0.001)	(0.001)	(0.001)	0.000	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
constant	0.1184	0.3564***	0.2379***	0.1196**	0.6031***	0.5434**	constant	0.2665***	0.5851***	0.4760***	0.2178***	0.4249***	0.4521***
	(0.082)	(0.102)	(0.086)	(0.055)	(0.184)	(0.219)		(0.094)	(0.134)	(0.122)	(0.080)	(0.133)	(0.148)
Obs	145	138	137	141	146	141	Obs	146	136	136	139	139	133
Provinces	30	30	30	30	30	30	Provinces	30	30	30	30	30	30
Instruments	21	24	24	24	24	24	Instruments	21	24	24	21	24	30
AR(2) p	0.739	0.906	0.340	0.279	0.533	0.182	AR(2) p	0.398	0.238	0.318	0.476	0.855	0.801
Hansen p	0.223	0.127	0.352	0.115	0.130	0.796	Hansen p	0.265	0.163	0.222	0.512	0.741	0.520
Diff-in-Sargan p	0.156	0.089	0.436	0.398	0.927	0.735	Diff-in-Sargan p	0.118	0.400	0.498	0.545	0.860	0.347

Note: Inno is log of invention patent granted per 10000 persons. Loan is log of loans as percentage of GDP. LTD is log of loans as percentage of deposit. Stock is log of stock market capitalisation as percentage of GDP. Turnover is log of value of share traded as percentage of Stock.
Y0 is log of initial real GDP per capita; inv is log of gross fixed capital formation as percentage of GDP; inf is log of consumer price index; gov is log of government expenditure as percentage of GDP; open is log of the sum of export and import as percentage of GDP; hc is log of average year of schooling; fdi is the log of foreign direct investment as percentage of GDP.
Time dummies are included but not reported.
Robust standard error is in the parentheses.

legend:* p-value<.1; ** p-value<.05; *** p-value<.01.

insignificant when innovation is controlled. This result seems to imply that the effect of *LTD* only goes through innovation channel and separating this effect leads to insignificant coefficient of *LTD*. This possibility is confirmed by column (3) which shows that coefficient of interaction term between *LTD* and *Inno* is positive and significant. Thus, a more cost-efficient banking sector can provide more support to innovation and further stimulate economic growth in China.

Turning to TFP growth, we find that the direct effect of *loan* is negative but insignificant as shown in column (4). This result suggests that bank loans are not significantly harmful to TFP growth, which is consistent with firm-level findings (Cull and Xu 2005, Ayyagari et al. 2010). In terms of *LTD*, its direct effect is significantly positive as shown in column (4) but becomes insignificant after controlling for innovation (see column (5)). Column (6) shows that the coefficient of *Inno***LTD* is significantly positive. Hence, positive effect of *LTD* on TFP growth primarily comes from innovation channel. Taking into account column (1) to (6) together, we find that the cost-efficient operation of banking sector stimulates innovation to enhance TFP growth and further promotes per capita GDP growth in China. Moreover, this is likely to be the only positive channel through which bank-growth nexus runs. These findings are important in that they provide evidence on a positive bank-growth nexus in China. Although the overall efficiency of Chinese banking sector is low, it is not entirely harmful to Chinese economy. Furthermore, these findings suggest that the Chinese banking sector is not counter-example to cross-country findings in every aspect.

We use right panel (columns (7) to (12)) of Table 1.1 to show effects of stock market development in China. Columns (7) to (9) suggest that stock market development measured by both *depth* and *function* dimensions seems to be orthogonal to per capita GDP growth in China. Despite of this, we do find that stock market depth and function both negatively and significantly affect per capita growth through innovation channel. Turning to TFP growth, we do not find significant effect of stock market development, as suggested by columns (10) to (12). These results basically confirm findings from existing literature but we further show that the effect of stock market development on TFP growth is weak. More importantly, our results suggest that equity is not favourable financing source for innovation in China. The latter is consistent with the fact in that Chinese stock market does not favour technology-focused firms during our sample period and advantages of equity finance are far from well-exploited. Ayyagari et al. (2010) documents that the Chinese stock market serves as a vehicle for SOE reform to diversify ownership structure of SOEs rather than raising fund for growth opportunities. Moreover, there was no technology-based sub market[38] like Nasdaq Stock Exchange to support funding for technology firms. Thirdly, the process of initial public offering in China follows an approved based approach rather than the commonly adopted registration approach in developed country, which further increases difficulty for innovative firms to raise funds.

Therefore, financial development does affect productivity and economic growth through innovation channel in China. Banking sector encourages innovation while stock market discourages it. This Chinese pattern differs from cross-country findings (Brown et al. 2013, Hsu et al. 2014) that equity is more favourable source

[38]The Science and Technology Innovation Board was announced in 2018. This sub stock market can be regarded as a counterpart of Nasdaq Stock Exchange in China.

of finance for innovation. It is likely that the role of fostering innovation largely rely on banking sector in a country without sound equity market and China does achieve it.

Finally, the effects of control variables on per capita GDP growth and TFP growth are similar to those found in other literature and diagnostic tests are passed. Among control variables, *Inv* and *Y0* are the most significant predictors of per capita GDP growth and TFP growth, which are robust across all specifications. More specifically, *Inv* shows growth enhancing effects, while *Y0* exhibits convergence effect. *inf*, *hc* and *fdi* are found to have some stimulating effects on per capita GDP growth and TFP growth, while *gov* have negative effects. Moreover, we find coefficient of *open* is almost insignificant in all specifications. That is likely because *open* and *fdi* are highly correlated (0.67) with each other and adding them all together leads to insignificant coefficient of *open*. In terms of diagnostic check, the p-value of AR(2) statistics, Hansen statistics and difference-in-Sargan statistics are above 10% except for column (2) where that of difference-in-Sargan statistics is above 5%. The number of instruments is smaller than that of provinces. Results of diagnostic check suggest that AR(2) test, J-test and C-test are passed and there is no evidence against the validity of the instruments and the mean stationary assumption.

1.4.2 Nonlinear Finance-Growth Nexus

Considering inverted-U shaped finance-growth relationship proposed by cross-country studies (Samargandi et al. 2015, Arcand et al. 2015), we add square terms of *FD* in regression equations (1.1) to (1.3) to investigate if there is a nonlinear effect of financial development on economic and productivity growth in China. As argued by Arcand et al. (2015), if the non-linearity is excluded in the model while it is true, the result would be biased.

Table 1.2 reports the results related to the nonlinear finance-growth relationship. Our results relative to innovation and banking sector development are very similar as in section 1.4.1. One may note that *LTD* loses significance when we use a nonlinear regression model (see column (1) of Table 1.2). This is very likely due to the specification issue. If the true *LTD*-growth relationship is linear but nonlinear model is used to fit data, it is likely that results fail to capture the true effect of *LTD*. Thus, Table 1.1 and 1.2 together suggest that *LTD*-growth relationship should be linear and positive. Another major change compared with section 1.4.1 is the effect of stock market depth on per capita GDP growth. Columns (7) to (9) show that *Stock* has inverted-U shaped impact on per capita GDP growth. Such an effect is significant in (7), (8) and marginally significant in (9)[39]. Accordingly, it is very likely that the true stock market-growth relationship is weakly nonlinear. To be more specific, there exists positive effect of stock market depth on economic growth but it is subject to diminishing marginal return. There are two possible explanations for this nonlinearity. Firstly, over-expanded stock market can crowd out resources from other more productive sectors, for example innovative sector. Secondly, expansion of stock market may be due to factors irrelevant to firm value and stock market capitalization can be excessively higher than its real value. The difference between the two is so-called stock market bubble which is harmful to economic growth. Our findings provide support for Pistor

[39] $Stock^2$ is marginally insignificant in (9). Due to the high correlation between $Stock^2$ and *Inno*Stock*, their standard errors are inflated and hence both are not significant.

Table 1.2: Long-run Finance-Growth Relationships: Nonlinear Effects

	Per capita GDP growth			TFP growth				Per capita GDP growth			TFP growth		
	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0172**	0.0215**		0.0207**	0.0428*	Inno		0.0140**	0.0219*		0.0190*	0.0277**
		(0.008)	(0.008)		(0.008)	(0.024)			(0.006)	(0.012)		(0.011)	(0.013)
Loan	-0.0515***	-0.0494*	-0.0408***	-0.0117	0.0025	-0.0561	Stock	0.0689*	0.0658**	0.0595*	0.0591*	-0.0079	0.0108
	(0.018)	(0.028)	(0.014)	(0.013)	(0.025)	(0.050)		(0.038)	(0.026)	(0.030)	(0.034)	(0.035)	(0.022)
$Loan^2$	0.0311	0.0330	-0.0102	0.0195	-0.0044	-0.0479	$Stock^2$	-0.0070*	-0.0091***	-0.0044	-0.0077	0.0024	-0.0002
	(0.028)	(0.055)	(0.037)	(0.036)	(0.029)	(0.079)		(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
Inno*Loan			0.0067			0.0072	Inno*Stock			-0.0027			-0.0057*
			(0.004)			(0.020)				(0.003)			(0.003)
LTD	0.0335	0.0417	0.0303	0.0547***	0.0005	-0.0277	Turnover	0.0125	-0.0201	0.0399	-0.0168	0.0534	-0.0130
	(0.022)	(0.107)	(0.041)	(0.010)	(0.023)	(0.099)		(0.071)	(0.034)	(0.033)	(0.032)	(0.049)	(0.026)
LTD^2	-0.0425	-0.0251	0.0602	0.0147	-0.0453	-0.1181	$Turnover^2$	0.0061	0.0163	0.0334	0.0220	0.0198	0.0172
	(0.045)	(0.175)	(0.091)	(0.026)	(0.029)	(0.174)		(0.046)	(0.026)	(0.023)	(0.023)	(0.031)	(0.032)
Inno*LTD			0.0209*			0.0510*	Inno*Turnover			0.0079			0.0003
			(0.012)			(0.028)				(0.008)			(0.009)
Y0	-0.0429***	-0.0544***	-0.0501***	-0.0217***	-0.0406***	-0.0399	Y0	-0.0400***	-0.0751***	-0.0565***	-0.0068	-0.0399**	-0.0414***
	(0.011)	(0.013)	(0.015)	(0.007)	(0.009)	(0.024)		(0.009)	(0.025)	(0.014)	(0.011)	(0.015)	(0.012)
inv	0.0303**	0.0436***	0.0432***	-0.0248**	-0.0190	-0.0441	inv	0.0299	0.0345**	0.0335	-0.0358**	-0.0287*	-0.0400**
	(0.011)	(0.015)	(0.012)	(0.009)	(0.011)	(0.034)		(0.018)	(0.013)	(0.021)	(0.013)	(0.016)	(0.017)
inf	0.0113**	0.0085*	-0.0010	0.0097**	0.0096*	-0.0029	inf	0.0071	0.0148*	0.0080	-0.0041	0.0194*	0.0093
	(0.004)	(0.005)	(0.007)	(0.005)	(0.005)	(0.020)		(0.007)	(0.009)	(0.008)	(0.010)	(0.010)	(0.012)
gov	-0.0066	-0.0156	-0.0203*	0.0085	-0.0030	0.0453	gov	-0.0546*	-0.0237	-0.0581***	0.0057	-0.0155	-0.0056
	(0.012)	(0.020)	(0.011)	(0.009)	(0.013)	(0.032)		(0.028)	(0.019)	(0.021)	(0.016)	(0.024)	(0.014)
open	0.0120*	0.0064	0.0008	0.0010	-0.0033	0.0001	open	-0.0047	0.0027	-0.0006	-0.0057	-0.0078	0.0018
	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)	(0.012)		(0.009)	(0.007)	(0.006)	(0.006)	(0.009)	(0.004)
hc	0.0772***	0.0088	0.0111	0.0563**	-0.0069	0.0353	hc	0.0284	0.0231	-0.0360	0.0397*	-0.0116	0.0163
	(0.024)	(0.048)	(0.023)	(0.023)	(0.038)	(0.097)		(0.021)	(0.034)	(0.057)	(0.023)	(0.041)	(0.026)
fdi	0.0020***	0.0027*	0.0024***	0.0031***	0.0027***	0.0013	fdi	0.0009	0.0045*	0.0003	0.0000	0.0047**	0.0010
	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)		(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
constant	0.0963	0.3328**	0.3600**	0.1212*	0.4549***	0.4422*	constant	0.3275***	1.3718**	0.6559***	0.1529**	0.4870**	0.4956***
	(0.073)	(0.140)	(0.133)	(0.068)	(0.136)	(0.258)		(0.112)	(0.600)	(0.232)	(0.069)	(0.196)	(0.141)
Obs	146	140	136	138	143	137	Obs	139	139	140	138	140	146
Provinces	30	30	30	30	30	30	Provinces	30	30	30	30	30	30
Instruments	22	24	28	22	24	28	Instruments	22	24	28	22	24	28
AR(2) p	0.739	0.452	0.284	0.140	0.665	0.257	AR(2) p	0.369	0.669	0.746	0.545	0.501	0.671
Hansen p	0.216	0.643	0.239	0.129	0.108	0.763	Hansen p	0.872	0.524	0.578	0.456	0.387	0.461
Diff-in-Sargan p	0.141	0.565	0.321	0.462	0.575	0.736	Diff-in-Sargan p	0.814	0.508	0.492	0.381	0.347	0.410

Note: as above in Table 1.1.

and Xu (2005) and Allen et al. (2005) who suggest that Chinese stock market can be largely deviated from its true value and expansion of the stock market can be owing to active speculation. In these cases, stock market depth becomes high but its marginal effect can become low and even turn to be negative.

1.5 Robustness Checks

1.5.1 Fixed Effect estimation

Considering that fixed effect (FE) estimator has bounds on the coefficient of the lagged dependent variable to avoid potential problems in regressions, we re-examine the finance-TFP growth relationship using FE estimation.

Table 1.9 and 1.10 show results based on FE estimation. They basically confirm main findings in terms of effects of *Inno*, *Inno*LTD* and *Inno*Stock* on both TFP growth and per capita GDP growth.

1.5.2 Re-estimation of TFP Growth

Is finance-TFP growth relationship sensitive to different estimation of TFP growth? The question is addressed in this section. To this end, TFP growth is reestimated using the Malmquist index based on Data Envelopment Analysis (DEA). As a non-parametric method, DEA is not subject to the error of misspecification of production function (Färe et al. 1994). Thus, we do not need to worry about potential bias in capital share when constructing TFP growth.

In data envelopment analysis, an optimal frontier is constructed by enveloping all production units (provinces in this study). Then each production unit is compared with the optimal frontier to compute a distance function. Based on the distance functions for one unit in periods t and $t+1$, we can take their ratios to obtain the Malmquist index which yields us TFP growth in one province over t to $t+1$. More details about this method and application can be found in the extensive literature, for example Kumar and Russell (2002). Table 1.11 shows the results related to TFP growth based on DEA method. To summarize, we do not find fundamental change in terms of effect of *Inno*, *LTD*, *Inno*LTD* and *Inno*Stock*.

1.6 Is the Finance-Growth Nexus Changing over Time?

Since this study covers a long period of 24 years during which a rapid development and several reforms took place in China, the relationships found in section 1.4 might not exactly hold for the whole sample period. Indeed, the existing literature implies that Chinese finance-growth nexus might differ in different periods or development stages. In addition, using averaged data might conceal some valuable information. Hence, we divide our sample and run regressions based on sub-samples using annual data to check whether above findings change over time or differ in different development stages. We interpret the results in this section as short-term relationship in each sub-period. It is worthy to point out that there could be lagged effects of innovation and financial development especially for annual sample. In order to keep consistency between short-term and long-term results, we do not include lag terms of *inno* and FD. Studying lagged effects can be a good extension and it is firmly on our research agenda.

1.6.1 Banking Sector Development

Here we re-examine the effects of banking sector development using sub-samples based on sub-periods. The sample split for banking development is based on the Corporatisation reform of state-owned commercial banks (SOCBs) at the end of 2003 (Lin et al. 2015). This reform was intended to diversify ownership of state-owned commercial banks and force them to be more market-oriented and profit-driven. Accordingly, we divide the sample by year 2004 into two sub-periods. The first one (1991-2003) is marked with administrative-driven banking behaviours and the second (2004-2014) is marked with relatively profit-driven banking behaviours.

Table 1.3 shows the effects of banking sector development in sub-period one. The direct effects of *loan* on per capita GDP growth and TFP growth are basically consistent with those in the long run. While for *LTD*, its direct effects on per capita GDP growth and TFP growth are positive yet the former is insignificant (see column (1)). This finding implies that the direct effect of *LTD* on per capita GDP growth in the sub-period one is less favourable than in the whole sample period and the unfavourable factor might come from capital accumulation channel. Moreover, we find positive coefficients of *inno*loan* and *inno*LTD* but with inconsistent significance across different specifications. This finding implies that the bank-innovation-growth relationship may be weak in this sub-period.

Table 1.4 shows that the effects of banking sector development in the sub-period two are similar as in the long-run and are more favourable than in the

Table 1.3: Bank-Innovation-Growth (1991-2003)

	Per capita GDP growth						TFP growth					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0286***	0.0339***		0.0232***	0.0407***		0.0223**	0.0200**		0.0308***	0.0144**
		(0.006)	(0.007)		(0.007)	(0.012)		(0.008)	(0.008)		(0.009)	(0.006)
Loan	-0.0513*	-0.0962**	-0.0851**	0.0942	-0.0219	-0.0561*	-0.0396	-0.0299	0.0036	0.0050	-0.0514	-0.0069
	(0.028)	(0.041)	(0.041)	(0.105)	(0.048)	(0.031)	(0.044)	(0.048)	(0.037)	(0.033)	(0.050)	(0.029)
$Loan^2$				-0.0180	0.0619	-0.1125				0.0398	-0.0181	-0.0079
				(0.059)	(0.053)	(0.074)				(0.034)	(0.059)	(0.049)
Inno*Loan			0.0178***			0.0232			0.0035			0.0119
			(0.005)			(0.020)			(0.008)			(0.011)
LTD	0.0086	0.0255	0.0646	-0.1318	0.0181	0.0058	0.1236*	0.0234	0.0637	0.0746*	0.0470	0.0299
	(0.052)	(0.037)	(0.050)	(0.132)	(0.034)	(0.037)	(0.068)	(0.052)	(0.050)	(0.043)	(0.043)	(0.025)
LTD^2				-0.1667	-0.1082	-0.0097				-0.0672	-0.1677	-0.0166
				(0.212)	(0.080)	(0.103)				(0.074)	(0.148)	(0.059)
Inno*LTD			0.0054			0.0319			0.0421*			0.0032
			(0.026)			(0.026)			(0.023)			(0.017)
Y0	-0.0951*	-0.0510**	-0.0516*	-0.0378	-0.0624**	-0.1445**	-0.0126	-0.1344***	-0.0262	-0.0170***	-0.0678**	-0.0570*
	(0.049)	(0.021)	(0.026)	(0.037)	(0.023)	(0.062)	(0.008)	(0.033)	(0.026)	(0.005)	(0.025)	(0.031)
inv	0.0698**	0.0512***	0.0465***	0.0122	0.0390***	0.0917***	0.0005	0.0281	-0.0146	-0.0119	-0.0041	-0.0023
	(0.031)	(0.017)	(0.014)	(0.027)	(0.014)	(0.029)	(0.015)	(0.018)	(0.015)	(0.011)	(0.015)	(0.014)
inf	0.0167	-0.0072	-0.0083	0.0137*	-0.0059	-0.0239*	0.0065	-0.0162*	0.0041	0.0063	-0.0103	-0.0051
	(0.018)	(0.006)	(0.008)	(0.008)	(0.006)	(0.012)	(0.005)	(0.009)	(0.006)	(0.004)	(0.009)	(0.006)
gov	-0.0323*	-0.0079	-0.0104	-0.0597	-0.0353	-0.0464	0.0109	-0.0286	-0.0082	-0.0056	-0.0026	-0.0102
	(0.018)	(0.020)	(0.020)	(0.045)	(0.022)	(0.029)	(0.016)	(0.021)	(0.015)	(0.013)	(0.019)	(0.013)
open	0.0378*	0.0086	0.0076	0.0041	0.0160	0.0327*	0.0110	0.0326***	0.0021	0.0089	0.0164	0.0107
	(0.020)	(0.009)	(0.009)	(0.009)	(0.010)	(0.019)	(0.009)	(0.010)	(0.007)	(0.005)	(0.013)	(0.011)
hc	0.0152	0.0018	-0.0032	-0.0047	-0.0025	0.0101	0.0086	0.0165**	0.0018	0.0047	0.0057	0.0066
	(0.010)	(0.007)	(0.006)	(0.008)	(0.006)	(0.013)	(0.007)	(0.007)	(0.007)	(0.005)	(0.008)	(0.006)
fdi	0.0006	0.0029***	0.0035***	0.0008	0.0023***	0.0022**	0.0027***	0.0026***	0.0016*	0.0017***	0.0028**	0.0025***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	0.000	(0.001)	(0.001)
constant	0.3753*	0.3438**	0.4074**	0.5110	0.5491***	0.9662**	-0.0429	0.9095***	0.3215*	0.1399	0.5796***	0.4680**
	(0.205)	(0.147)	(0.185)	(0.449)	(0.189)	(0.414)	(0.167)	(0.233)	(0.166)	(0.093)	(0.153)	(0.192)
Obs	390	363	366	357	355	352	361	358	361	357	345	352
Provinces	30	30	30	30	30	30	30	30	30	30	30	30
Instruments	27	20	24	22	24	28	20	20	24	26	24	28
AR(2) p	0.095	0.275	0.793	0.719	0.402	0.756	0.838	0.776	0.412	0.597	0.170	0.176
Hansen p	0.048	0.194	0.500	0.036	0.184	0.039	0.934	0.406	0.585	0.715	0.871	0.110
Diff-in-Sargan p	0.095	0.308	0.421	0.621	0.237	0.100	0.788	0.295	0.477	0.813	0.802	0.143

Note: as above in Table 1.1.

