The University of Manchester

MANCHESTER 1824

Centre for Growth & Business Cycle Research

CGBCR

Discussion Paper Series

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By

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September 2018

Number 244

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

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**Abstract**

This paper investigates the contrasting business cycle characteristics of China and the US, specifically in terms of economic activity and total factor productivity. To help explain the differing profiles for these two variables for both countries, we build and estimate a DSGE model with extended financial markets and endogenous technology creation to identify key structural parameters, comparing the decomposition of the shock processes in our analysis. We reveal stark differences in the contributing factors of business cycle fluctuations for both countries, and demonstrate the importance of the stock market for economic recovery after a sizable and persistent financial shock. Macroeconomic intervention in China works well but is unable to smooth total factor productivity (TFP) due to the presence of multiple shocks transmitted through the endogenous technology creation channel. Whilst the US achieves a similar profile for economic activity with less volatility in TFP, it also contends with additional risks, fed in by the existence of the stock market. The stock market allows firms to hedge finance during periods of financial instability, though this is not cost free.

**JEL classification:** E32,E44,O11,O16

**Keywords:** Business Cycles, TFP, DSGE, Bayesian Estimation

# 1 Introduction

With such rapid and recent economic development recently, it is perhaps surprising that China has received relatively little country specific attention from the field of business cycle research, especially when considering that this development has occurred alongside recent financial market reform. Even though China and the US share similar profiles in terms of economic activity, the subject and comparison of the driving forces behind that activity appears to have been rather overlooked. In terms of macroeconomic models, a one size fits all approach might help our understanding at the surface, but little else. In this study, we compare Chinese and US business cycle behaviours, the latter country chosen as a benchmark due to the more developed nature of its financial infrastructure. We find that, whilst both countries use fiscal policy to smooth fluctuations in ouput, Chinese intervention comes at the cost of higher volatility in total factor productivity (TFP). Further we find that a well developed stock market can enable 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.

We estimate a dynamic stochastic general equilibrium (DSGE) model to investigate the volatility of our two main variables of interest, economic activity and total factor productivity. In doing so, we attempt to explain two key facts from the macroeconomic data for both countries. Chinese TFP is significantly more volatile than is the case for the US over the business cycle; and yet despite this, China shares a relatively similar profile in terms of output volatility. The set up of our model is chosen to capture a key difference between the US and China in terms of macroeconomic infrastructure, namley access to a well developed and fluid stock market for US producers, with Chinese producers more limited to bank finance. A key question for our research is to understand why the Chinese business cycle is relatively smooth, in comparison to what we would expect from an emerging economy where both TFP and output experience much larger fluctuations; (Aguiar & Gopinath 2007, Comin et al. 2014). What are the factors or characteristics behind the combination of a more volatile TFP and yet relatively smooth profile for output in China?

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 public equity. Considering the fact that financial development is a critical determinant of TFP, and equity can be an alternative funding source against debt in business cycles, it is possible that the diverse financial system in 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. Some earlier works (Le et al. 2014, Dai et al. 2015, Ma & Li 2015) have considered whether a DSGE model, already successfully applied to the US, could model Chinese business cycle behaviour, (e.g.Smets & Wouters (2007)). A major concern is that the US-based DSGE models often assume a closed economy which seems to contradict the fact that China has a very large import and export sector since 2001[1].

[1] China joined the World Trade Organization in 2001 and since then, the international trade sector has developed rapidly.

In light of recent evidence from Le et al. (2014), Dai et al. (2015), we make a key assumption that China is a price-taker in international markets with net exports mainly affected by factors overseas; external shocks are transmitted through international trade and, as such, we can model this as an exogenous process through aggregate demand. More specifically, we combine a workhorse Smets & Wouters (2007) DSGE model with Comin & Gertler (2006), Anzoategui et al. (2016) type endogenous technology