Table 1.4: Bank-Innovation-Growth (2004-2014)

	Per capita GDP growth						TFP growth					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0562**	0.0633***		0.0355**	0.0328**		0.0654**	0.0405***		0.0450**	0.0376**
		(0.027)	(0.020)		(0.017)	(0.013)		(0.028)	(0.012)		(0.020)	(0.015)
Loan	-0.0628	-0.1337	-0.1421**	-0.0330	-0.0652	-0.0246	0.0421*	0.0056	0.0079	0.0825	0.0078	-0.0708
	(0.070)	(0.092)	(0.063)	(0.052)	(0.042)	(0.031)	(0.025)	(0.081)	(0.060)	(0.050)	(0.070)	(0.042)
$Loan^2$				0.0255	0.1049**	0.0141				-0.0383	-0.0416	-0.1137
				(0.073)	(0.048)	(0.126)				(0.067)	(0.082)	(0.083)
Inno*Loan			0.0284**			0.0034			0.0200**			0.0450**
			(0.014)			(0.018)			(0.009)			(0.020)
LTD	0.0437*	0.0065	-0.0176	0.2608	0.0264	-0.0823	0.0355**	0.0033	0.0024	-0.0075	0.0094	-0.0016
	(0.026)	(0.107)	(0.053)	(0.222)	(0.085)	(0.075)	(0.017)	(0.091)	(0.050)	(0.091)	(0.146)	(0.119)
LTD^2				0.3994	0.0221	0.0126				0.1016	0.0313	0.0683
				(0.322)	(0.124)	(0.071)				(0.114)	(0.155)	(0.171)
Inno*LTD			0.0479*			0.0417***			0.0368*			0.0452*
			(0.025)			(0.011)			(0.021)			(0.033)
Y0	-0.0351	-0.1881***	-0.1960***	-0.0248	-0.1178**	-0.1484***	-0.0134*	-0.0639	-0.0242**	0.0867**	-0.0315	-0.0106
	(0.028)	(0.041)	(0.054)	(0.020)	(0.046)	(0.030)	(0.008)	(0.044)	(0.012)	(0.036)	(0.049)	(0.018)
inv	0.0584*	0.1232**	0.0939***	0.0440	0.0981***	0.0860***	-0.0285**	0.0233	-0.0022	-0.0385	0.0024	-0.0003
	(0.030)	(0.048)	(0.031)	(0.027)	(0.029)	(0.023)	(0.013)	(0.036)	(0.013)	(0.024)	(0.028)	(0.017)
inf	0.0067	-0.0391	-0.0501**	-0.0054	-0.0137	-0.0406***	0.0353***	0.0464*	0.0321***	0.0575***	0.0428*	0.0331***
	(0.010)	(0.036)	(0.020)	(0.021)	(0.017)	(0.012)	(0.008)	(0.023)	(0.010)	(0.016)	(0.024)	(0.010)
gov	-0.0442	-0.0295	-0.0374*	-0.0202	-0.0356***	-0.0627***	-0.0210	-0.0262	0.0015	-0.0100	-0.0101	0.0137
	(0.034)	(0.055)	(0.021)	(0.026)	(0.012)	(0.017)	(0.014)	(0.055)	(0.012)	(0.033)	(0.036)	(0.018)
open	0.0000	0.0400**	0.0453***	0.0020	0.0216*	0.0324***	-0.0090	-0.0234	-0.0071	-0.0404**	-0.0193	-0.0091*
	(0.005)	(0.019)	(0.014)	(0.012)	(0.013)	(0.009)	(0.006)	(0.019)	(0.005)	(0.018)	(0.023)	(0.005)
hc	-0.0028	-0.0003	0.0034	-0.0083	-0.0119**	0.0086	-0.0052	-0.0283**	-0.0173***	-0.0258***	-0.0227*	-0.0143*
	(0.006)	(0.017)	(0.009)	(0.008)	(0.004)	(0.005)	(0.005)	(0.013)	(0.006)	(0.007)	(0.012)	(0.007)
fdi	0.0037**	0.0059***	0.0044***	0.0061***	0.0051***	0.0045***	0.0013	0.0027	0.0013	0.0000	0.0014	0.0029
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
constant	0.2902	1.2912***	1.4759***	0.3059*	0.8889***	1.1273***	1.9368	17.6199**	9.0798***	21.6309***	17.2029	13.8760***
	(0.210)	(0.372)	(0.388)	(0.169)	(0.301)	(0.209)	(2.471)	(7.316)	(3.178)	(7.635)	(10.758)	(4.571)
Obs	312	306	305	313	299	296	314	319	319	317	312	312
Provinces	30	30	30	30	30	29	30	30	30	30	30	30
Instruments	22	20	24	28	24	24	15	22	27	26	22	30
AR(2) p	0.234	0.244	0.269	0.816	0.213	0.306	0.584	0.327	0.273	0.974	0.986	0.773
Hansen p	0.150	0.819	0.178	0.198	0.243	0.139	0.239	0.170	0.283	0.227	0.891	0.455
Diff-in-Sargan p	0.036	0.717	0.028	0.036	0.298	0.120	0.350	0.054	0.219	0.715	0.848	0.227

Note: as above in Table 1.1.

earlier period. The direct effect of *Loan* on per capita GDP growth is negative (see column (1)) although it becomes insignificant compared with the earlier period. The direct effect of *LTD* on per capita GDP growth is significantly positive (see column (1)) and is run through innovation channel (see column (3)). This finding implies that LTD-innovation-growth relationship is strengthened in the late period. With regard to TFP growth, column (7) shows that both *loan* and *LTD* have significantly positive direct effect. This is the most stark difference compared with the early period and long-run results. It seems that the effects of banking sector development have become more productivity-enhancing in the recent period. When investigating the channel through which bank-TFP growth nexus is run, we find that both interaction terms *inno*loan* and *inno*LTD* have significant positive coefficients, (see column (9) and (12)). The last two findings together suggest that banking sector development in both depth and function dimensions becomes more conducive to TFP growth through stimulating more innovation in China.

Comparing the results from two sub-periods, we find that the effect of banking sector development in recent period has become less harmful for economic growth and more favourable for productivity growth. In addition, the bank-innovation-growth nexus is strengthened. We offer three explanations for these findings. Firstly, with banking sector reform, banking industrial structure and behaviours of SOCBs[40] become more conducive to productivity and economic growth. On one hand, Chinese banking sector becomes less concentrated by SOCBs and there are ever-increasingly more share of private banks and small banks. These banks

[40] Although we do not measure banking industrial structure and behaviours of SOCBs, their effects are likely to be embodied in our measured banking sector development.

are more profit-driven and hence they are more able to fund private firms (Lin et al. 2015) who usually have higher productivity and more productive projects than SOEs. On the other hand, Chinese SOCBs become more market-driven and hence, their lending bias is partially alleviated. Secondly, reform in the user-side of credit may also help explain our findings. With deep SOE reforms, SOEs are catching-up with POEs in terms of productivity and their gaps were gradually reduced (Li et al. 2018). It is very likely that efficiency of fund usage in SOEs is improved and hence the effect of banking sector development becomes more growth- and productivity-enhancing. Thirdly, our findings about strengthened bank-innovation-growth relationships may be partially due to increased attention and effectiveness of government policies on innovation. Since the middle of 2000s, Chinese government implemented several rounds of policies[41] to heavily stress on credit support for innovation such as discounted loans. These policies are very likely to encourage banks to supply more credits to innovation projects in China. As a consequence, bank-innovation-growth relationship is strengthened.

1.6.2 Stock Market Development

This sub-section re-examines the effects of stock market development in different sub-periods. The sample split is based on the level of stock market regulation and government intervention. The first ten years of Chinese stock market were chaotic and there was extensive government intervention. In the 1990s, there were very active speculation and government indirectly controlled the growth rate of Chinese stock market capitalization by intervening in price and quantities

[41] For example, the Decision on Implementing the Independent Innovation Capacity in 2006 and National guidance for Medium and Long-run Plan for Science and Technology Development (2006-2020) in 2006.

in firms' IPO[42]. At the end of 1990s regulations were reinforced to constrain speculation and government gradually stepped away from intervention. In 1999, the Securities Law of the Peoples' Republic of China was issued and growth target of stock market was abandoned. Accordingly, we choose 1999 to split the whole sample into two sub-periods. The first one (1991-1999) is marked with lack of regulation and heavy government intervention. The second one (2000-2014) is marked with strengthened regulation and relatively less government intervention. Note that the sample split here is different compared to section 1.6.1 as the reforms or development in Chinese banking sector and stock market have taken place in different periods.

Table 1.5 shows the effects of stock market development in the sub-period one. Interestingly, neither *stock* nor *turnover* shows strong significant effect on per capita GDP growth and TFP growth. With regard to *stock*, its effects, especially the direct effects (see column (1), (4), (7) and (10)), are almost insignificant. This implies that *stock*-growth relationship could be weak in this sub-period.[43] Such a finding is likely due to the fact that stock market expansion was largely subject to administrative order before 2000. As such, variation of stock market capitalization is largely orthogonal to the economic performance, which leads to the weak *stock*-growth relationship. In terms of another measure *turnover*, it shows some evidence of significantly negative effect on per capita GDP growth (see column (2), (3) and (5)) but not on TFP growth. Thus, it is possible there is weakly negative *turnover*-growth relationship through capital accumulation

[42] In 1990s, stock market was mainly serving as a vehicle of SOE reform so that mainly SOEs have access to equity.

[43] We want to mention that the insignificant findings could be also a reflection of absence of evidence in terms of the *stock*-growth relationship. However, given the significant problems in the Chinese stock market, we favour the weak *stock*-growth relationship as more probable interpretation.

Table 1.5: Stock Market-Innovation-Growth (1991-1999)

	Per capita GDP growth						TFP growth					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0109*	0.0205**		0.0066*	0.0180***		0.0164*	0.0140**		0.0085*	0.0133**
		(0.005)	(0.008)		(0.004)	(0.005)		(0.009)	(0.005)		(0.005)	(0.005)
Stock	0.0038	-0.0047	0.0064	0.0108	0.0302**	-0.0148	0.0014	0.0014	-0.0051	-0.0032	0.0212	0.0003
	(0.003)	(0.007)	(0.008)	(0.014)	(0.013)	(0.011)	(0.010)	(0.010)	(0.006)	(0.011)	(0.015)	(0.007)
$Stock^2$				0.0004	-0.0052***	-0.0005				0.0025	-0.0050**	-0.0025
				(0.002)	(0.002)	(0.002)				(0.002)	(0.002)	(0.002)
Inno*Stock			-0.0085**			-0.0032			-0.0003			0.0038
			(0.003)			(0.005)			(0.003)			(0.002)
Turnover	-0.0066	-0.0134**	-0.0839***	-0.0035	-0.0381*	-0.0373	-0.0142	0.0061	-0.0263	-0.0036	-0.0173	0.0711
	(0.006)	(0.005)	(0.029)	(0.013)	(0.020)	(0.034)	(0.009)	(0.013)	(0.024)	(0.008)	(0.015)	(0.055)
$Turnover^2$				0.0223	-0.0376	-0.0167				-0.0080	-0.0034	0.0233
				(0.029)	(0.032)	(0.015)				(0.007)	(0.018)	(0.016)
Inno*Turnover			-0.0317**			-0.0178			-0.0234*			0.0234
			(0.013)			(0.017)			(0.013)			(0.016)
Y0	-0.0100	-0.0073	-0.0467**	-0.0248***	-0.0109	-0.0055	-0.0560**	-0.0987***	-0.0377***	-0.0298**	-0.0266*	-0.0468**
	(0.008)	(0.009)	(0.018)	(0.008)	(0.011)	(0.026)	(0.024)	(0.035)	(0.013)	(0.012)	(0.014)	(0.020)
inv	0.0185***	0.0134	0.0271**	0.0241***	0.0095	0.0245	-0.0272**	0.0002	-0.0204	-0.0353***	-0.0397**	-0.0196
	(0.007)	(0.010)	(0.012)	(0.008)	(0.012)	(0.017)	(0.013)	(0.019)	(0.017)	(0.011)	(0.018)	(0.018)
inf	0.0104**	-0.0046	0.0406**	0.0230	0.0268**	-0.0088	0.0234**	-0.0191	-0.0198	-0.0065	0.0159	-0.0147
	(0.005)	(0.014)	(0.017)	(0.016)	(0.012)	(0.013)	(0.009)	(0.023)	(0.014)	(0.012)	(0.028)	(0.022)
gov	-0.0273***	-0.0262***	-0.0520***	-0.0380***	-0.0262***	-0.0238*	-0.0141	-0.0217	-0.0023	-0.0033	0.0105	0.0090
	(0.006)	(0.007)	(0.015)	(0.008)	(0.008)	(0.013)	(0.015)	(0.017)	(0.012)	(0.012)	(0.011)	(0.012)
open	0.0031	-0.0015	0.0204**	0.0052	0.0054	-0.0065	0.0107	0.0242**	0.0024	0.0042	0.0006	0.0063
	(0.003)	(0.004)	(0.008)	(0.004)	(0.004)	(0.009)	(0.009)	(0.011)	(0.006)	(0.005)	(0.007)	(0.008)
hc	-0.0029*	-0.0086***	-0.0019	-0.0011	-0.0075***	-0.0117**	0.0121***	0.0113	0.0013	0.0078**	0.0061	0.0089*
	(0.001)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.007)	(0.004)	(0.003)	(0.005)	(0.005)
fdi	0.0013***	0.0022***	-0.0005	0.0015*	0.0005	0.0026***	0.0006	0.0019*	0.0023***	0.0011*	0.0023**	0.0028**
	0.000	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
constant	0.1587***	0.2816***	0.3407***	0.1830**	0.1972*	0.2675	0.4067**	0.7947***	0.4723***	0.3868***	0.2814*	0.4340**
	(0.052)	(0.081)	(0.118)	(0.077)	(0.105)	(0.191)	(0.164)	(0.261)	(0.117)	(0.099)	(0.149)	(0.163)
Obs	217	219	212	211	202	199	225	218	207	226	225	219
Provinces	30	30	30	30	30	30	30	30	30	30	30	30
Instruments	25	26	22	25	22	27	21	24	28	20	22	36
AR(2) p	0.893	0.586	0.895	0.169	0.331	0.647	0.102	0.570	0.356	0.347	0.105	0.495
Hansen p	0.212	0.285	0.516	0.219	0.165	0.090	0.128	0.222	0.377	0.378	0.144	0.952
Diff-in-Sargan p	0.851	0.845	0.454	0.374	0.113	0.351	0.145	0.464	0.987	0.332	0.348	0.999

Note: as above in Table 1.1.

channel. The results in Table 1.5 are consistent with the fact that the Chinese stock market functioned very poorly in the 1990s and there was over-liquidity issue (see page 21).

Table 1.6 shows that the effects of stock market development have changed dramatically in sub-period two and are consistent with the findings in the long-run analysis. The major change is in the *stock* whose effects become significantly positive on both per capita GDP growth and TFP growth for all specifications. When applying nonlinear models, we find positive effect of *stock* is subject to diminishing marginal returns, which is consistent with cross-country findings (e.g. Shen and Lee (2006)). In terms of another measure, *turnover*, its effects on per capita GDP growth and TFP growth are negative, as similar to sub-period one while it gains significance in TFP growth regressions (see column (8), (11) and (12)). It seems the adverse effect of *turnover* on TFP growth is slightly exacerbated. Furthermore, *inno*stock* has negative and significant coefficients for both per capita GDP growth and TFP growth, which is consistent with the findings in long-run analysis.

Comparing the results from two sub-periods, we find the effects of stock market depth basically evolve in a proper direction but stock market still function poorly in terms of liquidity supply and promoting innovation. We offer two explanations for these findings. On the one hand, government intervention is gradually reduced in 2000s, and stock market capitalization is not severely influenced by growth target. Hence, stock market depth becomes more relevant and informative to real side of the economy. In addition, stock market gradually becomes a "market" of fund raising and serves less as a vehicle of privatization. Hence, it

Table 1.6: Stock Market-Innovation-Growth (2000-2014)

	Per capita GDP growth						TFP growth					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0107**	0.0226***		0.0295**	0.0549**		0.0113**	0.0180**		0.0161**	0.0620*
		(0.005)	(0.006)		(0.011)	(0.027)		(0.005)	(0.008)		(0.006)	(0.032)
Stock	0.0220***	0.0038*	0.0136***	0.0764**	0.0132**	0.1467*	0.0172***	0.0096*	0.0131*	0.0503***	0.0127*	0.0185**
	(0.006)	(0.002)	(0.003)	(0.030)	(0.006)	(0.086)	(0.005)	(0.005)	(0.008)	(0.017)	(0.006)	(0.009)
$Stock^2$				-0.0100**	-0.0133	-0.0155				-0.0065***	-0.0062*	0.0015
				(0.004)	(0.010)	(0.013)				(0.002)	(0.003)	(0.005)
Inno*Stock			-0.0045***			-0.0164**			-0.0057**			-0.0128**
			(0.001)			(0.007)			(0.003)			(0.005)
Turnover	-0.0119	-0.0006	-0.0070	-0.0248**	-0.0109	-0.0393**	-0.0074	-0.0102*	-0.0126	0.0054	-0.0165**	-0.0191*
	(0.009)	(0.005)	(0.005)	(0.010)	(0.010)	(0.016)	(0.009)	(0.005)	(0.009)	(0.009)	(0.007)	(0.010)
$Turnover^2$				-0.0115	0.0191	-0.0114				-0.0081	0.0007	-0.0095
				(0.007)	(0.014)	(0.013)				(0.005)	(0.008)	(0.009)
Inno*Turnover			0.0010			-0.0047			0.0034			0.0035
			(0.002)			(0.012)			(0.004)			(0.004)
Y0	-0.0259**	-0.0162*	-0.0214**	-0.0716***	-0.0341	-0.0577**	-0.0157**	-0.0177	-0.0288*	-0.0081	-0.0318**	-0.0359**
	(0.011)	(0.009)	(0.008)	(0.024)	(0.022)	(0.022)	(0.007)	(0.011)	(0.016)	(0.009)	(0.013)	(0.016)
inv	0.0601***	0.0397***	0.0376***	0.0611***	0.0332**	0.0343*	-0.0098	-0.0051	-0.0163	-0.0289***	-0.0076	-0.0258
	(0.012)	(0.009)	(0.008)	(0.012)	(0.016)	(0.020)	(0.009)	(0.008)	(0.012)	(0.009)	(0.009)	(0.016)
inf	0.0462***	0.0341***	0.0371***	0.0470***	0.0389***	0.0647***	0.0450***	0.0423***	0.0390***	0.0373***	0.0450***	0.0357***
	(0.006)	(0.004)	(0.004)	(0.009)	(0.009)	(0.012)	(0.009)	(0.006)	(0.009)	(0.008)	(0.007)	(0.008)
gov	-0.0512***	-0.0204***	-0.0251***	-0.0437***	-0.0178	-0.0436***	-0.0211*	-0.0145	-0.0071	0.0062	-0.0133	-0.0035
	(0.012)	(0.005)	(0.006)	(0.016)	(0.016)	(0.015)	(0.011)	(0.009)	(0.012)	(0.011)	(0.009)	(0.014)
open	-0.0034	-0.0044	-0.0014	0.0117*	-0.0097	0.0103	-0.0052*	-0.0083***	-0.0043	-0.0015	-0.0065	0.0004
	(0.003)	(0.003)	(0.002)	(0.006)	(0.007)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
hc	-0.0035	-0.0056**	0.0011	0.0157***	-0.0026	0.0214***	-0.0040	-0.0084**	-0.0002	0.0050	-0.0046	0.0074
	(0.004)	(0.003)	(0.002)	(0.005)	(0.008)	(0.008)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
fdi	0.0026***	0.0026***	0.0018***	0.0028***	0.0027**	0.0000	0.0013*	0.0017**	0.0008	0.0003	0.0019*	-0.0004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
constant	0.0515	0.0844	0.0468	0.1486	0.2442	-0.1201	0.1321***	0.2170**	0.2704**	-0.0087	0.3008***	0.2906**
	(0.047)	(0.073)	(0.062)	(0.128)	(0.204)	(0.185)	(0.047)	(0.082)	(0.127)	(0.044)	(0.107)	(0.120)
Obs	403	400	400	389	375	390	394	389	381	389	387	382
Provinces	30	30	30	30	30	30	30	30	30	30	30	30
Instruments	30	28	30	23	28	28	24	28	30	27	30	28
AR(2) p	0.251	0.455	0.939	0.171	0.322	0.089	0.443	0.924	0.850	0.530	0.809	0.495
Hansen p	0.057	0.160	0.316	0.162	0.100	0.370	0.436	0.107	0.740	0.300	0.587	0.149
Diff-in-Sargan p	0.211	0.876	0.997	0.815	0.597	0.376	0.391	0.906	0.999	0.114	0.985	0.983

as above in Table 1.1.

is sensible that the equity raised from stock market starts to generate positive effect. On the other hand, many issues still exist in the Chinese stock market in the recent period. For instance, the issue of over-liquidity has long been unresolved and might be even exacerbated by financial liberalization in 2000s. An essential liberalization is the Full Circulation of Reform for Listed Companies which gradually allow two thirds of untradable shares to circulate in the Chinese stock market. This liberation injects substantial liquidity into stock market. However, it seems such a reform encourages more active speculation in Chinese stock market. As a consequence, the negative effect of turnover is strengthened. Furthermore, the Chinese stock market is still dominated by firms which are not from technology-focused industries. Despite this, the policy markers have started addressing this issue recently by promoting more hi-tech firms to be listed, such as the preparation to establishing Science and Technology Innovation Board. It is possible that positive stock market-innovation-growth relationship will emerge in near future.

1.7 Conclusion

Over the past 25 years, China's economic development is accompanied with high GDP growth, moderate productivity improvement and seemingly unimportant financial development. In order to understand what is the real role played by financial sector, we extensively analyse the role of financial development in economic and productivity growth within the Chinese framework and examine the role of innovation within this finance-growth relation using provincial level data of 1991-2014. In order to address these issues, firstly, we revisit the impact of banking sector and stock market development on economic and productivity growth by distinguishing the innovation channel against others. This can help us understand the contrasting findings 1) between cross-country and Chinese case studies and 2) among different Chinese case studies. Secondly, two dimensions of measure–depth and function–are differentiated to capture relative size or functions of each sub financial sector separately. This is helpful to link favourable or unfavourable elements with different aspects of financial development. Thirdly, non-linear finance-growth nexus is examined. Fourthly, we have investigated whether effects of financial development differ in different development stages. Finally, a new provincial dataset on Chinese stock market, human capital and TFP growth is constructed as these data are not available at provincial level.

This study firstly shows that there is a positive bank-innovation-growth relationship and this seems to be the only positive bank-growth nexus in China. In this sense, Chinese finance-growth relationship is not contradictory to cross-country findings in all aspects and accordingly this study provides a reconciliation. However, this study further identifies a special pattern in China that stock market discourages innovation and hence there is negative stock-innovation-growth relationship. After all, the initial purpose of Chinese stock market development was to raise funds for SOEs instead of productive and innovative projects. As a result, Chinese stock market functions in a different way than that of other countries. Furthermore, the effects of bank and stock market development exhibit time-varying pattern and finance-growth nexus differs in different development stages. Therefore, this study provides another reconciliation in terms of contradictory findings in Chinese finance-growth literature based on different periods.

Finally, this study sheds light on China's financial reforms. Our findings suggest that the banking reforms appear in the right direction while stock market reforms may generate subtle consequences. Further attention of financial reforms might need to be paid to specific areas of financial sector.

Appendix A

We used five steps to obtain provincial level data.

1. Obtain firm-level annual data from China Stock Market and Accounting Research (CSMAR) database including market value and value of share traded for each listed firm in Shanghai Stock Exchange (SHSE) and Shenzhen Stock Exchange (SZSE). Annual data refers to the value on the last trading day of a year.

2. Convert shares denoted in US dollars or HK Yuan into Renminbi using annual closing exchange rates.

3. Check the registration location for each firm at the end of each year to attach province to each firm-year observation. By the end of step 3, we obtain a firm-level panel with each firm attached to its registration location.

4. Add up market value and value of share traded by year and by province to generate provincial level market value (stock market capitalization) and value of share traded. We use Stata command "Collapse" to achieve it.

5. Divide stock market capitalization by GDP to generate *Stockdepth* and divide value of share traded by stock market capitalization to generate $Turnover$.

One may raise a concern as to how Chinese firms choose registration locations. According to the Regulations of the People's Republic of China on Administration of Registration of Companies, firms are required to register in the area where they conduct their major business. Otherwise, there would be punishment and the firms would be required to change either registration location or business address.

Appendix B

The real physical capital stock data from 1990 to 2013 are obtained from Wu (2016). The dataset was updated to 2014. The estimation is based on perpetual inventory method. In this method, the physical capital stock is evaluated by $K_{it} = (1 - \delta_i)K_{it-1} + I_{it}$ where K_t is real physical capital stock in the current period, K_{t-1} is that in the previous period, I_t is the current capital formation, δ is the depreciation rate. The δ_i is assumed to be province-specific (Wu 2008a). The price deflator is available from 1990 up to 2013 and we have extrapolated the data into 2014. The capital formation is obtained from China Data Online.

There is no official Human capital data at the provincial level. So we have estimated this data based on the average year of schooling according to the following formula, $YS = (6PS + 9JS + 12SS + 16HE)/POP$ where YS is the average year of schooling, PS is number of people who have primary degree without taking further education, JS is number of people who have junior secondary degree without taking further education, SS is number of people who have senior secondary degree without taking further education, HE is number of people who have undergraduate tertiary degree and POP is number of people with age greater than six. In China, a student needs to spend 6 years to complete primary school, then 3 years for junior high school, followed by 3 years for senior high school and then 4 years for undergraduate education. It should be noted that statistics about undergraduate education cover special college and students only need 3 years to achieve this degree. Since education data related to specially college is not available, we simply assume those who hold undergraduate degree have undertaken 4 years of education. Furthermore, there are no data related to number of people holding postgraduate degree. Hence, we our estimate is undergraduate level human capital.

In order to construct provincial TFP growth, we assume a Cobb-Douglas production function across province and time $Y_{it} = A_{it}K_{it}^{\alpha_i}L_{it}^{(1-\alpha_i)}$ as in (Beck et al. 2000) where Y_{it} is GDP, K_{it} physical capital stock, L_{it} labour, A_{it} TFP and α_i province-specific capital share. All variables are at provincial level. Then we take log on both side of the production function and calculate TFP as follows: $lnA_{it} = lnY_{it} - \alpha_i lnK_{it} - (1-\alpha_i)lnL_{it}$. Finally, we take difference of lnA_{it} to obtain TFP growth as following: ΔlnA_{it}=$lnA_{it} - lnA_{it-1}$

We construct α_i using the following formula: $\alpha_i = \overline{1 - (labour\ compensation/GDP)_{it}}$. That is, we calculate capital share by one minus labour compensation over GDP ratio for each province at each year. Then we take average for each province over year for the whole sample to get province-specific capital share.

Appendix C

Table 1.7: Summary Statistics

(a) 5-year average

Variable	Obs	Mean	Std. Dev.	Min	Max
Growth	720	0.1086627	0.0278179	-0.0090424	0.3378976
TFPgrowth	720	0.0403019	0.0337032	-0.1115884	0.2787168
Inno	710	-2.848098	1.816759	-6.656083	2.379534
Loan	720	4.594783	0.278064	3.975801	5.422917
LTD	720	-0.1749668	0.2662572	-0.8035448	0.6911619
Stock	659	2.960029	1.149451	-0.9084292	7.338329
Turnover	659	5.156553	0.625975	1.414896	6.525421

(b) annual data

Variable	Obs	Mean	Std. Dev.	Min	Max
Growth	720	0.1086627	0.0278179	-0.0090424	0.3378976
TFPgrowth	720	0.0403019	0.0337032	-0.1115884	0.2787168
Inno	710	-2.848098	1.816759	-6.656083	2.379534
Loan	720	4.594783	0.278064	3.975801	5.422917
LTD	720	-0.1749668	0.2662572	-0.8035448	0.6911619
Stock	659	2.960029	1.149451	-0.9084292	7.338329
Turnover	659	5.156553	0.625975	1.414896	6.525421

Inno, Loan, LTD, Stock, Turnover are in logarithmic.

Table 1.8: Correlation Matrix

(a) 5-year average

	Growth	TFPgrowth	Inno	Loan	Banke	Stock	Turnover
Growth	1.0000						
TFPgrowth	0.3987*	1.0000					
Inno	0.0042	-0.3740*	1.0000				
Loan	-0.3372*	-0.0177	0.3707*	1.0000			
LTD	-0.0710	0.2135*	-0.6735*	-0.0028	1.0000		
Stock	-0.1125	-0.1485	0.5840*	0.4345*	-0.5996*	1.0000	
Turnover	0.0991	-0.1899*	0.1106	-0.2160*	0.0073	-0.2503*	1.0000

(b) annual data

	Growth	TFPgrowth	Inno	Loan	Banke	Stock	Turnover
Growth	1.0000						
TFPgrowth	0.5309*	1.0000					
Inno	0.0518	-0.2100*	1.0000				
Loan	-0.2318*	-0.0403	0.3706*	1.0000			
LTD	-0.1347*	0.0947*	-0.6467*	0.0254	1.0000		
Stock	-0.1448*	-0.0434	0.4937*	0.5089*	-0.4420*	1.0000	
Turnover	-0.0284	-0.1891*	0.1643*	-0.1905*	-0.1127*	-0.1410*	1.0000

Legend:* 5% significance level.

Table 1.9: Linear Finance-Growth: FE estimation

	Per capita GDP growth			TFP growth				Per capita GDP growth			TFP growth		
	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0178***	0.0204***		0.0094**	0.0110**	Inno		0.0166***	0.0202***		0.0094**	0.0215***
		(0.005)	(0.005)		(0.004)	(0.004)			(0.005)	(0.005)		(0.004)	(0.007)
Loan	-0.0147	-0.0192	-0.0308**	-0.0022	-0.0120	-0.0010	Stock	-0.0073	-0.0133*	-0.0089**	-0.0034	-0.0066*	0.0001
	(0.016)	(0.013)	(0.014)	(0.013)	(0.018)	(0.016)		(0.007)	(0.006)	(0.003)	(0.004)	(0.004)	(0.004)
Inno*Loan			0.0008			0.0023	Inno*Stock			-0.0022*			-0.0030**
			(0.005)			(0.004)				(0.001)			(0.001)
LTD	-0.0018	-0.0044	0.0078	0.0349*	0.0272	0.0016	Turnover	-0.0064	-0.0127	-0.0107*	-0.0029	-0.0059	-0.0225*
	(0.022)	(0.018)	(0.012)	(0.022)	(0.027)	(0.022)		(0.009)	(0.008)	(0.006)	(0.006)	(0.006)	(0.013)
Inno*LTD			0.0144***			0.0178***	Inno*Turnover			-0.0051**			-0.0058*
			(0.004)			(0.006)				(0.002)			(0.003)
Y0	-0.0786***	-0.0757***	-0.1002***	-0.0147	-0.0414***	-0.0384**	Y0	-0.0980***	-0.1047***	-0.1056***	-0.0219*	-0.0463***	-0.0303*
	(0.012)	(0.010)	(0.009)	(0.012)	(0.013)	(0.015)		(0.021)	(0.018)	(0.012)	(0.012)	(0.014)	(0.015)
inv	0.0453***	0.0514***	0.0369***	-0.0272***	-0.0209*	-0.0367***	inv	0.0492***	0.0477***	0.0384***	-0.0301***	-0.0259**	-0.0269
	(0.009)	(0.008)	(0.007)	(0.007)	(0.010)	(0.011)		(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.018)
inf	0.0023	0.0006	-0.0010	0.0099***	0.0046	0.0056	inf	0.0043*	0.0028	0.0051	0.0077**	0.0068*	0.0095*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)		(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
gov	0.0036	0.0109	-0.0029	0.0184	0.0099	0.0015	gov	0.0248	0.0247	0.0129	-0.0043	-0.0052	0.0168
	(0.016)	(0.012)	(0.011)	(0.016)	(0.019)	(0.017)		(0.019)	(0.015)	(0.015)	(0.012)	(0.016)	(0.016)
open	-0.0087	-0.0113*	-0.0036	-0.0001	-0.0035	-0.0010	open	-0.0093	-0.0076	-0.0061	-0.0017	-0.0016	0.0013
	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)	(0.007)		(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.008)
hc	0.1311**	0.1233***	0.0937*	0.0983**	0.1921**	0.1014**	hc	0.0860	0.0692	0.1212**	0.1448***	0.1419***	0.1847**
	(0.056)	(0.044)	(0.048)	(0.046)	(0.077)	(0.046)		(0.066)	(0.057)	(0.054)	(0.052)	(0.045)	(0.076)
fdi	0.0021***	0.0020***	0.0015***	0.0036***	0.0031***	0.0034***	fdi	0.0024***	0.0022***	0.0017***	0.0033***	0.0036***	0.0020***
	(0.001)	(0.001)	0.000	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	0.000	(0.001)	(0.001)	(0.001)
constant	0.2681**	0.2546**	0.5772***	-0.0155	0.0591	0.2682	constant	0.4246***	0.5466***	0.5142***	0.0334	0.2295	-0.0130
	(0.121)	(0.095)	(0.106)	(0.139)	(0.189)	(0.182)		(0.153)	(0.194)	(0.124)	(0.155)	(0.182)	(0.197)
Obs	145	138	137	141	146	141	Obs	146	136	136	139	139	133
Provinces	30	30	30	30	30	30	Provinces	30	30	30	30	30	30
Adjusted R^2	0.685	0.719	0.782	0.561	0.518	0.653	Adjusted R^2	0.670	0.671	0.761	0.565	0.580	0.499

Note: as above in Table 1.1.

Table 1.10: Nonlinear Finance-Growth: FE estimation

	Per capita GDP growth			TFP growth		
	(1)	(2)	(3)	(4)	(5)	(6)
Inno		0.0129***	0.0188***		0.0070*	0.0092**
		(0.003)	(0.007)		(0.004)	(0.003)
Loan	-0.0191	-0.0344***	-0.0325**	-0.0054	-0.0167	-0.0154
	(0.013)	(0.012)	(0.014)	(0.011)	(0.016)	(0.015)
$Loan^2$	0.0019	-0.0180	-0.0342	-0.0036	0.0032	0.0189
	(0.020)	(0.018)	(0.038)	(0.015)	(0.016)	(0.017)
Inno*Loan			0.0031			-0.0082
			(0.008)			(0.005)
LTD	-0.0083	0.0013	0.0086	0.0507**	0.0166	0.0332
	(0.019)	(0.015)	(0.013)	(0.020)	(0.024)	(0.020)
LTD^2	-0.0604***	-0.0527***	-0.0141	-0.0673***	-0.0514***	-0.0277
	(0.021)	(0.019)	(0.025)	(0.020)	(0.018)	(0.026)
Inno*LTD			0.0105**			0.0114**
			(0.005)			(0.005)
Y0	-0.0777***	-0.0906***	-0.0978***	-0.0173	-0.0395***	-0.0359**
	(0.013)	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)
inv	0.0355***	0.0443***	0.0320***	-0.0326***	-0.0314***	-0.0385***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.009)	(0.011)
inf	0.0032	0.0005	-0.0012	0.0075**	0.0074	0.0073*
	(0.004)	(0.004)	(0.005)	(0.003)	(0.005)	(0.004)
gov	0.0110	0.0141	0.0048	0.0237	0.0124	0.0194
	(0.014)	(0.014)	(0.012)	(0.015)	(0.017)	(0.019)
open	-0.0044	-0.0037	-0.0036	0.0018	0.0022	-0.0012
	(0.006)	(0.007)	(0.005)	(0.007)	(0.006)	(0.006)
hc	0.0929	0.0656	0.0879	0.0502	0.0986*	0.1037**
	(0.067)	(0.065)	(0.056)	(0.057)	(0.054)	(0.046)
fdi	0.0017***	0.0014**	0.0015***	0.0031***	0.0029***	0.0029***
	(0.001)	(0.001)	0.000	(0.001)	(0.001)	(0.001)
constant	0.3437**	0.4799***	0.5660***	0.1020	0.2219	0.2064
	(0.145)	(0.129)	(0.138)	(0.163)	(0.160)	(0.171)
Obs	146	141	136	138	143	137
Provinces	30	30	30	30	30	30
Adjusted R^2	0.716	0.769	0.781	0.627	0.603	0.647

	Per capita GDP growth			TFP growth		
	(7)	(8)	(9)	(10)	(11)	(12)
Inno		0.0072**	0.0121**		0.0113**	0.0172**
		(0.003)	(0.005)		(0.004)	(0.007)
Stock	0.0253***	0.0091**	0.0037	0.0146**	0.0009	-0.0069
	(0.007)	(0.004)	(0.005)	(0.006)	(0.008)	(0.007)
$Stock^2$	-0.0036***	-0.0018**	-0.0018*	-0.0016*	-0.0005	0.0008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Inno*Stock			-0.0008			-0.0020*
			(0.001)			(0.001)
Turnover	0.0059	-0.0014	-0.0145*	0.0089	-0.0073	-0.0057
	(0.010)	(0.008)	(0.008)	(0.009)	(0.011)	(0.009)
$Turnover^2$	0.0213**	0.0092	0.0031	0.0141*	0.0051	0.0097
	(0.009)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
Inno*Turnover			-0.0049*			-0.0022
			(0.003)			(0.002)
Y0	-0.0939***	-0.0870***	-0.0809***	-0.0354***	-0.0311**	-0.0478***
	(0.015)	(0.014)	(0.013)	(0.012)	(0.015)	(0.012)
inv	0.0267**	0.0401***	0.0444***	-0.0331***	-0.0257**	-0.0297**
	(0.013)	(0.008)	(0.009)	(0.012)	(0.012)	(0.011)
inf	0.0088*	0.0026	0.0064**	0.0060	0.0065	0.0090*
	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
gov	-0.0529	0.0116	0.0050	0.0043	0.0144	0.0029
	(0.037)	(0.012)	(0.016)	(0.016)	(0.017)	(0.016)
open	-0.0052	-0.0096*	-0.0128**	-0.0028	0.0001	-0.0018
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
hc	0.1703**	0.1111**	0.1074**	0.1543***	0.1895***	0.1661***
	(0.062)	(0.042)	(0.049)	(0.056)	(0.067)	(0.058)
fdi	0.0024***	0.0019***	0.0024***	0.0025***	0.0028***	0.0032***
	(0.001)	0.000	(0.001)	(0.001)	(0.001)	(0.001)
constant	0.4756***	0.3790***	0.3514***	0.1100	-0.0243	0.1964
	(0.153)	(0.114)	(0.122)	(0.160)	(0.198)	(0.159)
Obs	139	138	141	138	137	146
Provinces	30	30	30	30	30	30
Adjusted R^2	0.636	0.754	0.707	0.619	0.522	0.609

Note: as above in Table 1.1.

Table 1.11: Finance-TFP Growth: Reestimation of TFP Growth

	TFP growth													
	(1)	(2)	(3)	(4)	(5)	(6)		(7)	(8)	(9)	(10)	(11)	(12)
Inno			0.0233**	0.0352**	0.0400**	0.0436*	Inno			0.0848*	0.0305*	0.0480**	0.0829**
			(0.009)	(0.017)	(0.016)	(0.025)				(0.046)	(0.017)	(0.021)	(0.036)
Loan	-0.0447	-0.0081	-0.0215	-0.0051	-0.0187	-0.0327	Stock	-0.0437	0.0410**	0.0282	0.0507	0.0303	0.0637
	(0.028)	(0.031)	(0.041)	(0.049)	(0.036)	(0.058)		(0.066)	(0.017)	(0.061)	(0.052)	(0.022)	(0.068)
$Loan^2$		0.0337		-0.0487		-0.0979	$Stock^2$		-0.0049*		-0.0016		0.0023
		(0.052)		(0.053)		(0.125)			(0.002)		(0.006)		(0.007)
Inno*Loan					-0.0023	0.0270	Inno*Stock					-0.0137*	-0.0180**
					(0.007)	(0.024)						(0.007)	(0.008)
LTD	0.0881**	0.0191	0.0384	-0.0061	0.0320	-0.0724	Turnover	0.0380	-0.0519	0.0848	0.1216**	0.0277	-0.0118
	(0.043)	(0.079)	(0.035)	(0.041)	(0.034)	(0.092)		(0.069)	(0.060)	(0.098)	(0.047)	(0.034)	(0.057)
LTD^2		-0.0468		-0.0399		0.1509	$Turnover^2$		-0.0078		0.0444		0.0527
		(0.119)		(0.053)		(0.140)			(0.036)		(0.043)		(0.062)
Inno*LTD					0.0162*	0.0546*	Inno*Turnover					-0.0007	0.0197
					(0.008)	(0.031)						(0.013)	(0.018)
Y0	0.0090	0.0089	-0.0062	-0.0148	-0.0155	0.0057	Y0	-0.0174	0.0238	-0.1558*	-0.0332	-0.0981*	-0.1374*
	(0.012)	(0.011)	(0.015)	(0.021)	(0.020)	(0.022)		(0.033)	(0.018)	(0.091)	(0.043)	(0.056)	(0.078)
inv	-0.0020	0.0014	0.0228*	0.0211	0.0150	0.0201	inv	-0.0150	0.0002	0.0478	0.0246	0.0140	-0.0081
	(0.016)	(0.021)	(0.012)	(0.015)	(0.017)	(0.033)		(0.039)	(0.018)	(0.038)	(0.030)	(0.026)	(0.052)
inf	0.0163**	0.0241**	0.0157	0.0088	0.0110	-0.0014	inf	0.0223*	0.0002	0.0053	0.0212	0.0107	0.0072
	(0.007)	(0.010)	(0.012)	(0.012)	(0.014)	(0.020)		(0.013)	(0.017)	(0.017)	(0.019)	(0.017)	(0.026)
gov	0.0366*	0.0248	0.0169	0.0128	0.0191	0.0293	gov	0.0434	0.0383	-0.0634	-0.0467	-0.0542	-0.0689
	(0.019)	(0.025)	(0.026)	(0.030)	(0.022)	(0.037)		(0.051)	(0.030)	(0.048)	(0.029)	(0.039)	(0.049)
open	0.0188**	0.0154*	0.0068	0.0014	0.0030	-0.0094	open	0.0316	0.0095	0.0180	0.0000	0.0346*	0.0423
	(0.007)	(0.008)	(0.008)	(0.010)	(0.008)	(0.015)		(0.025)	(0.011)	(0.038)	(0.020)	(0.020)	(0.027)
hc	0.0529	0.0452	-0.0171	-0.0524	-0.0303	-0.1152	hc	0.1668	0.0521	-0.1242	-0.0460	0.0469	0.0412
	(0.050)	(0.048)	(0.056)	(0.062)	(0.061)	(0.094)		(0.160)	(0.053)	(0.205)	(0.091)	(0.080)	(0.105)
fdi	0.0026***	0.0016	0.0019	0.0023	0.0021	0.0019	fdi	0.0042	-0.0010	0.0024	0.0012	-0.0053	-0.0081
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)		(0.004)	(0.002)	(0.005)	(0.004)	(0.004)	(0.005)
constant	-0.3356***	-0.2969**	-0.0479	0.1652	0.1329	0.1823	constant	-0.3491	-0.3583***	1.4496*	0.3396	0.9055	1.3798
	(0.117)	(0.121)	(0.200)	(0.263)	(0.223)	(0.287)		(0.224)	(0.123)	(0.738)	(0.287)	(0.563)	(0.826)
Obs	145	148	148	149	148	145	Obs	144	145	141	148	143	144
Provinces	30	30	30	30	30	30	Provinces	30	30	30	30	30	30
Instruments	21	27	24	24	30	28	Instruments	18	22	20	24	30	28
AR(2) p	0.379	0.153	0.121	0.260	0.456	0.428	AR(2) p	0.708	0.942	0.099	0.625	0.160	0.813
Hansen p	0.759	0.589	0.035	0.088	0.050	0.645	Hansen p	0.769	0.607	0.155	0.173	0.062	0.593

Note: as above in Table 1.1.

Table 1.12: Definition of variables and data sources

Variable	Definition	Sources
Growth	log difference of real GDP per capita	Constructed by the author
TFPgrowth	growth rate of total factor productivity	Constructed by the author
Inno	log of number of invention patent granted per 10000 persons	Annual issued China Scientific and Technological Yearbook (various versions)
Loan	log of loan balance as percentage of GDP	Loan and deposit data from China Data Online
LTD	log of loan balance as percentage of deposit balance	and annual issued Almanac of China's Finance and banking(AFCB, various years)
Stock	log of stock market capitalisation as percentage of GDP	Firm level stock data (market value and value traded) from
Turnover	log of value of share traded as percentage Stock	China Stock Market and Accounting Research Database (CSMAR)
priva[a]	log of ratio of non-stated-owned fixed investment to overall investment	China Center of Economic and Research (CCER) Database
Y0	log of initial real GDP per capita	Y0, inv, inf, gov, open and fdi from China Data Online
inv	log of gross fixed capital formation as percentage of GDP	and annual issued China Statistical Yearbooks (various versions)
inf	log of consumer price index (log of 10+consumer price index for annual data)	
gov	log of government expenditure as percentage of GDP	
open	log of the sum of export and import as percentage of GDP	
fdi	log of foreign direct investment as percentage of GDP	
hc	log of average year of schooling	Constructed by the author
labour	labour force in 10000 persons	China data online
capital	real physical capital stock	Wu (2016), data in 2014 extrapolated by the author
$1-\alpha$	labour compensation over GDP	labour compensation data[b] from National Bureau of Statistics, China

[a] *priva* is not included in the final version of regressions
[b] labour compensation is available only since 1993

Chapter 2

Financial development and innovation: A Bayesian DSGE comparison of Chinese and US business cycles

2.1 Introduction

One of the most notable macroeconomic outcomes from the last decade is the extraordinary growth of the Chinese economy, to a position where it ranks second only to the United States in terms of nominal GDP. Whilst the business cycle literature has yet to turn due attention to the emergence of China as a major economy, interesting macroeconomic characteristics are already emerging form the observations presented by the macroeconomic data. Rapid economic growth in China has come at a cost; even though the US and Chinese profiles for economic activity might be described as similar, this is where the similarities end. China suffers from much higher volatility in total factor productivity (TFP), a problem currently associated with the misallocation of capital (Asker et al. 2014) and rather inconsistent with what one might expect from an emerging economy where volatility in TFP comes 'hand in hand' with volatility in output (Aguiar and Gopinath 2007, Comin et al. 2014). This paper uses a DSGE model with Bayesian estimation to analyse the driving factors behind the business cycles for both countries and suggests that government policy might play an important role in the outcome for volatility in productivity.

To compare Chinese and US business cycle behaviours we build and estimate a DSGE model with extended financial markets and endogenous technology creation, elements chosen to capture key differences between the US and China in terms of macroeconomic infrastructure. Our set up allows us to control for the banking sector and stock market separately; to identify the differences between a developed country with developed stock market, such as the US, and a rapid developing country with less developed stock market, such as China. We nest the model during estimation to allow us to control for the differing structures, with China being a nested case of the full model with firms denied access to equity markets. Following Bayesian estimation and analysis of the shock process decomposition, we find that Chinese intervention comes at a cost, namely higher volatility in total factor productivity (TFP); this contrasts to the case of the US where access to a well developed stock market enables firms to hedge away from credit markets in times of financial stress, though this also exposes firms to an additional source of volatility from movements in the stock market.

The Chinese financial system is primarily dominated by its banking sector while the US has a more diverse financial system including large stock markets. In addition, US hi-tech firms have better access to market-based finance, particularly through public equities. Considering the fact that financial development is a critical determinant of TFP, and that equities might act as an alternative funding source against debt in business cycles, it is possible that the diverse financial system of the US stabilises its TFP.

In this study, we focus on the differences between the two countries in terms of financial development for our model set up. More specifically, we combine a workhorse Smets and Wouters (2007) DSGE model with Comin and Gertler (2006), Anzoategui et al. (2019) type endogenous technology creation through R&D. Further, we add a financial intermediary to investigate and compare the finance-productivity nexus over the business cycles for China and the US. By doing this, we aim to explain the movements in TFP using the residuals from the estimation. One concern for our research is the question of whether or not Chinese TFP can be modeled using an endogenous technology creation mechanism. To help justify this choice we rely on empirical evidence from Zheng et al. (2009), that Chinese TFP is mainly driven by improvements in technology, and that historically the business sector tends to be the main contributor of R&D; with the share of business R&D[1] around 60% to 75% in the 2000s.

We further incorporate a stock market for R&D firms who, in turn, determine the optimal levels of debt and equity in the economy. Furthermore, credit and risk (or equity) premium shocks are differentiated to disentangle their individual effects, motivated by Caldara et al. (2016), who suggest that these two processes are independent. During our empirical investigation we will also be making use of Bayesian estimation techniques, exploited to identify shocks and structural parameters for China and the US separately over 1995Q1 to 2016Q4. Nine shocks are added in this study including a credit premium shock, risk (or equity) premium shock, exogenous TFP shock, investment shock, price mark-up shock, wage mark-up shock, monetary policy shock, government spending shock

[1] Sourced from the National Bureau of Statistics, China

and exogenous demand shock.

This study contributes to the business cycle literature in three ways: by considering the finance-innovation-TFP nexus, investigating the contribution of financial development towards macro-stability, and extending the business cycle literature for China.

In terms of the finance-innovation-TFP nexus, the standard endogenous TFP mechanisms in business cycles such as Comin and Gertler (2006), Comin et al. (2014), Jinnai (2015), Kung and Schmid (2015) and Anzoategui et al. (2019) use endogenous innovation to show short-, mid- and long-run productivity dynamics in response to various shocks. Extending from these studies, especially Anzoategui et al. (2019), we explicitly incorporate financial shocks in the framework to enable a comparison between China and the US. Our study is also related to Bianchi et al. (forthcoming) who estimate a model with a finance-innovation-TFP nexus and distinguish the levels of debt and equity as different sources of firm finance using vertical innovation. Unlike them, we focus specifically on the variation of risks in the debt and equity markets and make use of a horizontal innovation framework to allow the separation of tech and non-tech firms, and thus identify the effects of financial development on tech firms specifically.

Within the area of financial development, one question arises as to whether or not financial structure matters for macroeconomic volatility. While some studies, such as Easterly et al. (2001), da Silva (2002) and Raddatz (2006) have found positive for financial development, this is by no means unanimous, see Özbilgin (2010) for an example. Raddatz (2006) and da Silva (2002) suggest that it is the level of financial development that matters while others such as

Yeh et al. (2013) have found that market-based financial systems can actually magnify macroeconomic volatility. Our study contributes by suggesting exactly how these structures might transmit, magnify or dampen the effects of economic shocks, particularly by making use of two risk premium shocks.

In terms of the literature on the Chinese business cycle, some earlier works (Le et al. 2014, Dai et al. 2015, Ma and Li 2015) have considered whether a DSGE model, already successfully applied to the US, could model Chinese business cycle behaviour (e.g. Smets and Wouters (2007)). For example, Le et al. (2014) and Dai et al. (2015) study the impact of standard shocks on output volatility, while Ma and Li (2015) focus on monetary policy transparency within this framework; nevertheless they do not investigate fluctuations of TFP in China. Following these studies, we make a key assumption that China is a price-taker in international markets with net exports mainly affected by factors overseas. However, we extend this literature by utilizing an endogenous technology creation mechanism to examine the forces behind TFP movements in China, including a stock market to show potential interactions between stock market volatility and TFP's volatility. As far as the authors are aware, this study is the first to apply finance-innovation-productivity channels to the Chinese scenario. Furthermore, we provide implications for ongoing financial reform, particularly that concerned with the subject of deleveraging reforms.

Our results show that policy plays a more important role for output in China than is the case for the US, suggesting that China makes significant use of intervention to reduce its volatility in output. The majority of shocks that hit the Chinese economy have larger variance compared with the case for the US, this variance is often driven by international disturbances and requires the heavy and sporadic use of counteracting fiscal policy and other indirect investment interventions. Policy smooths output for China, but this comes at the cost of higher volatility in TFP, at times exacerbating the effects of shocks already driving the direction of TFP. For the US, shocks are less volatile and follow a more cyclical fashion as one would expect in the case of a developed economy, so there is less of a disturbance upon TFP.

Based on the impulse response functions, we show that the presence of a stock market has a dual effect on the volatility of TFP; the stock market can dampen the effect of the credit premium shock, but in doing so, also magnifies the risk (or equity) premium shock. Finally, based on the counter-factual experiments, we find that the accumulated dampening effect dominates the accumulated magnification effect on the volatility of TFP in the US. The US experience is in contrast to the case of China, because the magnification effect only dominates the dampening effect if the Chinese innovator has access to the stock market; an important implication of our research is a need for the cautious development of equity markets in China.

The rest of the paper is organized as follows. Section 2.2 presents some empirical evidence and descriptive analysis of the cyclical behavior of the Chinese and US macroeconomic variable profiles. Section 2.3 presents the DSGE model with extended financial markets and endogenous technology creation. Section 2.4 describes the Bayesian econometric methodology and presents our estimation results; making use of the estimated model parameters for an impulse response exercise, before a variance and historical decomposition of the shock processes.

Section 2.4 makes further analysis of the cyclical behaviour of TFP between China and the US, before Section 2.5 concludes with comments.

2.2 Empirical Facts: China vs US

This section provides empirical facts and a descriptive analysis of some, business cycle relevant, Chinese and US macroeconomic variables over the last few decades.

2.2.1 Economic and Productivity Performance

The profile of output for both China and the US in Figure 2.1, shown in both first-differenced and linearly-detrended forms, appear to have similar magnitude of fluctuation. Table 2.1 confirms this and further shows that the standard deviations of output for China and the US are of similar magnitude. Moreover, output in China is very stable compared with that of developing and emerging economies separately. In this sense, China shares features that one might associate with more developed countries.

Figure 2.1: Output comparison: China vs US

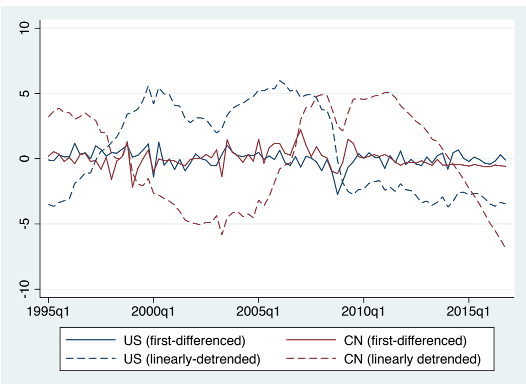
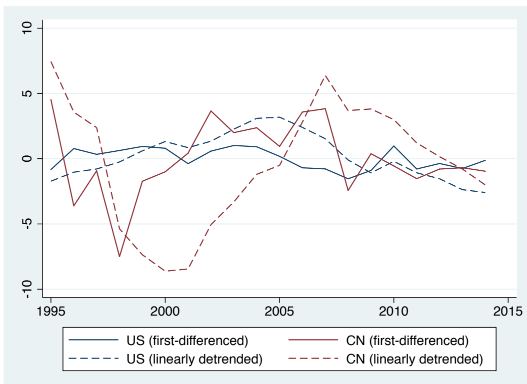


Figure 2.2: TFP comparison: China vs US



Note: first-differenced variables are demeaned. Output is quarterly per capita GDP, whereas TFP is annual frequency due to data availability; see appendix A for more details.

Turning to TFP [2], we can see from Figure 2.2 that the fluctuations of both first-differenced and linearly-detrended TFP in China are of a larger magnitude than those of the US. These findings are confirmed in Table 2.1. Table 2.1 also confirms that TFP for China is significantly more volatile than that of the US and other developed economies; compared with emerging economies, the volatility of TFP in China is above average.

Table 2.1: Macroeconomic volatility comparisons

	China	US	Emerging Economies (average)	Advanced Economies (average)
$\sigma(Y)$	3.576	3.814	4.653	3.689
$\sigma(gY)$	1.800	1.788	3.375	2.153
$\sigma(TFP)$	4.754	1.757	4.539	2.758
$\sigma(gTFP)$	2.874	0.804	2.563	1.422

Note [1]: gY is annualized 4-quarter growth in output. $gTFP$ is TFP growth in annual frequency due to data availability.
Note [2]: $\sigma(Y)$ and $\sigma(TFP)$ are calculated based on linearly detrended output and TFP.
Note [3]: see appendix A for more details about data description and sources.

Summing up, our descriptive analysis suggests that Chinese output is relatively stable but TFP is more volatile. Conversely, for the US, movements in both output and TFP are simultaneously smooth. Our data shows that China is a special case and one worthy of investigation, in that it displays mixed features normally associated with both developed and emerging economies. For the following analysis, we will focus on the volatility of our four key variables including output, TFP and their growth, between China and the US. We provide evidence to direct our investigations into the differences between Chinese and US business cycle behaviours.

In Table 2.2 we present some measures of volatility for both the US and China

[2] The definition of total factor productivity (TFP) in Figure 2.2 and Table 2.1 is derived as defined by the Solow residual. For later analysis in Section 2.3.6, we consider multiple and more comprehensive definitions.

Table 2.2: Macroeconomic volatility: further comparisons

	$\sigma(Emp)$	$\sigma(gI)$	$corr(gTFP, gI)$	$\sigma(gRD)$	$\sigma(gBusinessRD)$	$\sigma(gPatent)$
China	0.514	4.894	-0.038	5.989	9.611	16.213
US	3.516	6.967	0.587	2.526	3.884	5.271

Note [1]: *Emp* is employed labour, *gI* annualized 4-quarter investment growth, *gR&D* growth of overall R&D expenditure, *gBusinessR&D* growth of business R&D expenditure, *gPatent* growth rate of number of triadic patent applications scaled by population. *gR&D*, *gbusinessR&D* and *gPatent* are in annual frequency due to data availability. Other variables are in quarter frequency; more details about which can be found in Appendix A.

in terms of selected key indicators. One striking comparison is that given for the volatility of employed labour, China being much less volatile than the US. This follows the pattern found in other literature, for instance Dai et al. (2015). The cause of this relative stability is most probably due to the characteristics of the Chinese labour market. Chinese state-owned enterprises (SOEs) provide implicit guarantees for their employees. Secondly, the correlation between TFP growth and growth in investment is positive for the US but weakly negative for China. This could be explained by significant capital misallocation in China. Thirdly, in terms of innovation, the standard deviation of gross R&D growth and that of business R&D growth suggest that Chinese R&D is more than twice as volatile than that found in the US.

Finally, the growth rate of triadic patent [3] applications in China is much more volatile than that of the US. The volatility of growth of R&D and patents suggest that both inputs and outputs of technology creation in China are substantially more volatile than the US counterparts. This finding is critical for our purposes, as it provides some empirical justification for our proposition that Chinese TFP volatility might be explained by technology creation through R&D, as reflected

[3]Triadic patents are a series of corresponding patents filed at the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO) and the Japan Patent Office (JPO), for the same invention, by the same applicant or inventor.

in our choice of theoretical framework.

2.2.2 Financial Access and Financial Volatility

In this section we discuss evidence that reflects the differences in financial development between China and the US. We focus on the two dimensions of financial development: financial access and financial volatility. In China the financial system is predominantly bank-based and bank loans are the dominant source of finance for firms. The stock market exists, but is relatively small in comparison to the Chinese banking sector; and further to this, the technology-based sub stock market was not existed. Another problem for Chinese equity markets is that of stability in regulation, with the Chinese Security and Regulation Committee suspending initial public offering (IPO) and seasoned equity offerings on occasions; innovative firms in China find it difficult to raise equity from home equity markets[4].

On the other hand, the US financial system is more diverse and features a banking sector, a corporate bond market as well as a stock market. The technology-based NASDAQ stock market allows US innovative firms to get access to equity finance relatively easy. Contrasting this to the Chinese approval-based IPO process, the registration-based IPO process in the US provides a fast track for hi-tech firms to raise equity finance. Studies in the area of the relationship between financial structure and economic activity, such as (Covas and Den Haan

[4]Although some Chinese firms are listed in the US and Hong Kong stock markets, their numbers are not comparable with the number of Chinese domestic firms. For instance, there are 104 thousand Chinese domestic hi-tech firms in 2016 (see http://www.innocom.gov.cn). At the same time, total number of NASDAQ-listed Chinese firms is only 150 (see http://www.nasdaq.com).

2012, Jermann and Quadrini 2012), suggest that debt and equity finance are alternative sources of finance over different phases of the business cycle. It is likely that a diverse financial system enable US firms, especially innovative ones, to smooth their activities more easily and successfully over the business cycle.

Figure 2.3: Credit premium: China vs US

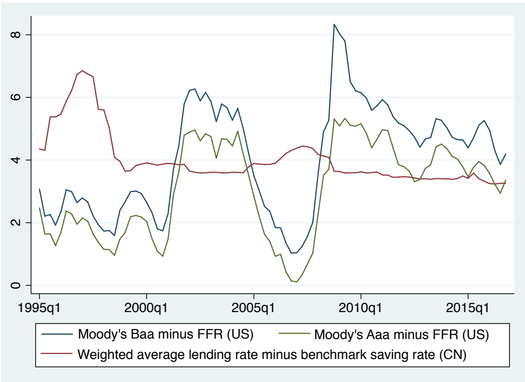
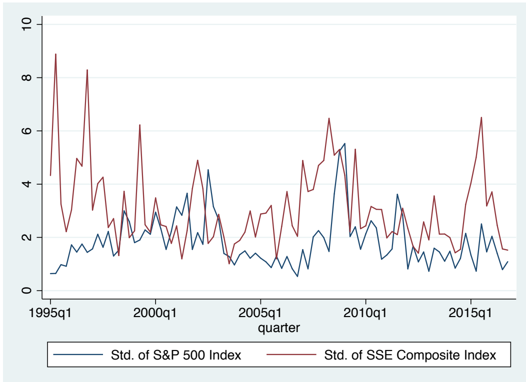


Figure 2.4: Stock market volatility: China vs US



With regards to financial volatility, the data can highlight some distinguishing features between China and the US. In Figure 2.3, we provide some time-series on credit premiums, a well known proxy for risk in credit markets[5] to show the level of credit risk for China and the US separately.

We measure the Chinese credit premium by differencing the one-year weighted average lending rate and the one-year benchmark saving rate[6], the profile of which is noticeably smooth, probably due to restrictive regulations in the Chinese banking sector. For the US the credit premium which is measured by either Moody's BAA yield minus the Federal Reserve Fund rate or Moody's AAA yield minus the Federal Reserve Fund rate, the profile shows pronounced variation in both the pre-crisis and post-crisis periods. The dramatic difference in profiles for

[5]The Chinese corporate bond market was established in 2007 but its size is quantitatively incomparable with the banking sector. Hence, the Chinese credit market is approximately equivalent to a banking sector.

[6]The benchmark saving rate is a policy rate determined by the People's Bank of China and can be treated as a counterpart of the Federal Reserve Fund rate.

the credit premium provides evidence that the Chinese credit market is relatively stable while that of the US is much more volatile.

In Figure 2.4, we use stock market volatility as a proxy for stock market risk to compare China and the case of the US. The Chinese stock market is more volatile than that of the US. Specifically, the standard deviation of the Shanghai Stock Exchange Composite Index rose sharply during the Asian financial crisis, 2005-2009 and the 2015 stock market disaster period. The difference in volatility most probably reflects the sensitivity of equity markets to disturbances. The US stock market is comparatively stable, though we can see an increase in volatility around the turn of the millennium and in the lead up to the financial crisis, as we would expect.

Figure 2.5: quarterly risk premium

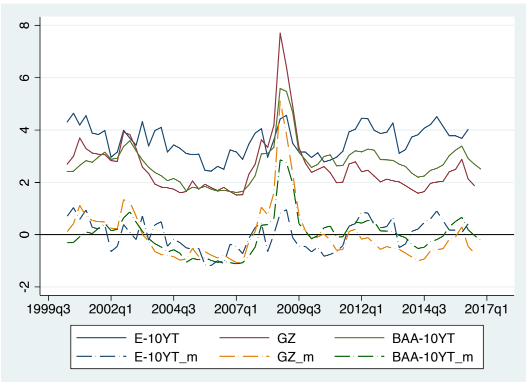
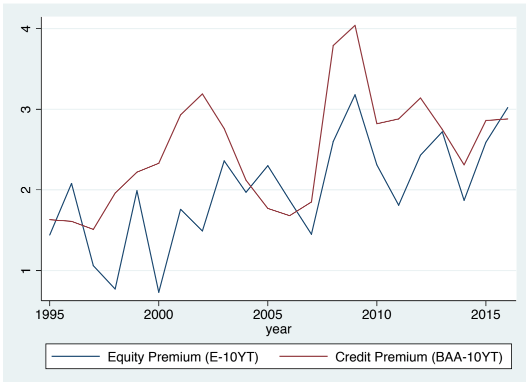


Figure 2.6: annual risk premium



Note [1]: E-10YT is difference between equity risk premium and ten-year treasury bond yield, a measure of equity premium. GZ is the GZ spread (Gilchrist and Zakrajšek 2012). BAA-10YT is difference between Moody BAA corporate bond yield and ten-year treasury bond yield. Quarterly equity risk premium data are from Duke CFO-Survey; Annual equity risk premium data are from NYU Stern Business School. Variables with _m refers deviation from mean value.
Note [2]: Quarterly equity risk premium data are available since 2000q2.

Shifting our attention to the US, we make use of Figures 2.5 and 2.6 to show the risk premiums associated with commercial debt and equity. The movements of the credit and equity premiums allow us to investigate the financial-macroeconomic volatilities. Based on quarterly data, Figure 2.5 shows a different magnitude in movement and change in the relative position of the credit premium and equity premium. When the US slips into recession, the credit premium moves closer to the equity premium and even surpasses the latter. In other words, credit tends to be more expensive than equity in a recession or financial crisis. This pattern can also be found in Figure 2.6, based on annual data. In addition, the lower part of Figure 2.5 shows that the credit premium increases more than the equity premium during the turn of the millennium and the financial crisis period. Thus, if firms are able to switch to equity finance, the cost of finance in a recession can be lessened.

Furthermore, Figures 2.5 and 2.6 show another interesting characteristic; that movement of the credit premium is more persistent than the equity premium. We find the autocorrelation for the credit premium is 0.80-0.85 while that for the equity premium is 0.65, using quarterly data. This pattern is also confirmed by the annual data, though both credit and equity premiums become less persistent in this case. This suggests that a credit premium shock has potential to generate a longer-lasting effect which might be mitigated by the presence of an equity market. Thus, the ability of US innovative firms to switch to alternative sources of finance may be helpful to smooth out US TFP volatility.

2.3 The Model

We expand Smets and Wouters (2007)'s model, incorporating a financial intermediary and endogenous technology creation via R&D, in a similar way to Comin and Gertler (2006) and Anzoategui et al. (2019). The financial intermediary supplies credit to both intermediary goods producers and innovators. There are two channels for the propagation of shocks into innovation: the incentive channel and the cost channel. The former channel indirectly affects the incentive for innovation by linking it with the profit margin of the intermediate goods producer; with the latter channel directly affecting the cost of innovation. After building the benchmark model, we make further extension to incorporate a stock market for the innovator. In this augmented model, innovators are able to use equity to smooth their R&D but are subjected to an extra source of fluctuations in doing so, through the cost channel. The benchmark model is corresponding to the case for China while the augmented model corresponds to the case of the US.

In both the benchmark and the augmented model, there are five sectors: a final goods producer who buys intermediate goods and transforms them into differentiated final goods, intermediate goods producers who use labour and capital services to produce differentiated intermediate goods, innovators who use final goods as an input to conduct R&D with which to produce new technologies, to sell on to new intermediate goods producers; financial intermediaries who obtain deposits from households and supply credit to innovators and intermediate goods producers separately; households who consume, save, supply labour, adjust the utilisation rate of capital and invest to accumulate capital. For the case that we switch on the stock market, households also invest in equity issued from innovators.

2.3.1 Final Goods Producer

The final goods sector is very similar to Anzoategui et al. (2019). There are a continuum of monopolistic competitive final goods producers, measuring unity, each of which is like a retailer, who buys intermediate goods and transfers them into differentiated final goods Y_t. For each final goods producer i, Y_{it}^m units of intermediate goods composite are used as an input to produce output. The production technology is as follows:

$$Y_{it} = Y_{it}^m \tag{2.1}$$

The following CES technology is used to aggregate them into a final good composite:

$$Y_t = (\int_0^1 Y_{it}^{1/\varepsilon_t^s} di)^{\varepsilon_t^s} \tag{2.2}$$

where ε_t^s is a price mark-up shock following an AR(1) process as follows: $ln\varepsilon_t^s = (1-\rho_s)ln\varepsilon^s + \rho_s ln\varepsilon_{t-1}^s + \eta_t^s$ where η_t^s follows an i.i.d $N(0, \sigma_S^2)$ process. The demand schedule for the final good producer is:

$$Y_{it} = Y_t(\frac{P_{it}}{P_t})^{\varepsilon_t^s/(1-\varepsilon_t^s)} \tag{2.3}$$

where the price index is given by

$$P_t = (\int_0^1 P_{it}^{1/(1-\varepsilon_t^s)})^{1-\varepsilon_t^s} \tag{2.4}$$

We follow Anzoategui et al. (2019) where the final goods producer sets price on a staggered basis, modeled as in Calvo (1983). In each period there is a probability $1-\epsilon_p$ that a final goods firm can reset its optimal price P_{it}^* otherwise firms set prices according to the following index rule $P_{it} = P_{i,t-1}\pi^{1-\iota_p}\pi_{t-1}^{\iota_p}$ where π is steady state inflation and ι_p is the degree of indexation.

The final goods producer maximizes expected profit

$$\max_{P_{it}} E_t \sum_{l=0}^{\infty} \epsilon_p^l \Lambda_{t,t+l}[(\frac{(\pi_{t-1}^{t+l-1})^{\iota_p}\pi^{1-\iota_p}P_{it}}{P_{t+l}})^{1+\varepsilon_t^s/(1-\varepsilon_t^s)} - MC_{t+l}^f(\frac{(\pi_{t-1}^{t+l-1})^{\iota_p}\pi^{1-\iota_p}P_{it}}{P_{t+l}})^{\varepsilon_t^s/(1-\varepsilon_t^s)}]Y_{i,t+l}$$

where MC_t^f is the marginal cost of the final goods producer and $\Lambda_{t,t+l}$ is the stochastic discount factor. $MC_t^f = P_t^m$ where the latter is the nominal price of intermediate goods composite[7], to obtain the optimally chosen reset price:

$$E_t \sum_{l=0}^{\infty} \epsilon_p^l \Lambda_{t,t+l}[\frac{P_t^*(\pi_{t-1}^{t+l-1})^{\iota_p}\pi^{1-\iota_p}}{P_{t+l}} - \varepsilon_t^s MC_{t+l}^f]Y_{i,t+l} = 0 \qquad (2.5)$$

where $\Lambda_{t,t+l}$ is the stochastic discount factor decided by the household.

2.3.2 Intermediate Goods Producer

There exists a continuum A_t of monopolistic competitors indexed by j, using labour and capital services to produce intermediate goods.

$$Y_{jt}^m = \varepsilon_t^a (u_t K_{jt})^{\alpha} (H_{jt})^{1-\alpha} \qquad (2.6)$$

where u_t is the utilization rate of the capital stock, determined by households, and ε_t^a is an aggregate productivity shock following an AR(1) process as follows: $ln\varepsilon_t^a = (1-\rho_a)ln\varepsilon^a + \rho_a ln\varepsilon_{t-1}^a + \eta_t^a$. ε^a is the steady state level of level of exogenous productivity and η_t^a follows i.i.d $N(0, \sigma_A^2)$.

The following CES technology is used to aggregate differentiated intermediate

[7] In next subsection we will see P_{jt}^m is the same for all intermediate goods producers due to symmetric equilibrium. As the result, $P_t^m = P_{jt}^m$

goods into an intermediate goods composite:

$$Y_t^m = (\int_0^{A_t} (Y_{jt}^m)^{1/\lambda_m} dj)^{\lambda_m} \tag{2.7}$$

In order to allow a financial shock to affect marginal cost and inflation as suggested by empirical evidence (Gilchrist et al. 2017), we follow DSGE literature (e.g. Christiano et al. (2015)) to treat the wage bill and capital rent as working capital which needs to be financed[8] (from a financial intermediary). The outlay or cost function is written

$$Cost_{jt} = (W_t H_{jt} + R_t^k u_t K_{jt}) R_t^b \tag{2.8}$$

where W_t is the nominal wage, R_t^b is the borrowing rate and R_t^k the nominal capital rental rate. Let L_{jt} denote the total amount of borrowing in nominal terms. Thus, $L_{jt} = (W_t H_{jt} + R_t^k u_t K_{jt})$.

The cost minimisation problem yields the following first order condition

$$W_t R_t^b = (1 - \alpha) M C_t^M Y_{jt}^m / H_{jt} \tag{2.9}$$

$$R_t^k R_t^b = \alpha M C_t^M Y_{jt}^m / (u_t K_{jt}) \tag{2.10}$$

[8]Intermediate goods producers are assumed to have no funding at the beginning of each period. In addition, the sale of production is realized at the end of each period, but working capital is paid at the beginning.

Equation (2.6), (2.9) and (2.10) together yield the nominal marginal cost MC^m_{jt} for an intermediate goods producer is as follows:

$$MC^m_{jt} = \frac{(R^k_t)^\alpha W^{1-\alpha}_t R^b_t}{(1-\alpha)^{(1-\alpha)}\alpha^\alpha \varepsilon^a_t} \tag{2.11}$$

Equation (2.11) suggests that marginal cost is the same across all intermediate goods firms. Hence, $MC^m_{jt} = MC^m_t$. Dividing MC^m_t by price P_t we can get real marginal cost

$$mc^m_t = \frac{(r^k_t)^\alpha w^{1-\alpha}_t R^b_t}{(1-\alpha)^{(1-\alpha)}\alpha^\alpha \varepsilon^a_t}$$

where r^k_t and w_t are the real capital rental rate and real wage separately.

Following Anzoategui et al. (2019), we assume the intermediate goods producer can set prices flexibly, so that each intermediate goods producer sets price P^m_{jt} as a constant markup (λ_m) times its expected marginal cost.

$$P^m_t = P^m_{jt} = \lambda_m MC^m_t \tag{2.12}$$

where $\lambda_m > 1$. (2.12) suggests $MC^f_t = P^m_t = \lambda_m MC^m_t$. Nominal profits ($\Pi^m_t$) for individual intermediate goods producer can be calculated as follows, using (2.9)-(2.12).

$$\Pi^m_t = \frac{P^m_t Y^m_t - (W_t H_t + R^k_t u_t K_t) R^b_t}{A_t} = (\lambda_m - 1)\frac{W_t H_t R^b_t}{(1-\alpha)A_t} \tag{2.13}$$

Dividing two sides by P_t yields real profit π^m_t which is critical to link the intermediate goods producer's performance with innovation.[9]

[9] With flexible price, the profit maximisation problem can be reduced to a static form.

2.3.3 Innovator

We first lay out the common part of our innovation sector and describe financing issues in the two subsections. There are a continuum of innovators that use final output to create new types of intermediate good, with the total amount of output used denoted as RD, R&D expenditure. We assume that innovators have no initial funding so that they need external financing via a financial intermediary and a financial market.

Let φ_t be the technology coefficient, which reflects the efficiency of creating new technology. That is, each unit of $R\&D_t$ expenditure at period t can create φ_t amount of new technologies at the end of period t, and then innovators sell them to a new intermediate goods producer at the beginning of period $t+1$. The technology coefficient is determined based on Comin and Gertler (2006) and Anzoategui et al. (2019) but we have modified it. φ_t is given by

$$\varphi_t = \chi(\frac{A_t}{RD_t})^{1-\mu} \tag{2.14}$$

where χ is a parameter governing the efficiency of the creation of technology. A_t is the current stock of technology, reflecting public learning-by-doing or standing-on-the-shoulder effect. This effect is scaled by aggregate R&D expenditure, RD_t, to introduce a congestion externality. That is to say, the marginal return of R&D expenditure is diminished at the aggregate level. μ is assumed to lie between 0 and 1 to maintain balanced growth in the steady state.

The evolution of technology is expressed as follows:

$$
\begin{aligned}
A_{t+1} &= \varphi_t RD_t + \phi A_t \\
&= \chi A_t (\frac{RD_t}{A_t})^{\mu} + \phi A_t
\end{aligned}
$$

where ϕ is the survival rate of a technology. Then, we follow Comin and Gertler (2006) and Anzoategui et al. (2019) to construct the endogenous part of technology growth, g_t^A, as:

$$
g_{t+1}^A = \frac{A_{t+1}}{A_t} = \chi(\frac{RD_t}{A_t})^{\mu} + \phi \tag{2.15}
$$

Financing of R&D: No Stock Market

Innovators are assumed to have no initial funds and so have to borrow from a financial intermediary at the borrowing rate R_t^b, in order to finance R&D expenditure. For the benchmark model, we consider debt as the only source of finance. Later we will incorporate a stock market so that there are both debt and equity forms of finance. For a typical innovator, expected profit can be written:

$$
E_t \pi_t^I = E_t(\Lambda_{t,t+1} V_{t+1}) \varphi_t RD_t - R_t^b RD_t \tag{2.16}
$$

where V_t is the value or real price of a new technology, which can be in the form of a patent, blueprint and so forth. Since a new technology represents a perpetual license to produce a new intermediate good, the price of a new technology is equal to expected value of profits from producing this intermediate good.

$$
V_t = E_t(\pi_t^m + \phi \Lambda_{t,t+1} V_{t+1}) \tag{2.17}
$$

where ϕ is the survival rate of technology.[10] Due to the free-entry condition, innovators will compete until they break-even so that

$$E_t(\Lambda_{t,t+1} V_{t+1} \varphi_t) = R_t^b \tag{2.18}$$

Equation (2.18) suggests that the marginal return of R&D should be equal to its marginal cost. Then this condition can be rewritten to obtain optimal RD_t.

$$RD_t = [\frac{\chi A_t^{1-\mu} E_t(\Lambda_{t,t+1} V_{t+1})}{R_t^b}]^{1/(1-\mu)} \tag{2.19}$$

When there is a credit premium shock R_t^b will increase, affecting R&D in two ways. On the one hand, a rise in R_t^b has a direct impact on the cost of R&D, meaning that the innovator will reduce R&D to increase the marginal return of innovation, consistent with (2.19). On the other hand, a rise in R_t^b indirectly affects innovation through the value of technology. Intermediate goods producers will reduce output, which is likely to reduce profits. Consequently, the value of technology will be depreciated so that the innovator has less incentive to invest in R&D.

Financing of R&D: with Stock Market

With access to the stock market, innovators can issue equity publicly so that they have two sources of finance: debt and/or equity. The representative innovator will choose an optimal level of equity to maximize discounted sum of expected

[10] Following Anzoategui et al. (2019), we allow some technologies to be expired.

profit (2.20)

$$E_t\pi_t^I = E_t(\Lambda_{t,t+1}V_{t+1})\varphi_t RD_t - R_t^b B_t - R_t^e E_t^I - \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t} \tag{2.20}$$

where B_t is the amount of borrowing, E_t^I is the amount of equity[11], R_t^e is the required return of equity in gross terms, $\frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t}$ is the equity issuance cost, ζ is a parameter governing the magnitude of the adjustment cost and A_t serves as a scaling factor to ensure a balanced growth path and also implies endogenous development of the stock market. The equity issuance cost is modeled using a quadratic function, consistent with Covas and Den Haan (2012) and empirical evidence (Altınkılıç and Hansen 2000) that equity issuance exhibits an increasing marginal cost[12]. All variables are expressed in real terms.

The forward-looking representative innovator maximizes expected profit to yield

$$R_t^b = R_t^e + \zeta\frac{E_t^I - E_{t-1}^I}{A_t} - E_t(\Lambda_{t,t+1}\zeta\frac{E_{t+1}^I - E_t^I}{A_{t+1}}) \tag{2.21}$$

Equation (2.21) implies that the marginal cost of debt is equal to that for equity. With the presence of the stock market, the innovator's decision becomes dynamic[13]. Using the break-even condition $E_t\pi_t^I = 0$ and defining $\theta_t^e = \frac{E_t^I}{RD_t}$ as a proportion of R&D financed by equity, we can derive the equilibrium level of

[11] We want to remind readers that E_t^I is not an expectation operator.

[12] Equity issuance costs might involve underwriting, accounting or legal fees.

[13] The innovator is forward-looking regardless of the stock market. In the benchmark case, forward-looking innovators faces static decision making problems, meaning that there is no inter-temporal first order condition.

R&D.

$$
\begin{aligned}
E_t(\Lambda_{t,t+1}V_{t+1})\varphi_t RD_t &= R^b_t B_t + R^e_t E^I_t + \frac{\zeta}{2}\frac{(E^I_t - E^I_{t-1})^2}{A_t} \\
&= R^b_t(1-\theta^e_t)RD_t + R^e_t\theta^e_t RD_t + \frac{\zeta}{2}\frac{(E^I_t - E^I_{t-1})^2}{A_t}
\end{aligned}
\tag{2.22}
$$

The right hand side of (2.22) shows the total cost of innovation consists of three components: the borrowing cost, equity cost and equity issuance cost. The former two components together can be interpreted as the weighted average cost of innovation. Using (2.14), we can obtain an equilibrium level of R&D in a comparable form with (2.19)

$$
RD_t = [\frac{\chi A_t^{1-\mu} E_t(\Lambda_{t,t+1}V_{t+1})}{R^b_t - (R^b_t - R^e_t)\theta^e_t + \frac{\zeta}{2}\frac{(E^I_t - E^I_{t-1})^2}{RD_t A_t}}]^{1/(1-\mu)} \tag{2.23}
$$

Compared with equation (2.19), the denominator of the right hand side of (2.23) has an extra term $-(R^b_t - R^e_t)\theta^e_t + \frac{\zeta}{2}\frac{(E^I_t - E^I_{t-1})^2}{RD_t A_t}$.[14]

Compared to equity, debt is a less favourable sources of finance for R&D as it is very risky and lacks collateral, meaning that the financial intermediary will discourage finance for R&D. This is consistent with the existing literature, where firms with higher level of R&D prefer to use equity finance. We can think that equity finance is relatively cheaper for the innovator and access to the stock market should lead to more R&D.

Furthermore, we assume that R^b_t and R^e_t are linked to risks in both the credit sector and stock market separately. If a sizable financial shock occurs, R^b_t is much larger than R^e_t and the stock market should mitigate such an adverse effect. If

[14]If $R^b_t > R^e_t$ and access to equity market is not too costly (ζ not too high), there would be lower denominator and higher level of R&D in (2.23) compared with (2.19) and vice versa.

the stock market crashes this could magnify its own adverse effect.

2.3.4 Financial Intermediary

There exists a continuum of competitive financial intermediaries gathering money at the savings rate (R_t) from households. Financial intermediaries conducts business with both intermediate goods producer and the innovator. We assume financial intermediaries acquire information about their borrowers and monitor their activities at the intermediation cost, ε_t^f, and that the intermediation cost is common for both types of borrowers. Since ε_t^f creates a wedge between the borrowing and savings rate, ε_t^f can be treated as the credit premium. We assume ε_t^f is exogenous and captured by an AR(1) process: $ln\varepsilon_t^f = (1-\rho_f)ln\varepsilon^f + \rho_f ln\varepsilon_{t-1}^f + \eta_t^f$ and η_t^f follows i.i.d $N(0, \sigma_F^2)$.

When a credit premium shock occurs, financial intermediaries find it harder and more costly to identify the quality of borrowers and to monitor their activities. Furthermore, perfect competition implies that each financial intermediary must break even in equilibrium.

We can express the break-even condition for the typical financial intermediaries in the following form:

$$R_t^b L_t = (R_t \varepsilon_t^f) L_t \tag{2.24}$$

where R_t^b is the borrowing rate and L_t is the total amount of lending. Hence

$$R_t^b = R_t \varepsilon_t^f \tag{2.25}$$

Equation (2.25) means that the borrowing rate is equal to the savings rate times the credit premium.

2.3.5 Households

We first specify the most common elements of the household sector, which are irrelevant to the stock market. Then, we incorporate the stock market to highlight the elements that its inclusion will change. The representative household derives utility from consumption and leisure, consumes and saves money with the financial intermediaries, and experiences external habit formation in consumption. Households supply labour measured in hours H_t, used for the production of intermediate goods.

The household faces the following problem:

$$\max_{C_t, D_t, I_t, K_t, H_t} E_t \sum_{l=0}^{\infty} \beta^l [log(C_{t+l} - bC_{t+l-1}) - \psi \frac{H_{t+l}^{1+\eta}}{1+\eta}] \tag{2.26}$$

subject to the (no share) budget constraint and accumulation of capital.

$$P_t C_t + \frac{1}{\varepsilon_t^b} D_t = R_{t-1} D_{t-1} + W_t H_t + R_t^k u_t K_t - a(u_t) P_t K_t + \Pi_t^f - P_t I_t \tag{2.27}$$

$$K_{t+1} = (1-\delta) K_t + \varepsilon_t^i [1 - S(\frac{I_t}{(1+g^y) I_{t-1}})] I_t \tag{2.28}$$

where C_t denotes consumption, D_t saving, K_t capital stock, I_t investment, $a(u_t)$ is the capital utilization function with $a(1) = 0$, Π_t^f are profits from the ownership of monopolistic competitive firms, b is the habit parameter, $1 + g^y$ is the steady state growth rate of output and $S(\frac{I_t}{(1+g^y)I_{t-1}})$ is the adjustment cost function with S(1)=0, S'(1)=0 and S"( )>0. We deviate slightly with the conventional investment adjustment cost and introduce a trend growth rate $(1+g^y)$ because investment is not stationary and grows over time.

If investment deviates from the steady state growth path, there will be an adjustment cost (see a similar theory in Anzoategui et al. (2019)). ε_t^i is an investment efficiency shock following an AR(1) process: $ln\varepsilon_t^i = \rho_i ln\varepsilon_{t-1}^i + \eta_t^i$ and η_t^i follows an i.i.d $N(0, \sigma_I^2)$. ε_t^b is a risk premium shock following an AR(1) process: $ln\varepsilon_t^b = \rho_b ln\varepsilon_{t-1}^b + \eta_t^b$ and η_t^b follows an i.i.d $N(0, \sigma_B^2)$. This risk premium shock is similar to that in Smets and Wouters (2007) and induces a precautionary saving effect when the household is worried about the economy (ε_t^b increases). Utility maximisation yields the following first order conditions:[15]

$$\frac{\partial L}{\partial C_t} = MU_{c,t} - \lambda_t P_t = \frac{1}{C_t - bC_{t-1}} - \lambda_t P_t = 0 \tag{2.29}$$

$$\frac{\partial L}{\partial D_t} = -\lambda_t + E_t \lambda_{t+1} \beta R_t \varepsilon_t^b = 0 \tag{2.30}$$

$$\begin{aligned}\frac{\partial L}{\partial I_t} = -\lambda_t P_t + \lambda_t^k P_t \varepsilon_t^i [(1 - S(\frac{I_t}{(1+g^y)I_{t-1}})) - S'(\frac{I_t}{(1+g^y)I_{t-1}})\frac{I_t}{(1+g^y)I_{t-1}}] \\ +E_t[\beta \lambda_{t+1}^k P_{t+1} \varepsilon_{t+1}^i S'(\frac{I_{t+1}}{(1+g^y)I_t})(\frac{I_{t+1}}{(1+g^y)I_t})^2] = 0\end{aligned} \tag{2.31}$$

$$\frac{\partial L}{\partial K_{t+1}} = \beta E_t\{\lambda_{t+1}[R_{t+1}^k u_{t+1} - a(u_{t+1})P_t]\} + \beta E_t\{\lambda_{t+1}^k P_{t+1}(1-\delta)\} - \lambda_t^k P_t = 0 \tag{2.32}$$

$$\frac{\partial L}{\partial u_t} = -\lambda_t (R_t^k - a'(u_t)P_t) K_t = 0 \tag{2.33}$$

[15]Note that K_t is a predetermined variable and household in period t determine capital in period $t+1$.

With regard to wage setting, the household supplies differentiated labour to a competitive labour agency which differentiates it, packs it into labour services and sells labour services to intermediate goods producers. As standard in the New Keynesian literature, there is a wage rigidity and wage adjustment, based on the Calvo scheme. Households re-optimise wages with probability 1-ϵ_w in each period. With probability ϵ_w households cannot re-optimise and index past inflation to adjust the wage, $W_t = W_{t-1}\pi^{1-\iota_w}\pi_{t-1}^{\iota_w}(1+g^y)$, where ι_w is the degree of wage indexation. The first order condition for the wage is:

$$E_t \sum_{l=0}^{\infty} \epsilon_w^l \Lambda_{t,t+l}[\frac{W_t^* \prod_{s=0}^{l}[\pi_{t+s-1}^{\iota_w}\pi^{1-\iota_w}(1+g^y)^s]}{P_{t+l}} - \varepsilon_{t+l}^w \psi \frac{H_{t+l}^{\eta}}{MU_{c,t+l}}]H_{t+l} = 0 \quad (2.34)$$

where ε_t^w is a wage mark-up shock following an AR(1) process: $ln\varepsilon_t^w = \rho_w ln\varepsilon_{t-1}^w + \eta_t^w$ and η_t^w follows an i.i.d $N(0, \sigma_W^2)$.

With the presence of a stock market, there will be two changes to the household sector. Since households buy equity issued by innovators, they will get a return from equity investment. Consequently, the budget constraint needs to include income from equity return and money invested in equity. With equity, (2.27) becomes

$$P_tC_t + \frac{1}{\varepsilon_t^b}D_t + P_tE_t^I = R_{t-1}D_{t-1} + R_{t-1}^e P_{t-1}E_{t-1}^I + W_tH_t + R_t^k u_t K_t - a(u_t)P_tK_t + \Pi_t^f - P_tI_t \quad (2.35)$$

The inclusion of an equity market also adds an extra first order condition

$$\frac{\partial L}{\partial E_t^I} = -\lambda_t P_t + E_t \lambda_{t+1} P_t \beta R_t^e = 0 \quad (2.36)$$

Combining (2.30) and (2.36) yields us

$$R_t^e = R_t \varepsilon_t^b \tag{2.37}$$

Therefore, with the stock market added, ε_t^b not only affects the intertemporal decisions of households but also affects the required return to equity. An increase in ε_t^b increase the required return of equity R_t^e. In this sense, ε_t^b is not only a demand shock but also an equity premium shock.

Critical for our analysis, ε_t^b has a distinct propagation mechanism compared with the credit premium shock ε_t^f. A rise in ε_t^b leads to a decrease in aggregate demand and prices so that inflation declines (see Smets and Wouters (2007) for more details). While a rise of ε_t^f increases marginal cost and hence pushes up inflation. The differences in propagation are helpful to identify ε_t^b and ε_t^f and to distinguish the credit premium and equity premium. Furthermore, we check the profiles of the premiums generated from our model and find that their persistence and relative movements are consistent with data as shown in Figure 2.5.

2.3.6 Aggregation and Equilibrium

Following Anzoategui et al. (2019), we can obtain aggregate output as the following:

$$Y_t = \varepsilon_t^a A_t^{\lambda_m - 1} (u_t K_t)^\alpha H_t^{1-\alpha} \tag{2.38}$$

We consider two definitions of TFP. The first is the Solow residual $\varepsilon_t^a A_t^{\lambda_m - 1} u_t^\alpha$ containing three components: the first ε_t^a is an exogenous shock, the second $A_t^{\lambda_m - 1}$ technology and the third u_t^α utilization of capital. Another definition we can consider is utilization-adjusted TFP $\varepsilon_t^a A_t^{\lambda_m - 1}$ which excludes utilization. Equations (2.9) and (2.10) can be rewritten as

$$W_t R_t^b = (1-\alpha)\varepsilon_t^a MC_t^M (u_t K_t / H_t)^\alpha \tag{2.9'}$$

$$R_t^k R_t^b = \alpha \varepsilon_t^a MC_t^M (u_t K_t / H_t)^{\alpha - 1} \tag{2.10'}$$

The resource constraint

$$Y_t = C_t + I_t + RD_t + G_t + NX_t + a(u_t)K_t + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t} \tag{2.39}$$

G_t[16] is a government spending shock following AR(1) process: $lng_t = (1-\rho_g)g + \rho_g lng_{t-1} + \eta_t^g$ and η_t^g follows i.i.d $N(0, \sigma_G^2)$. NX_t is an exogenous demand shock[17] following AR(1) process: $lnnx_t = (1-\rho_x)nx + \rho_x lnnx_{t-1} + \eta_t^x$ and η_t^x follows i.i.d $N(0, \sigma_X^2)$. Alternatively way of modeling NX is to relate it with TFP, as suggested by Smets and Wouters (2007). However, we find there is significant gap between model generated net export and data especially for China, implying that the alternative setup is inappropriate.

The financial market clears in (in real terms): $D_t^r = L_t^r = w_t H_t + r_t^k K_t + RD_t$ or $D_t^r = L_t^r = w_t H_t + r_t^k K_t + (1-\theta_t^e)RD_t$ if the stock market is included.

The policy rate which is also the savings rate is given by the Taylor rule

$$R_t = R_{t-1}^{\rho_r}[R(\frac{\pi_t}{\overline{\pi}})^{\rho_\pi}(\frac{Y_t}{(1+g^y)^t})^{\rho_y}(\frac{Y_t}{Y_{t-1}})^{\rho_{\Delta y}}]^{1-\rho_r}\varepsilon_t^m \tag{2.40}$$

[16]For later analysis, we focus on the efficiency unit of G_t which is defined as $g_t = G_t/(1+g^y)^t$. Government spending is anchored with output (in the steady state) so that it is unnecessary to specify government expenditure separately.

[17]NX captures net export. In this paper, we call NX as exogenous demand or net export interchangeably. $nx_t = NX_t/(1+g^y)^t$

where ε_t^m is a monetary policy shock following an AR(1) process: $ln\varepsilon_t^m = \rho_m ln\varepsilon_{t-1}^m +$ η_t^m and η_t^m follows an i.i.d $N(0, \sigma_M^2)$. Equation (2.5), (2.9'), (2.10'), (2.13)-(2.15), (2.17)-(2.19), (2.25), (2.28)-(2.34) and (2.38)-(2.40) are equilibrium conditions for the benchmark case. When adding a stock market, (2.23) replaces (2.19) and there are two more conditions required, (2.21) and (2.37).

2.4 Bayesian Estimation and Simulation

In this section we report our results for the Bayesian estimation[18] and simulation of two DSGE models; one for China with a financial intermediary (the benchmark case), and one for the US, with both financial intermediary and equity markets. This framework allows the data to assist in the determination of the structural parameters for both economies. Simulations are then carried out, using the estimated parameters to measure the different responses from the economies to multiple shocks.

2.4.1 Data

Our sample period is 1995Q1 to 2016Q4 for China and the US. This period is selected for three reasons. Firstly, China's quarterly time-series for major macroeconomic indicators become available in the mid-1990s. Secondly, in terms of economic structure, China has become a more market-oriented economy since the mid-1990s, with significant growth in the private sector since. Thirdly, we prefer to keep the sample period consistent across US and China to facilitate comparison. We use nine macroeconomic variables as observables for estimation:

[18]We estimate our models using Dynare.

GDP, consumption, investment, government spending, hours worked, real wages, GDP deflator inflation, the policy interest rate and lending rate[19].

In terms of lending rate, Moody BAA corporate bond yield is used as a proxy for US while the weighted averaged lending rate is that proxy for China. Note that we use a bond-related variable for the US and a loan-related variable for China, due to the fact that debt in the US is mainly originated from the bond market while that in China is almost entirely from the banking sector. Thus, these two lending variables capture cost of borrowing associated with the majority of debt in US and China separately. To the best of our knowledge, there is no other borrowing rate data available for China, especially in terms of a corporate bond-related borrowing rate. Chinese enterprise and corporate bond markets develop very slowly and are much smaller than the banking sector.

We transform the data as follows. GDP, consumption, investment and government spending are expressed as real per capita, logarithmic first difference; the real wage is logarithmic first difference; labour hours are measured as per capita employment times hours worked. Following Christiano et al. (2014), all variables are demeaned separately. Before moving forward, it is worth discussing the widely debated issue of reliability for Chinese GDP data, specifically whether or not the Chinese government deliberately manipulates GDP. Holz (2014) finds little to no evidence that the Chinese government is actually making these manipulations. This result is later confirmed by Plekhanov (2017), based on a review for 88 publications over 2000 to 2015. Chen et al. (2019) points out that the National Bureau of Statistics in China (NBS) makes ongoing attempts to correct

[19]For more details of the observable variables used in our estimation, please refer to Appendix A.

GDP by using its own data collected through surveys, census and so on. Chen et al. (2019) further suggests that the adjustment made by NBS has corrected this bias in GDP until 2007, though the correction seems to become inaccurate after 2008. Other scholars that examine whether or not Chinese official GDP is informative in China are Mehrotra and Pääkkönen (2011) who, among others, find that Chinese GDP does reflect economic activities in China although there could be some small scale discrepancies.

In order to check the robustness of our output volatility for China, we recalculate it using real GDP growth data from Chen et al. (2019). We find that output growth volatility for China (2.195) is still around the averaged level of developed countries (see Table 2.12 in Appendix A) . With regard to TFP growth, one may raise concerns about the quality of capital or investment data which are critical for estimating TFP. We do not find unreasonable movements in capital and investment in China. Figures 2.12 to 2.14 (see Appendix A) show that the magnitude of variation of capital growth and investment growth in China are similar to that of the US. However, it should be noted that investment growth in China shows a less persistent pattern than the US counterpart (see Figure 2.14). This is probably due to government intervention or policy changes which can suddenly alter the movement of investment. Moreover, our investment data comes from Chang et al. (2016) where it has been checked for potential outliers[20]. In addition, to check the quality of investment and capital data, we also carry out a robustness exercise for TFP (details can be found in Appendix A). We find that the high TFP volatility in China is insensitive to alternative estimation methods

[20]Chang et al. (2016) do not find outliers for post-1995 investment data. Moreover, we use gross capital formation rather than fixed asset investment as a measure of investment. Chang et al. (2016) suggest that the latter might be exaggerated while the former is not.

and the selection of different input variables.

2.4.2 Calibration

In this section we present our calibration of the structural parameters chosen for the two economies, China and the US. Calibration is carried out where values of certain structural parameters are considered 'known' in the literature, and has the benefit of limiting the number of parameters that we are required to estimate through Bayesian techniques.

Table 2.3: Calibrated parameters

Parameters	Description	US	China
α	capital share	0.36	0.5
β	discount factor	0.995	0.995
δ	capital depreciation	0.02	0.025
μ	technology elasticity	0.8	0.7
ϕ	technology survival rate	0.965	0.95
λ_m	intermediate goods mark-up	1.64	1.5
ζ	equity issuance cost parameter	0.12	/
g^y	deterministic trend growth rate	0.48%	2.2%
RD/Y	ss R&D intensity	0.0259	0.0121
G/Y	ss exo. demand share	0.25	0.18
$\overline{H}$	ss working time	0.3	0.3
ε_f	ss credit premium	0.0075	0.0075
θ^e	ss percentage of equity finance	0.55	/

Table 2.3 shows calibrated parameters for China and the US together. These parameters are well identified in existing literature, for example (Chang et al. 2015, Dai et al. 2015, Anzoategui et al. 2019, Smets and Villa 2016). Hsieh and Klenow (2009) find that labour income share accounts for about half of GDP in China, which implies a capital share α of 0.5. For the US this is calibrated as 0.36, in line with other US-based DSGE studies. The discount factor β is calibrated

as 0.995 to match quarterly interest rate for the US (0.65%) and China (2.75%) separately. The technology elasticity with respect to R&D μ is calibrated based on the patent-R&D or R&D stock-R&D flow relationship. Following Comin and Gertler (2006), we choose μ as 0.8 for US. Its counterpart for China is set to 0.7 in order to match moments of Chinese business R&D growth. This value also implies the efficiency of Chinese R&D is lower than that in the US.

We follow Kung and Schmid (2015) and Jinnai (2015) to calibrate the quarterly technology obsolescence rate 1-ϕ for the US as 3.75%. 1-ϕ for China is calibrated as 5% which is consistent with a 20% annual obsoletion rate of Chinese invention patents (SIPO 2014). Following Kung and Schmid (2015) and Jinnai (2015), we calibrate the intermediate goods mark-up λ_m as 1.64 for the US, and 1.5 for China to ensure a balanced growth path[21]. Following Covas and Den Haan (2012), we calibrate ζ such that the equity issuance cost accounts for about 5.7% of equity issuance.

The lower part of Table 2.3 shows the calibrated value of steady-state parameters for the US and China. The steady-state per capita GDP growth rate is calibrated at 1.9% and 8.8% for US and China respectively in annual terms. Hence we calibrate g^y as 0.48% and 2.2% for US and China separately. R&D intensity shows the percentage of R&D in GDP which is around 2.59% for the US and 1.21% for China. The steady-state debt to total finance ratio for the innovator is calibrated as 0.45 based on debt and equity issuance data for hi-tech firms[22] between 1995 and 2016. Other parameters do not differ significantly

[21]Kung and Schmid (2015), Jinnai (2015) calibrate λ_m such that λ_m-1+α=1. This is to ensure a constant returns to scale for the aggregate production function, critical for a balanced growth path.

[22]Source: Thomson One Database.

between China and US in existing literature. Hence, we give them the same value.

2.4.3 Estimation

Bayesian estimation offers a useful tool to estimate and evaluate dynamic stochastic general equilibrium (DSGE) models. The aim of implementing this methodology is to characterize the posterior distribution of the models parameters conditional on prior beliefs of the estimated parameters, a distinct advantage over other estimation methods such as classical maximum likelihood, GMM and indirect difference. The classical maximum likelihood method does not exploit prior information and other two methods rely on a GMM criterion mainly based on information of first moments rather than all moment conditions on which Bayesian method engages (Guerrón-Quintana and Nason 2013).

The posterior distribution is obtained by employing the Bayesian updating:

$$p(\theta/Y^T) = \frac{L(Y^T|\theta)p(\theta)}{\int L(Y^T|\theta)p(\theta)d\theta} \propto L(Y^T|\theta)p(\theta)$$

gives the Bayesian relationship between the posterior density, $p(\theta/Y^T)$, the unconditional sample density, $\int L(Y^T|\theta)p(\theta)d\theta$, and the prior density, $p(\theta)$. The posterior density evolves from a weighted average of prior non sample information and the conditional densities. These weights are related to the variances of the prior distributions and the data. A tighter prior, therefore, will result in a more constrained, and perhaps less informative, estimation. The parameters are estimated by maximizing the likelihood function and then combining with the prior distributions of the parameters in the model, to form the posterior density functions.

Estimation of the model's structural parameters relies on the use of 'informative' priors to enable the data to pin down the correct value of the estimates, inevitably it is the choice of these priors that becomes key to successful identification. If the data do not contain enough information to adequately identify the value of the conditional mean of the parameter, then the posterior distribution is only informed by the prior, though this does not necessarily mean that the prior is incorrect. The priors for this study, come from values found in other studies, and which have become widely accepted; others from steady state valuations and micro level studies.

Table 2.4: Prior and posterior distribution of structural parameters and shock processes

Parameters	Prior			Posterior	
	Distribution	Mean	St.Dev.	Mean (US)	Mean(China)
b habit	Beta	0.7	0.1	0.61 [0.54, 0.69]	0.56 [0.46, 0.67]
ϵ_p calvo price	Beta	0.5	0.15	0.93 [0.91, 0.95]	0.93 [0.92, 0.95]
ι_p price indexation	Beta	0.5	0.1	0.23 [0.09, 0.45]	0.29 [0.11, 0.44]
ϵ_w calvo wage	Beta	0.7	0.15	0.93 [0.89, 0.95]	0.92 [0.87, 0.97]
ι_w wage indexation	Beta	0.5	0.1	0.40 [0.17, 0.63]	0.44 [0.22, 0.65]
η inverse labour elasticity	Gamma	2	0.5	1.91 [1.07, 2.71]	1.79 [1.07, 2.48]
s" Invest. adj. cost	Gamma	5	1	4.10 [2.83, 5.46]	6.53 [4.69, 8.28]
ξ elasticity of K utilization	Beta	0.5	0.1	0.75 [0.65, 0.84]	0.83 [0.75, 0.90]
ρ_r taylor smoothing	Beta	0.7	0.15	0.89 [0.85, 0.92]	0.97 [0.96, 0.98]
ρ_π taylor parameter	Gamma	1.5	0.25	1.76 [1.38, 2.13]	1.22 [0.85, 1.57]
ρ_y taylor parameter	Gamma	0.12	0.05	0.05 [0.02, 0.08]	0.17 [0.09, 0.26]
$\rho_{\Delta y}$ taylor parameter	Gamma	0.12	0.05	0.14 [0.11, 0.17]	0.03 [0.01, 0.04]
ρ_a per. of exo. TFP	Beta	0.5	0.2	0.82 [0.74, 0.90]	0.93 [0.90, 0.96]
ρ_b per. of risk premium	Beta	0.5	0.2	0.91 [0.87, 0.95]	0.95 [0.90, 0.99]
ρ_m per. of mon. policy	Beta	0.5	0.2	0.29 [0.18, 0.42]	0.43 [0.30, 0.56]
ρ_s per. of price mark-up	Beta	0.5	0.2	0.36 [0.08, 0.59]	0.45 [0.25, 0.64]
ρ_w per. of wage mark-up	Beta	0.5	0.2	0.07 [0.01, 0.13]	0.19 [0.05, 0.34]
ρ_i per. of inv. efficiency	Beta	0.5	0.2	0.71 [0.61, 0.82]	0.56 [0.40, 0.73]
ρ_f per. of credit premium	Beta	0.5	0.2	0.98 [0.96, 0.99]	0.94 [0.91, 0.98]
ρ_g per. of gov. spending	Beta	0.5	0.2	0.98 [0.96, 0.99]	0.94 [0.89, 0.98]
ρ_x per. of exo. demand	Beta	0.5	0.2	0.99 [0.98, 0.99]	0.96 [0.95, 0.98]
σ_a std. of exo. TFP	Inv_Gamma	0.1	2	0.52 [0.45, 0.59]	1.23 [1.06, 1.41]
σ_b std. of risk premium	Inv_Gamma	0.1	2	0.19 [0.13, 0.25]	0.33 [0.10, 0.56]
σ_m std. of mon. policy	Inv_Gamma	0.1	2	0.10 [0.09, 0.11]	0.06 [0.05, 0.07]
σ_s std. of price mark-up	Inv_Gamma	0.1	2	0.11 [0.08, 0.14]	0.35 [0.25, 0.44]
σ_w std. of wage mark-up	Inv_Gamma	0.1	2	0.48 [0.42, 0.55]	0.80 [0.66, 0.94]
σ_i std. of inv. efficiency	Inv_Gamma	0.1	2	0.31 [0.25, 0.38]	1.21 [0.92, 1.51]
σ_f std. of credit premium	Inv_Gamma	0.1	2	0.16 [0.14, 0.18]	0.06 [0.05, 0.07]
σ_g std. of gov. spending	Inv_Gamma	0.1	2	0.16 [0.14, 0.17]	0.78 [0.68, 0.87]
σ_x std. of exo. demand	Inv_Gamma	0.1	2	0.43 [0.38, 0.49]	1.51 [1.32, 1.71]

Note: 90% HPD in bracket.

Our estimation results are as expected. Table 2.4 suggests that US consumers are slightly more habitual than their Chinese counterparts; habit in consumption for the US is 0.61 and China 0.56. There is a similar level of stickiness in both prices and wages for the US (both 0.93) and China (0.93 and 0.92). Chinese goods producers index more on lagged prices and lagged wages respectively (0.29 and 0.44) than producers in the US (0.23 and 0.40). The Chinese capital utilization elasticity is estimated at 0.83, higher than that in the US (0.75). The investment adjustment cost parameter is higher in China (6.53) than in the US (4.10). The Taylor parameters suggest that the Chinese policy rate is more sticky (ρ_r=0.97 for China and ρ_r=0.89 for US) and the Chinese central bank appears to react less aggressively to inflation (ρ_π=1.22 for China and ρ_π=1.76 for the US).

With regards to the shock process, we find the most notable differences between China and the US, in terms of both depth and persistence. In terms of standard deviations, which reflect the depth of the shocks' effect on the economy, the majority of shocks in China are significantly larger. The exogenous TFP shock, risk premium shock, both mark-up shocks, investment shock, government spending shock and exogenous demand shock are all more volatile for China than those for the US.

On the contrary, the credit premium shock and monetary policy shock are less volatile in China than in the US. Turning to the persistence of shocks, we find the exogenous TFP shock, risk premium shock, monetary policy shock and two mark-up shocks in China are more persistent than in the US; while the investment shock, credit premium shock, government spending shock and exogenous demand shock are less persistent in China than in the US. The relative low persistence of the credit premium shock, plus the low variance, implies that the Chinese credit market is less likely to suffer from exogenous disturbances and can recover relatively quickly when this does happen.

Furthermore, we find that the persistence parameters of the exogenous TFP shock in both China and US are lower than in existing literature. This may well be owing to the fact that the persistence of TFP is generated from an endogenous technology channel[23]. Next we show relative importance of each shock in China and US respectively, starting with the unconditional variance decomposition for China, in Table 2.5.

Table 2.5: Unconditional Variance Decomposition (%): China

Variables	Structural Shocks								
	TFP (exo.)	Risk premium	Credit Premium	Mon. policy	Price mark-up	Wage mark-up	Invest. Efficiency	Gov. spending	Demand (exo.)
Δy	2.59	19.18	0.02	2.84	1.33	0.85	35.10	8.28	29.81
Δc	0.61	59.73	0.05	8.73	4.38	0.23	12.64	2.90	10.73
Δi	0.42	9.89	0.01	1.48	0.87	0.21	86.83	0.06	0.24
y	1.60	39.96	0.06	8.44	4.70	0.69	27.18	3.69	13.66
π	4.31	4.56	0.31	1.00	79.25	2.04	3.04	1.17	4.32
r	2.70	33.29	0.61	12.22	5.57	1.15	10.34	7.26	26.85
v	13.95	55.99	0.36	8.09	6.18	3.40	7.50	0.97	3.57
rd	10.73	53.21	0.09	9.90	6.23	2.61	13.49	0.80	2.94
A	7.75	45.58	0.22	13.30	7.65	1.05	19.12	1.13	4.20
$uTFP$	22.56	38.26	0.19	11.16	6.42	0.88	16.05	0.95	3.52
TFP	13.28	38.65	0.18	10.38	7.21	2.11	23.34	1.03	3.81
Δa	11.61	55.48	0.05	8.89	5.81	3.07	11.82	0.69	2.57
$\Delta uTFP$	59.79	24.09	0.02	4.06	2.85	1.19	6.62	0.29	1.08
ΔTFP	30.95	31.29	0.03	5.11	3.77	3.42	20.19	1.11	4.12

Note: $uTFP$ refers to utilization-adjusted TFP.

Not surprisingly, the credit premium is quantitatively less important in terms of explanatory power for Chinese macroeconomic fluctuations. The investment and exogenous demand shocks are two major driving factors for output growth variance in China (35% and 30%), followed by the risk premium and government spending shocks (19% and 8%). In terms of output, its variance is mainly explained by risk premium and investment shocks[24] (40% and 27%).

In terms of productivity-related variables including R&D, technology and TFP

[23]A similar case can be found from Anzoategui et al. (2019).

[24]The investment shock has the largest contribution to output in the very short run based on the conditional variance decomposition, e.g., about 37% is within 4 quarters. We also find government spending shocks contribute about 10% of the total variance for output and output growth within 4 quarters.

variables, the risk premium shock has the largest contribution, ranging from 38% to 53%. In addition, the investment shock, TFP shock and monetary policy shock are also important in explaining the variance of productivity related variables, with contributions between 8% to 23%. Furthermore, Table 2.5 suggests that non-TFP shocks together have a 77% and 87% contribution to utilization-adjusted TFP and Solow residual respectively. This finding implies that Chinese TFP is primarily explained by the technology creation channel.

Table 2.6: Unconditional Variance Decomposition (%): US

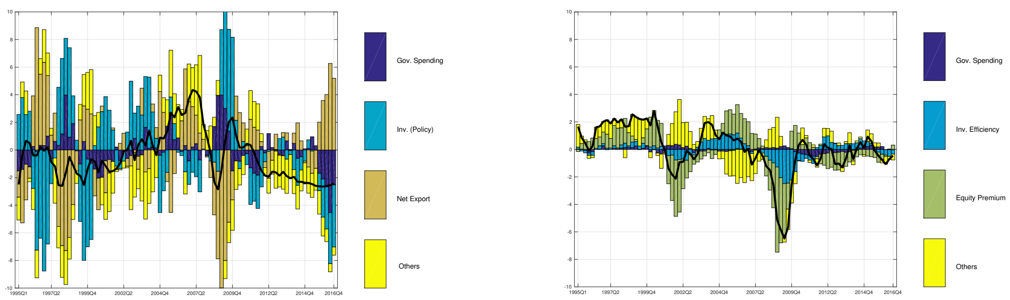
Variables	Structural Shocks								
	TFP (exo.)	Risk premium	Credit Premium	Mon. policy	Price mark-up	Wage mark-up	Invest. Efficiency	Gov. spending	Demand (exo.)
Δy	0.17	49.72	0.44	20.32	3.99	0.73	7.72	1.87	15.03
Δc	0.19	52.62	1.23	21.32	3.36	0.95	3.53	1.32	15.47
Δi	0.12	20.58	0.08	8.67	2.77	0.59	66.81	0.04	0.34
y	0.47	55.41	5.89	20.45	5.02	3.53	6.49	0.15	2.58
π	2.08	16.64	12.17	5.77	49.06	10.96	2.87	0.41	0.03
r	0.52	64.57	6.63	10.98	2.55	3.27	8.81	0.68	1.99
v	0.71	67.44	1.52	20.00	6.17	2.77	1.32	0.02	0.05
rd	0.52	56.67	6.55	24.18	6.77	2.81	2.22	0.09	0.19
A	0.34	53.23	14.48	21.31	5.46	2.69	2.26	0.19	0.04
$uTFP$	6.30	50.05	13.61	20.03	5.14	2.53	2.12	0.18	0.03
TFP	5.44	50.61	14.00	20.19	5.48	2.57	1.53	0.12	0.06
Δa	0.62	58.60	2.11	25.79	7.51	2.87	2.20	0.03	0.27
$\Delta uTFP$	61.80	21.87	1.02	9.94	3.17	1.11	1.01	0.01	0.07
ΔTFP	45.29	30.55	1.10	13.41	4.74	3.88	0.86	0.02	0.14

For the US, Table 2.6 shows that variance of US output and growth are mostly explained by the risk premium shock (50-55%), followed by the monetary policy shock (20%). With regards to the productivity-related variables, the two premium shocks account for 63% of R&D variance, 68% of technology variance, 67% of utilization-adjusted TFP variance and 65% of the Solow residual variance. The monetary policy shock is also an important driving force for productivity-related variables, with the contributions ranging from 10%-20% separately. The exogenous TFP shock has a non-negligible contribution to utilization-adjusted TFP (6%) and the Solow residual (5%).

Comparing China and the US, we find that the credit premium shock is important for the US model, especially for productivity-related variables, but not for China; investment, government spending and exogenous demand shocks are much more important in this case. The latter finding is consistent with the fact that Chinese output is largely affected by investment, government expenditure and net exports. After establishing the relative importance of each of the shocks, we now turn to investigate how these contributions help to explain our research question: why is Chinese output relatively stable but TFP more volatile?

Figure 2.7: Output growth historical decomposition

(a) China (b) US



Note: the two figures are expressed as percentage deviation from steady state.

Figure 2.7 shows the historical variance decomposition of 4-quarter output growth for the US and China separately. We find a marked difference in terms of the contribution of the shocks for output growth. For China, the contribution of shocks shows a more counteracting pattern. Figure 2.7(a) highlights a pattern in China that the investment shock and government spending shock together counteract effects from other shocks, particularly the exogenous demand shock, which we can think of as representing net exports. The latter hits the Chinese economy during several periods, such as the Asian and global financial crisis. For the US, however, there is no suggestion that the investment shock works strongly against the contribution from others (2.7(b)). We find that the government spending shock combats other shocks in the US, yet the effect of the former on output growth is small.

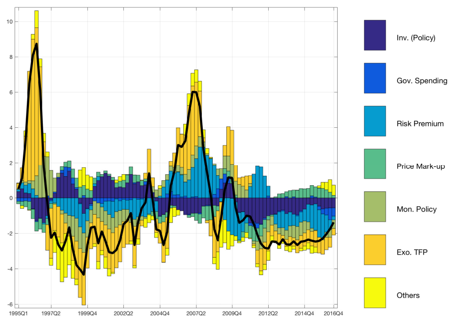
Another finding suggested by Figure 2.7 is that the investment shock in China does not display the same pro-cyclical contribution to output as in the case for the US. This is likely to be due to the investment shocks capturing investment policy effects, which is a key determinant of investment in China (Chen et al. 2011). A number of studies (Dunaway and Fedelino 2006, Chang et al. 2016, Chen and Zha 2018) document how the Chinese government often intervenes in the economy using such investment policies. In an economic slowdown the government tends to stimulate investment, especially in the real estate and infrastructure sectors, in order to revive the economy; if the economy is overheating, the government will direct resources away from investment to cool the economy as necessary.

We can classify the investment policies into three categories: (1) quantity-based measures, such as the 1998 Macroeconomic Policy Package (World Bank 1999) and the 2008–09 Chinese Economic Stimulus Plan (Zilibotti 2017) (2) price-based measures, such as "Notice on the Adjustment of Tax Policy and Collection Management of Fixed Assets Investment" in 1999, and (3) administrative measures such as "Opinions on Strengthening the Control of Fixed Assets Investment and Newly Launched Projects" in 2006. These policies affect investment behaviours of both state owned enterprises (SOEs) and private firms. Since these investment policies make up part of government intervention, it is reasonable to suggest that Chinese output is stabilised almost as if government intervention was applied liberally through direct spending and any indirect influence on firms' investment behaviours.

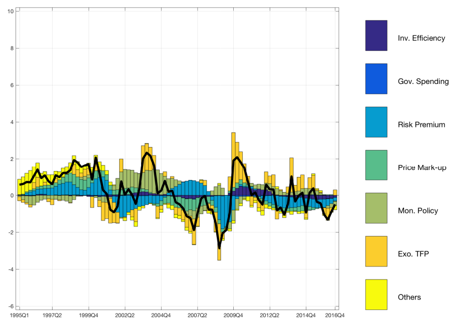
Turning to TFP, we find that for the US, the standard deviation of technology,

Figure 2.8: TFP growth historical decomposition

(a) China



(b) US



Note: the same as above.

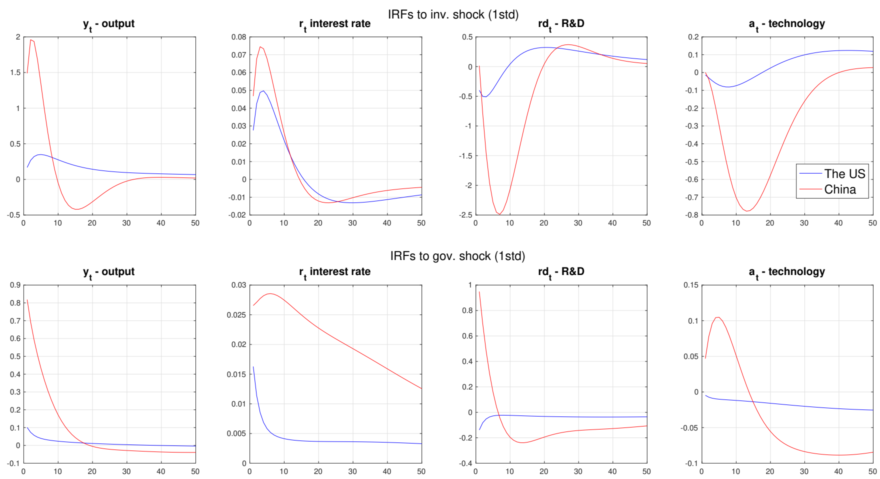
utilization–adjusted TFP and Solow residual generated from the model are 2.873, 2.016 and 1.907 respectively, whilst for China, the equivalent counterparts are 5.313, 6.365 and 6.057 respectively[25]. In addition to this, the model generated standard deviation of technology growth, utilization–adjusted TFP growth and Solow residual growth are 1.052, 1.000 and 1.072 for the US, and 2.682, 3.262 and 2.827 for China respectively. It is clear that the model generates significantly larger fluctuations and variance of the three types of TFP for China, relative to the US and consistent with the empirical facts we have mentioned in Section 2. Figure 2.8(a) shows that several non-TFP shocks, including the risk premium shock, monetary policy shock, price mark-up shock, and the investment shock, account for the significant variation in TFP growth overall in China; aside from investment, these shocks are major driven forces for US TFP growth. Considering that Chinese technology is about twice as volatile as that in the US, it appears that the endogenous technology channel could be responsible for Chinese TFP volatility.

Figure 2.8 further shows an interesting slowdown pattern in TFP growth for

[25]Similar to Anzoategui et al. (2019), there could be a discrepancy between our measure of TFP and that from other sources (e.g. BLS) because definitions of investment are different.

both the US and China since the global financial crisis. For the US, Figure 2.8(b) suggests this pattern is mainly due to the negative contribution from the risk premium shock, partially consistent with Anzoategui et al. (2019) although we do not model a diffusion mechanism as in their study. For China, the risk premium shock, investment shock and government spending shock adversely affect TFP growth through the technology creation channel, accounting for the slowdown in TFP in the last decade.

Figure 2.9: Impulse response to positive inv. and gov. spending shocks (1 std)



In order to understand the implications of government intervention for TFP in China, we next use impulse response functions to illustrate the mechanisms. As shown in Figure 2.9, positive investment shocks and government spending shocks increase output immediately. As a result, revenues from innovation increase and innovators will initially invest more in R&D. However, as the economy is expanding, the central bank will increase the interest rate which further increases the financing cost of R&D. Hence, R&D will be crowded out and technology levels will drop. Moreover, if we assume government intervention is counter-cyclical, these crowding-out effects are likely to magnify volatility in technology and TFP.

Considering that government intervention in China is discretionary, the impulse response analysis is not sufficient to provide the overall effect of government intervention on TFP in China. Hence we proceed with the following counter-factual analysis for our sample period. Firstly, we re-estimate[26] the model to allow the response of the investment shock and government spending shock to the net exports innovation.

The investment and government spending shock equations, in linearised form, are rewritten as

$$\hat{\varepsilon}_t^i = \rho_i \hat{\varepsilon}_{t-1}^i + \eta_t^i - \rho_{i,x}\eta_t^x, \qquad \hat{\varepsilon}_t^g = \rho_g \hat{\varepsilon}_{t-1}^g + \eta_t^g - \rho_{g,x}\eta_t^x$$

We then calibrate these response parameters $\rho_{i,x}, \rho_{g,x}$[27] as zero and simulate the model once more. Our underlying assumption is that the government does not respond to net exports, neither directly nor through investment policies. Some essential findings are presented in Table 2.7.

We find substantial differences in terms of volatility and correlation in two cases. Firstly, volatility in output increases significantly if the government does not respond to a change in net exports. In addition, the correlation between TFP and capital turns from negative to weakly positive. Such a change in correlation may signal less distortion in resource allocation. Furthermore, the volatility of three productivity variables would decrease, although magnitudes are relatively small compared to the change in output volatility. These results suggest that government intervention is very successful in smoothing output but that it is costly; volatility in TFP increases and risks misallocations.

[26]Structural parameters are calibrated based on values from Table 2.4.

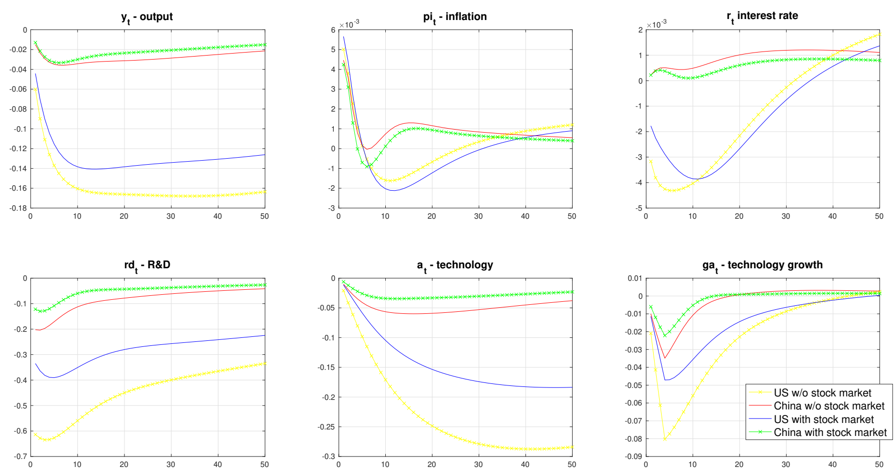
[27]$\rho_{i,x}, \rho_{g,x}$ are estimated as 0.65 and 0.10 separately.

Table 2.7: Comparison of volatility and correlation (with respect to feedback)

	$\sigma(Y)$	$\sigma(gY)$	$\rho(TFP, K)$	$\sigma(A)$	$\sigma(uTFP)$	$\sigma(TFP)$	$\sigma(gA)$	$\sigma(g\, uTFP)$	$\sigma(gTFP)$
With response	3.576	1.800	-0.200	5.313	6.388	6.004	2.682	3.262	2.827
No response	4.471	3.951	0.012	5.007	5.844	5.383	2.586	3.255	2.820

2.4.4 Financial Development and TFP Volatility

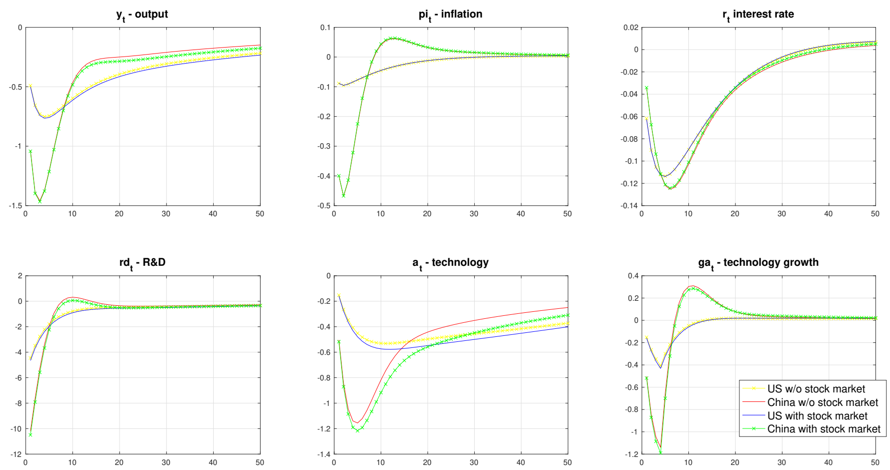
Figure 2.10: Impulse response to credit premium shock (1 std)



Since government intervention is not able to stabilise TFP, we proceed to investigate if smooth TFP can be achieved by financial development. To further understand the role of financial development in macroeconomic volatility, we turn our investigation to the connection between diversity in the financial system and fluctuations in TFP. There are two specific questions we are addressing; firstly, does a diverse financial system contribute to the stabilization of TFP in the US? and secondly, whether such an experience can apply to the case of China? We start from the impulse response analysis to study the propagation mechanisms of shocks and the role of debt and equity within those processes.

When there is a positive credit premium shock, the borrowing rate will rise immediately, pushing up the cost of R&D. In order for the equilibrium condition to remain intact, the innovator has to cut back on R&D expenditure, which reduces technology and slows down technology growth. Hence, the marginal efficiency of labour and capital will be reduced separately, eventually dragging down output. If there is access to an equity market for the innovator, R&D is only partially financed by debt, and so the cost of innovation will not increase as much as when compared to the benchmark case. Additionally, the innovator can use the option of equity to smooth their R&D; thus, in this case the stock market provides a shield to R&D. Consequently, technology and technology growth will suffer less and output is less affected also, and in this model the effect of the credit premium shock is dampened by the stock market. In Figure 2.10, we provide the impulse response functions (IRFs), which make use of the structural parameters obtained from the estimation. The reaction of our variables of interest to a credit premium shock captures the above propagation mechanism. If we compare the US and China, it is perhaps unsurprising to find that the credit premium shock has a larger and more persistent influence on the US than on China.

Figure 2.11: Impulse response to (equity) risk premium shock (1 std)



Whilst the presence of a stock market for the innovator will tend to dampen the effect of the credit premium shock, the impulse responses to a risk premium shock suggest the opposite; a stock market can provide a magnification effect. When there is a positive risk premium shock, households becomes worried about the economy and require higher returns on all types of assets that they hold. As a result, households will consume and invest less and demand a higher return from equities held; this leads to a decrease in aggregate demand and a higher equity cost; the former transmitting to the production sector resulting in a sharp decline in profits and depreciation of technology; the latter, to higher equity costs, discouraging the equity financing of new innovations. Both of these channels push down R&D expenditure. Compared with the benchmark case, access to the stock market will expose the innovator to an extra disturbance through the second channel, hence the fluctuation of R&D and technology will be exacerbated. In this sense, the stock market plays as an accelerator and the impulse response, from Figure 2.11, capture this.

Table 2.8: Comparison of dampening and magnification effects on technology

	Initial 8 quarters	Short run accumulation	Mid-to-long run accumulation
Dampening on A (US)	0.219%	2.028%	8.351%
Magnification on A (US)	0.262%	1.512%	3.009%
Dampening on A (China)	0.084%	0.663%	2.111%
Magnification on A (China)	0.354%	2.449%	5.664%

The impulse response analysis suggests that access to a stock market has dual effects; and to understand their quantitative importance, we calculate the accumulated dampening and magnification effects in different time horizons. Particular attention is paid to technology and these results are reported in Table 2.8. Notice that, within the first 8 quarters, for both the US and China, the magnification effect is larger than the dampening effect, and that the difference in China is more pronounced. When moving to about 32 quarters, the dampening effect becomes larger for the US. Furthermore, when moving to the medium to long run (up to 200 quarters), the accumulated dampening effect becomes much larger than the accumulated magnification effect in the US, whilst the reverse pattern persists in China. Therefore, only the US benefits more than suffers from the presence of a stock market, and that benefit dominates. Overall, it is not clear whether a country will benefit or suffer from access to a stock market. Thus, we proceed to show moments of the productivity-related variables.

Table 2.9: Standard deviation of productivity-related variables

Variables	US (without stock market)	US (with stock market)	China (without stock market)	China (with stock market)
A	3.093	2.873	5.313	5.547
$uTFP$	2.222	2.016	6.365	6.453
TFP	2.089	1.907	6.057	6.131
gA	1.111	1.052	2.682	2.741
$g\,uTFP$	1.029	1.000	3.262	3.305
TFP	1.099	1.072	2.827	2.871

We investigate the overall effect of stock market development on productivity volatility in our sample period. In order to address this question, we calculate the moments of the TFP-related variables for four cases: US without and with stock market (real case) and China without (real case) and with stock market. Table 2.9 shows the moments of the TFP-related variables including technology, utilization-adjusted TFP, the Solow residual. For the US, if we switch off the stock market, the volatility of all three TFP-related variables increases. Not surprisingly, the most substantial increase in volatility would be from technology which is directly affected by the two premium shocks. In which case, the dampening effect, especially in the medium to long run, outweighs the magnification effect and the presence of a stock market reduces volatility of TFP in the US.

For the case of China, we find the reverse pattern in the TFP-related variables; after switching on the stock market for the Chinese innovator, the standard deviation of three TFP-related variables would increase respectively. Similar to the US, the most significant change would come from technology, whose standard deviation would rise to 5.313 from 5.547. For China, the magnification effect outweighs the dampening effect, and the presence of a stock market increases the volatility of TFP. This last finding is consistent with the empirical facts that we have mentioned in Section 2.2. Hence, we can suggest that the Chinese stock market is too volatile than the US counterpart and the volatility which feeds through the equity premium channel dominates the potential gain from a diverse financial system.

2.5 Conclusion

In this study, we have carried out a comparative analysis on the driving factors behind the US and Chinese business cycle movements. To do so, we have built a DSGE model that facilitates a comparison between the two economies, both of which enjoy advance of new technology, but are distinguished in terms of financial development. We use Bayesian estimation techniques to capture the structural parameters for each economy, consistent with other literature, and go further by comparing the drivers behind the business cycle fluctuations using the shock decompositions obtained during the estimations. This method allows the information from the data and previous studies to contribute towards our findings, and answer the research question; why China suffers far greater volatility in total factor productivity, despite the fact that both countries display similar profiles in output.

The decomposition of the shock processes suggest that macroeconomic policies might be responsible. It is macroeconomic intervention, in terms of traditional fiscal policy and indirect financial interventions in investment, that is seen to counteract the volatility of output in China; likely due to the Chinese government's prior concern over economic activity. There are GDP growth targets in China each year and these targets are often achieved, despite a series of multiple and sizeable shocks hitting the economy, not least from overseas through net exports. The cost of this intervention is volatility in TFP for China, fueled by shocks transmitted through the endogenous technology creation channel, exacerbating the already volatile TFP movements.

Although the shock decompositions point to fiscal intervention as one cause of the swings in TFP, we are also interested in how China might develop its macroeconomic infrastructure in the future. To do so, we compare cases on both countries with and without access to a stock market to allow the model to predict the benefits of a deleveraging reform for China. Based on the impulse response functions, we propose that the stock market provides both magnifying and dampening effects. With access to a stock market, the US is better able to smooth fluctuations in TFP since the dampening effect of a stock market dominates the volatility magnification of TFP in the medium run. However, the same benefits do not apply to China, where the magnification effect dominates throughout, once firms have access to equity markets.

Our study has implications for policy currently aimed at the Chinese financial sector, which is undergoing deleveraging reform and whose purpose is to construct multiple-tiers of capital markets for future innovative and technology based enterprises. Our findings further suggest that the deleveraging reform should be implemented cautiously and alongside stock market reforms, to avoid the magnifying fluctuations we predict in TFP.

Appendix A Data

Table 2.10: Descriptions and sources for variables used in estimation

Variables	Description-China	Source
gdp GDP	Gross domestic product	NBS, China
c Consumption	household consumption expenditure	Chang et al. (2016)
i Investment	gross fixed capital formation excluding change of inventory, SOE and government investment	Chang et al. (2016)
π Inflation	GDP Deflator	Chang et al. (2016)
r Interest rate	3-month policy saving rate	PBC, China
h Labour	hour worked times employed labour	Chang et al. (2016) and PBC, China
w Wage	aggregate wage	Chang et al. (2016)
g Gov. spending	government consumption, investment and SOE investment	Chang et al. (2016)
Lending rate	weighted averaged lending rate	PBC, China
Population	total population	Chang et al. (2016)

Variables	Description-US	Source
gdp GDP	Gross domestic product	FRED
c Consumption	personal consumption expenditure	FRED
i Investment	private fixed investment	FRED
π Inflation	GDP Deflator	FRED
r Interest rate	effective federal fund rate	FRED
h Labour	hour worked times employed labour	FRED
w Wage	nonfarm business sector compensation	FRED
g Gov. spending	government consumption and gross investment	FRED
Lending rate	Moody's BAA corporate bond yield	FRED
Population	civilian noninstitutional population	FRED

Note: NBS, China refers to National Bureau of Statistics of China. PBC refers to People's Bank of China. FRED refers to Federal Reserve Bank of St. Louis.

All nominal variables are adjusted by GDP deflator. GDP, consumption, investment, labour and government spending are expressed as per capita term. We want to mention that government spending data for China cover investment of state-owned companies which is treated as public investment.

Chinese quarterly consumption, investment, GDP deflator, wage, employment level, government spending and population data are from Chang et al. (2016). Details about construction of data can be refereed to Higgins and Zha (2015).

Hour worked data for China is unavailable in Chang et al. (2016) and we obtain this data from the People's Bank of China.

Table 2.11: Emerging economies and developed countries

Emerging Economies	periods for output growth	Developed Economies	periods for output growth
Argentina	1995Q1-2016Q4	Australia	1995Q1-2016Q4
Brazil	1996Q1-2016Q4	Austria	1995Q1-2016Q4
Chile	1996Q1-2016Q4	Belgium	1995Q1-2016Q4
China	1995Q1-2016Q4	Canada	1995Q1-2016Q4
Colombia	2005Q1-2016Q4	Denmark	1995Q1-2016Q4
Czech Republic	1995Q1-2016Q4	Finland	1995Q1-2016Q4
Greece	1995Q1-2016Q4	France	1995Q1-2016Q4
Hungary	1995Q1-2016Q4	Germany	1995Q1-2016Q4
India	1996Q2-2016Q4	Italy	1995Q1-2016Q4
Indonesia	1995Q1-2016Q4	Japan	2007Q3-2016Q4
Israel	1995Q1-2016Q4	Luxemburg	1995Q1-2016Q4
Korea	1995Q1-2016Q4	Netherland	1995Q1-2016Q4
Mexico	2005Q1-2016Q4	New Zealand	1995Q1-2016Q4
Poland	1995Q1-2016Q4	Norway	1995Q1-2016Q4
Russia	2003Q1-2016Q4	Spain	1995Q1-2016Q4
Saudi Arabia	2009Q4-2016Q4	Sweden	1995Q1-2016Q4
Slovak Republic	1995Q1-2016Q4	Switzerland	1995Q1-2016Q4
South Africa	1995Q1-2016Q4	United Kingdom	1995Q1-2016Q4
Turkey	1998Q1-2016Q4	United States	1995Q1-2016Q4

Country Classification and GDP Data

Our selection of emerging and developed countries is limited by the common issue of data availability, classifications from Aguiar and Gopinath (2007), IMF and MSCI Emerging Market Index. The calculation of output volatility in Table 2.1 is based on the quarterly real per capita GDP data from the OECD Quarterly National Accounts except for China. Chinese quarterly per capita GDP is not available from the OECD database and we obtain it from National Bureau of Statistics of China. For the majority of countries, the sample length is 1995Q1 to 2016Q4. Details about the sample lengths are listed in Table 2.11. An example with similar sample lengths can be found from Aguiar and Gopinath (2007). Note that the quarterly per capita GDP data for Argentina, Brazil, Colombia, India, Indonesia, Russia, Saudi Arabia, South Africa and Turkey are not directly available. However, quarterly GDP for these nine countries are available from the OECD Quarterly National Accounts. We divide quarterly GDP by linearly interpolated population, based on annual data to obtain quarterly per capita GDP for the nine countries. The annual population data are from the World Development Indicators.

TFP and Capital Data

The calculation of TFP volatility in Table 2.1 is based on TFP data, *RTFPNA*, from the PennWorld Table 9.0 from 1990 to 2014 for all countries in our sample. Note that the TFP data in the PennWorld Table is only updated to 2014. *RTFPNA* is estimated based on an input-output framework (Feenstra et al. 2015). In details, they treat real capital stock, number of employment workers and human capital (measured by averaged year of schooling) as input factors and use the Tornqvist quantity index to calculate aggregate inputs; real GDP is treated as output, which is divided by the input index to calculate *RTFPNA*.

In order to check the robustness of TFP volatility for China, we conduct two alternative estimates. Using the same input and output variables, we estimate TFP for China using the growth accounting approach.

$$
\begin{aligned}
tfp_t =& ln(real\ per\ capita\ GDP_t) - \alpha * ln(capital_t) \\
&- (1-\alpha) * ln(employed\ labour_t * year\ of\ schooling_t)
\end{aligned}
$$

where α=0.5 (Hsieh and Klenow 2009). In addition, we use our quarterly dataset which is available up to 2016Q4 to estimate TFP for China. Following the standard TFP estimation approach in the business cycle literature (e.g., Fernald

Table 2.12: Alternative measures of output growth and TFP growth volatility in China

	Chen et al (2019)
$\sigma(gY)$	2.195

	Growth accounting based on PennWorld Table	Growth accounting based on quarterly data
$\sigma(gTFP)$	2.707	2.828

(2014)), we use the following formula

$$\begin{aligned} tfp_t = & ln(real\ per\ capita\ GDP_t) - \alpha * ln(capital_t) \\ & - (1-\alpha) * ln(employed\ labour_t * hour\ worked_t) \end{aligned}$$

Capital is estimated based on perpetual inventory method with quarterly depreciation rate δ equal to 0.025 (Wu 2008*b*). Initial capital is calculated as initial investment (investment in 1995Q1) over depreciation rate plus growth rate $Inv_{1995Q1}/(\delta + g^y)$. The results about alternative measures of TFP volatility are reported in right panel of Table 2.12. We find that the high TFP volatility in China is insensitive to alternative estimation methods and the selection of different input variables.

Technology and Financial Data

Gross R&D and business R&D data at constant price are from OECD MSTI database. Number of triadic patents application is from OECD Patent Statistics: Patents by main technology and by International Patent Classification (IPC).

Stock market index for China (Shanghai Stock Exchange Composite Index) and US (S&P 500 Index) are from China Stock Market and Accounting Research database via its Wharton Business School supplier. We take logarithms of these two stock market index and then use HP filter to extract their cyclical components. After that, we calculate three-month moving standard deviation using cyclical components of the two stock market index.

Quarterly equity premium data can be found from Duke CFO-Survey $https://www.cfosurvey.org/white-papers.html$. Annual equity premium data can be found from NYU Stern Business School

$http://pages.stern.nyu.edu/\ adamodar/New_Home_Page/home.htm$.

Figure 2.12: Annual capital growth: China vs US

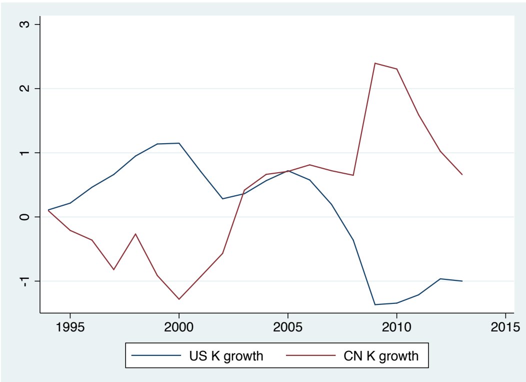
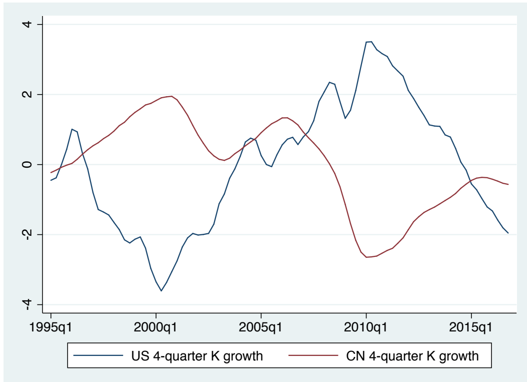


Figure 2.13: Quarterly capital growth: China vs US



Note: Annual capital data is *rkna* from PennWorld Table 9.0. Quarterly capital data is estimated based on perpetual inventory method. The investment data used in constructing capital for China is gross capital formation from Chang et al. (2016). For the US, private fixed investment from FRED is used. Variables shown in Figure 2.12 to 2.15 are demeaned.

Figure 2.14: Investment growth: China vs US

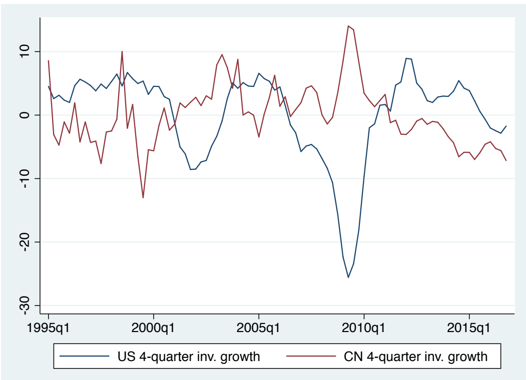
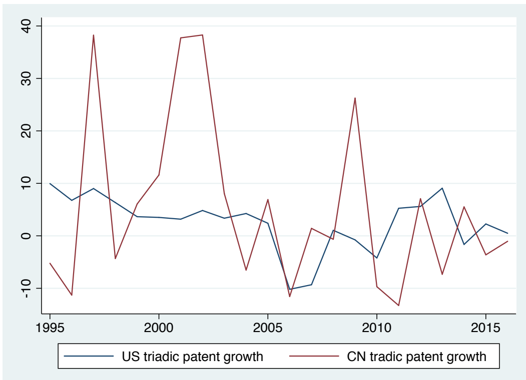


Figure 2.15: Triadic patents growth: China vs US



Appendix B Stationarised equations

The model can be detrended with deterministic growth trend g^y as similar in Anzoategui et al. (2019). We use lower case expressions to represent detrended real variables.

Let $y_t = \dfrac{Y_t}{(1+g^y)^t}$, $c_t = \dfrac{C_t}{(1+g^y)^t}$,$i_t = \dfrac{I_t}{(1+g^y)^t}$, $g_t = \dfrac{G_t}{(1+g^y)^t}$, $nx_t = \dfrac{NX_t}{(1+g^y)^t}$, $rd_t = \dfrac{RD_t}{(1+g^y)^t}$, $k_t = \dfrac{K_t}{(1+g^y)^t}$, $a_t = \dfrac{A_t}{(1+g^y)^t}$, $e_t^I = \dfrac{E_t^I}{(1+g^y)^t}$, $w_t = \dfrac{W_t}{P_t(1+g^y)^t}$, $r_t^k = \dfrac{R_t^k}{P_t}$, $mc_t^m = \dfrac{MC_t^M}{(1+g^y)^{(1-\alpha)t}P_t}$, $mu_{c,t} = MU_{c,t}(1+g^y)^t$, $\Pi_t^m = \dfrac{\pi_t^m}{P_t}$.

The Aggregate production function (2.38) becomes

$$y_t = \varepsilon_t^a a_t^{\lambda_m - 1}(u_t k_t)_t^{\alpha} H_t^{1-\alpha} \tag{B2.1}$$

The resource constraint (2.39) becomes

$$y_t = c_t + i_t + rd_t + g_t + nx_t + a(u_t)k_t + \frac{\zeta}{2}\frac{(e_t^I - e_{t-1}^I/(1+g^y))^2}{a_t} \tag{B2.2}$$

Equation (2.9') and (2.10') become

$$r_t^k R_t^b = \alpha mc_t^m \varepsilon_t^a (u_t k_t/H_t)^{\alpha-1} \tag{B2.3}$$

$$w_t R_t^b = (1-\alpha) mc_t^m \varepsilon_t^a (u_t k_t/H_t)^{\alpha} \tag{B2.4}$$

The profit function for individual intermediate goods producer (2.13) becomes

$$\pi_t^m = (\lambda_m - 1)\frac{w_t H_t R_t^b}{(1-\alpha)a_t} \tag{B2.5}$$

Equation (2.5) becomes

$$E_t \sum_{l=0}^{\infty} \epsilon_p^l \Lambda_{t,t+l} [\frac{p_t^* \prod_{s=0}^{l} \pi_{t+s-1}^{\iota_p} \pi^{1-\iota_p}}{\prod_{s=0}^{l} \pi_{t+s-1}} - \varepsilon_t^s mc_{t+l}^f] y_{i,t+l} = 0 \tag{B2.6}$$

The aggregate inflation in detrended form is

$$\pi_t = [(1-\epsilon_p)(p_t^*)^{1/(1-\varepsilon_t^s)} + \epsilon_p (\pi_{t-1}^{\iota_p} \pi^{1-\iota_p})^{1/(1-\varepsilon_t^s)}]^{(1-\varepsilon_t^s)} \tag{B2.7}$$

The value of technology remain the same as in (2.17)

$$V_t = E_t(\pi_t^m + \phi \Lambda_{t,t+1} V_{t+1}) \tag{B2.8}$$

The equilibrium condition of R&D in two cases (2.19) and (2.23) become

$$rd_t = [\frac{\chi a_t^{1-\mu} E_t(\Lambda_{t,t+1} V_{t+1})}{R_t^b}]^{1/(1-\mu)} \tag{B2.9}$$

$$rd_t = [\frac{\chi a_t^{1-\mu} E_t(\Lambda_{t,t+1} V_{t+1})}{R_t^b - (R_t^b - R_t^e)\theta_t^e + \frac{\zeta}{2} \frac{(e_t^I - e_{t-1}^I/(1+g^y))^2}{rd_t a_t}}]^{1/(1-\mu)} \tag{B2.9-1}$$

The evolution of technology (2.15) becomes

$$\frac{a_{t+1}(1+g^y)}{a_t} = \chi(\frac{rd_t}{a_t})^{\mu} + \phi \tag{B2.10}$$

The borrowing rate remains the same as in (2.25)

$$R_t^b = R_t \varepsilon_t^f \tag{B2.11}$$

The marginal utility of consumption (2.29) becomes

$$mu_{c,t} = \frac{1}{c_t - bc_{t-1}/(1+g^y)} = 0 \tag{B2.12}$$

The stochastic discount factor is

$$\Lambda_{t,t+1} = \beta E_t \frac{mu_{c,t+1}}{mu_{c,t}(1+g^y)} \tag{B2.13}$$

The household consumption Euler equation (2.30) becomes

$$\Lambda_{t,t+1} = E_t \frac{\pi_{t+1}}{R_t \varepsilon_t^b} \tag{B2.14}$$

Detrend investment Euler equation (2.31) and define Tobin's q $q_t = \dfrac{\lambda_t^k P_t}{\lambda_t P_t}$. After rearranging, equation (2.31) becomes

$$1 = q_t \varepsilon_t^i [(1 - S(\frac{i_t}{i_{t-1}})) - S'(\frac{i_t}{i_{t-1}}) \frac{i_t}{i_{t-1}}] + E_t[\beta q_{t+1} \Lambda_{t,t+1} \varepsilon_{t+1}^i S'(\frac{i_{t+1}}{i_t})(\frac{i_{t+1}}{i_t})^2] \tag{B2.15}$$

The first order condition for capital (2.32) becomes

$$\beta E_t \{\Lambda_{t,t+1}[r_{t+1}^k u_{t+1} - a(u_{t+1})] + q_{t+1}(1-\delta)\} - q_t = 0 \tag{B2.16}$$

Rearrange (2.33) and divide two sides by $\lambda_t K_t$. First order condition for utilization rate (2.33) becomes

$$r_t^k = a'(u_t) \tag{B2.17}$$

The capital accumulation (2.28) becomes

$$k_{t+1}(1+g^y) = (1-\delta)k_t + \varepsilon_t^i[1 - S(\frac{i_t}{i_{t-1}})]i_t \tag{B2.18}$$

The first order condition for wage (2.34) becomes

$$E_t \sum_{l=0}^{\infty} \epsilon_w^l \Lambda_{t,t+l}[\frac{w_t^* \prod_{s=0}^{l}[\pi_{t+s-1}^{\iota_w}\pi^{1-\iota_w}(1+g^y)^s]}{(1+g^y)^t \prod_{s=0}^{l}\pi_{t+s-1}} - \varepsilon_{t+l}^w \psi \frac{H_{t+l}^\eta}{MU_{c,t+l}}]H_{t+l} = 0 \tag{B2.19}$$

The aggregate wage in detrended form is

$$w_t = [(1-\epsilon_w)(w_t^*)^{1/(1-\varepsilon_t^w)} + \epsilon_w(w_{t-1}\pi_{t-1}^{\iota_w}\pi^{1-\iota_w}/\pi_t)^{1/(1-\varepsilon_t^w)}]^{(1-\varepsilon_t^w)} \tag{B2.20}$$

The policy rate (2.40) becomes

$$R_t = R_{t-1}^{\rho_r}[R(\frac{\pi_t}{\overline{\pi}})^{\rho_\pi}(y_t)^{\rho_y}(\frac{y_t(1+g^y)}{y_{t-1}})^{\rho_{\Delta y}}]^{1-\rho_r}\varepsilon_t^m \tag{B2.21}$$

The required return of equity remains the same as in (2.37)

$$R_t^e = R_t \varepsilon_t^b \tag{B2.22}$$

The first order condition of equity (2.21) becomes

$$R_t^b = R_t^e + \zeta \frac{e_t^I - e_{t-1}^I/(1+g^y)}{a_t} - E_t(\Lambda_{t,t+1}\zeta \frac{e_{t+1}^I - e_t^I/(1+g^y)}{a_{t+1}}) \tag{B2.23}$$

Appendix C Steady state

From (B2.7)

$$p^* = \pi \tag{C2.1}$$

From (B2.13)

$$\Lambda = \frac{\beta}{1 + g^y} \tag{C2.2}$$

From (B2.14) and set $\epsilon^b = 1$, $\pi = 1$

$$R = \frac{(1 + g^y)}{\beta} \tag{C2.3}$$

From (B2.15) and $\epsilon^i = 1$

$$q = 1 \tag{C2.4}$$

From (B2.16), (C2.2), (C2.4) and and set u=1

$$r^k = \frac{(1 + g^y)}{\beta} - (1 - \delta) \tag{C2.5}$$

From (B2.17)

$$a'(1) = r^k \tag{C2.6}$$

From (B2.6)

$$mc^f = 1/\epsilon^s \tag{C2.7}$$

From (B2.18)

$$\frac{i}{k} = g^y + \delta \tag{C2.8}$$

From (B2.1)-(B2.3) and (C2.6)

$$\frac{k}{y} = \frac{\alpha mc^f}{R^b r^k} = \frac{\alpha/\epsilon^s}{\dfrac{1+g^y}{\beta}\epsilon^f(\dfrac{1+g^y}{\beta} - (1-\delta))} \tag{C2.9}$$

$$\frac{wH}{y} = \frac{(1-\alpha)mc^f}{R^b} = \frac{(1-\alpha)/\epsilon^s}{\dfrac{1+g^y}{\beta}\epsilon^f} \tag{C2.10}$$

From (C2.7) and (C2.8)

$$\frac{i}{y} = (g^y + \delta)\frac{k}{y} \tag{C2.11}$$

From (B2.5) and (C2.10)

$$\frac{a\pi^m}{y} = (\lambda_m - 1)\frac{wH}{y}\frac{R^b}{(1-\alpha)} \tag{C2.12}$$

From (B2.8)

$$V = \frac{\pi^m}{1-\phi\Lambda} \tag{C2.13}$$

From (B2.23) and (C2.2)

$$\frac{e^I}{a} = \frac{R^b - R^e}{1-\Lambda}\frac{1+g^y}{\xi g^y} \tag{C2.14}$$

From given steady state R&D intensity rd/y and percentage equity finance ratio θ^e,

$$\frac{e^I}{y} = \frac{rd}{y}\theta^e \tag{C2.15}$$

From (C2.14) and (C2.15)

$$\frac{a}{y} = \frac{e^I/y}{e^I/a} \tag{C2.16}$$

From (B2.2),

$$\frac{c}{y} + \frac{i}{y} + \frac{g}{y} + \frac{rd}{y} + \frac{\zeta}{2}\frac{(e^I g^y/(1+g^y))^2}{ay} = 1 \tag{C2.17}$$

From (B2.10), (C2.16) and use R&D intensity rd/y

$$\frac{rd/y}{a/y} = \frac{rd}{a} = \frac{1+g^y-\phi}{\chi} \tag{C2.18}$$

From (B2.11)

$$R^b = R\epsilon^f \tag{C2.19}$$

Appendix D Linearised equations

$$\hat{y}_t = \hat{\varepsilon}_t^a + (\lambda_m - 1)\hat{a}_t + \alpha(\hat{u}_t + \hat{k}_t) + (1-\alpha)\hat{h}_t \tag{D2.1}$$

$$\hat{y}_t = \frac{C}{Y}\hat{c}_t + \frac{I}{Y}\hat{i}_t + \frac{RD}{Y}\hat{rd}_t + \hat{\varepsilon}_t^g + \hat{\varepsilon}_t^x + r^k\frac{K}{Y}\hat{u}_t + \zeta\theta^e\frac{RD}{Y}\frac{e^I}{a}\frac{g^y}{1+g^y}(\hat{e}_t^I - \frac{1}{1+g^y}\hat{e}_{t-1}^I - \frac{1}{2}\frac{g^y}{1+g^y}\hat{a}_t) \tag{D2.2}$$

$$\hat{r}_t^k + \hat{R}_t^b = \hat{mc}_t + \hat{\varepsilon}_t^a + \alpha(\hat{u}_t + \hat{k}_t - \hat{h}_t) \tag{D2.3}$$

$$\hat{w}_t + \hat{R}_t^b = \hat{mc}_t + \hat{\varepsilon}_t^a + (\alpha - 1)(\hat{u}_t + \hat{k}_t - \hat{h}_t) \tag{D2.4}$$

$$\hat{\pi}_t^m = \hat{w}_t + \hat{h}_t + \hat{R}_t^b - \hat{a}_t \tag{D2.5}$$

$$\hat{\pi}_t = \frac{1}{1+\epsilon_p\tilde{\beta}}\hat{\pi}_{t-1} + \frac{\epsilon_p\tilde{\beta}}{1+\epsilon_p\tilde{\beta}}E_t\hat{\pi}_{t+1} + \frac{(1+\epsilon_p\tilde{\beta})(1-\epsilon_p)}{(1+\epsilon_p\tilde{\beta})\epsilon_p}\hat{mc}_t^f + \hat{\varepsilon}_t^s \tag{D2.6}$$

$$\hat{V}_t = (1-\phi/R)\hat{\pi}_t^m + (\phi/R)E_t[(\hat{V}_{t+1} + \hat{\Lambda}_{t,t+1})] \tag{D2.7}$$

$$E_t(\hat{\Lambda}_{t,t+1} + \hat{V}_{t+1}) - (1-\mu)(\hat{rd}_t - \hat{a}_t) = \hat{R}_t^b \tag{D2.8}$$

$$E_t(\hat{\Lambda}_{t,t+1}+\hat{V}_{t+1})-(1-\mu)(\hat{rd}_t-\hat{a}_t)=\frac{\theta^b\hat{R}^b_t+\theta^e\hat{R}^e_t}{R^b\theta^b+R^e\theta^e+\frac{\zeta\theta^e e^I}{2a}(\frac{g^y}{1+g^y})^2}$$
$$+\frac{\zeta\theta^e\frac{e^I}{a}\frac{g^y}{1+g^y}(\hat{e}^I_t-\frac{1}{1+g^y}\hat{e}^I_{t-1}-\frac{1}{2}\frac{g^y}{1+g^y}(\hat{rd}_t+\hat{a}_t))}{R^b\theta^b+R^e\theta^e+\frac{\zeta\theta^e e^I}{2a}(\frac{g^y}{1+g^y})^2} \tag{D2.8-1}$$

$$(1+g^y)\hat{a}_{t+1}=(g^y-\phi)\mu rd_t+\phi\hat{a}_t \tag{D2.9}$$

$$\hat{R}^b_t=\hat{R}_t+\hat{\varepsilon}^f_t \tag{D2.10}$$

$$\hat{mu}_{c,t}=-\frac{1+g^y}{(1+g^y)-b}\hat{c}_t+\frac{b}{(1+g^y)-b}\hat{c}_{t-1} \tag{D2.11}$$

$$\hat{\Lambda}_{t,t+1}=E_t\hat{mu}_{c,t+1}-\hat{mu}_{c,t} \tag{D2.12}$$

$$0=E_t\hat{mu}_{c,t+1}-\hat{mu}_{c,t}+\hat{R}_t-E_t\hat{\pi}_{t+1}+\hat{\varepsilon}^b_t \tag{D2.13}$$

$$\hat{i}_t=(\frac{\beta}{1+g^y+\beta})\hat{i}_{t+1}+\frac{1+g^y}{1+g^y+\beta}\hat{i}_{t-1}+\frac{1+g^y}{(1+g^y+\beta)s"}q_t+\hat{\varepsilon}^i_t \tag{D2.14}$$

$$0=E_t\hat{mu}_{c,t+1}-\hat{mu}_{c,t}+E_t[\frac{r^k}{r^k+(1-\delta)}\hat{r^k}_{t+1}-\frac{(1-\delta)}{r^k+(1-\delta)}q_{t+1}]-q_t \tag{D2.15}$$

$$\hat{r}^k_t=\frac{\xi}{1-\xi}\hat{u}_t \tag{D2.16}$$

$$\hat{k}_{t+1}=\frac{1-\delta}{1+g^y}\hat{k}_t+\frac{g^y+\delta}{1+g^y}(\hat{i}_t+\hat{\varepsilon}^i_t) \tag{D2.17}$$

$$\begin{aligned}\hat{w}_t=&\frac{1}{1+\tilde{\beta}}(\hat{w}_{t-1}+\iota_w\hat{\pi}_{t-1}-(1+\iota_w\tilde{\beta})\hat{\pi}_t)+\frac{\tilde{\beta}}{1+\tilde{\beta}}E_t(\hat{w}_{t+1}+\hat{\pi}_{t+1})\\&+\frac{(1-\epsilon_w\tilde{\beta})(1-\epsilon_w)}{\epsilon_w(1+\tilde{\beta})(1+\eta(\epsilon_w-1))}(\eta\hat{H}_t-\hat{w}_t-\hat{mu}_{c,t})+\hat{\varepsilon}^w_t\end{aligned} \tag{D2.18}$$

$$\hat{R}_t=\rho_r\hat{R}_{t-1}+(1-\rho_r)(\rho_\pi\hat{\pi}_t+\rho_y\hat{y}_t+\rho_{\Delta y}(\hat{y}_t-\hat{y}_{t-1}))+\hat{\varepsilon}^m_t \tag{D2.19}$$

$$\hat{R}^e_t=\hat{R}_t+\hat{\varepsilon}^b_t \tag{D2.20}$$

$$R^b\hat{R}_t^b - R^e\hat{R}_t^e = \frac{(\hat{e}_t^I - \frac{1}{1+g^y}\hat{e}_{t-1}^I - \frac{g^y}{1+g^y}\hat{a}_t)}{\frac{g^y}{1+g^y}\frac{R-1}{R}} - \frac{\frac{1}{R}E_t(\hat{e}_{t+1}^I - \frac{1}{1+g^y}\hat{e}_t^I - \frac{g^y}{1+g^y}\hat{a}_{t+1}) - \frac{g^y}{R(1+g^y)}E_t\hat{\Lambda}_{t,t+1}}{\frac{g^y}{1+g^y}\frac{R-1}{R}} \tag{D2.21}$$

$$\hat{\theta}_t^e = \hat{e}_t^I - \hat{rd}_t \tag{D2.22}$$

$$\hat{\varepsilon}_t^a = \rho_a\hat{\varepsilon}_{t-1}^a + \eta_t^a \tag{D2.23}$$

$$\hat{\varepsilon}_t^s = \rho_s\hat{\varepsilon}_{t-1}^s + \eta_t^s \tag{D2.24}$$

$$\hat{\varepsilon}_t^f = \rho_f\hat{\varepsilon}_{t-1}^f + \eta_t^f \tag{D2.25}$$

$$\hat{\varepsilon}_t^b = \rho_b\hat{\varepsilon}_{t-1}^b + \eta_t^b \tag{D2.26}$$

$$\hat{\varepsilon}_t^i = \rho_i\hat{\varepsilon}_{t-1}^i + \eta_t^i \tag{D2.27}$$

$$\hat{\varepsilon}_t^w = \rho_w\hat{\varepsilon}_{t-1}^w + \eta_t^w \tag{D2.28}$$

$$\hat{\varepsilon}_t^g = \rho_g\hat{\varepsilon}_{t-1}^g + \eta_t^g \tag{D2.29}$$

$$\hat{\varepsilon}_t^m = \rho_m\hat{\varepsilon}_{t-1}^m + \eta_t^m \tag{D2.30}$$

$$\hat{\varepsilon}_t^x = \rho_x\hat{\varepsilon}_{t-1}^x + \eta_t^x \tag{D2.31}$$

where $\frac{C}{Y}, \frac{I}{Y}, \frac{RD}{Y} and \frac{K}{Y}$ denote steady state consumption to GDP ratio, investment to GDP ratio, R&D to GDP ratio and capital stock to GDP ratio. θ^b is steady state share of R&D financed by debt. $\theta^b = 1 - \theta^e$.

Summary and Conclusion

Motivated by the fundamental question of how the Chinese economy was/is working, this thesis uses comparative perspectives to study two puzzles in China: one concerning Chinese finance-innovation-growth relationship (in Chapter One) and the other concerning Chinese business cycles and finance-innovation-volatility relationship (in Chapter Two).

In Chapter One, we study effects of financial development on economic and productivity growth in China by using provincial level panel data over 1991 to 2014. Financial development is measured by two major financial sectors in China, namely the banking sector and the stock market, with two dimensions of measures, namely depth and function or efficiency. An essential and major finding is that there is an innovation channel through which banking sector development promotes productivity and economic growth. This finding is important in that it partially reconciles the puzzle that the Chinese financial-growth nexus seems to contradict cross-country findings. It also identifies a special pattern in China that stock market development decreases productivity and economic growth through an innovation channel. This special pattern should be due to the fact that the initial function of Chinese stock market development was facilitating SOEs reforms rather than fund raising.

Considering that finance-innovation-growth relationships for a developing country like China may change over a long period, we further examine if the above relationships differ in different development stages. Results from our sub-sample regressions suggest that Chinese banking-innovation-growth and stock market-innovation-growth relationships are becoming more growth-enhancing and less growth-diminishing respectively in recent periods. These findings imply that the Chinese finance-growth nexus are converging with the cross-country ones. Thus, we can interpret that specialties in Chinese finance-growth relationships could be due to Chinese development stages.

In chapter Two, we build and estimate a DSGE model with extended financial markets and endogenous innovation to compare business cycles between China and the US. Our analysis is motivated by a puzzling contrast; that despite a similar profile for economic activity, Chinese TFP is far more volatile than that for the US. To investigate these business cycle characteristics we estimate our model to identify key structural parameters, comparing the decomposition of the shock processes in our analysis. We reveal how the contributing factors of business cycle fluctuations in China differ with the US. Government interventions in China, including fiscal policy and investment policy, work well but add TFP volatility due to the crowding-out effect on R&D.

Since government interventions are not able to smooth TFP volatility, we further study whether TFP volatility can be smoothed by a developed stock market like that in the US. A developed stock market allows firms to switch to equity based finance during episodes of financial instability; though this hedging comes with a price, namely additional premiums required by stock market investors.

Owing to the high risk and huge volatility in Chinese stock market, fast expansion of the stock market could increase rather than reduce TFP volatility in China.

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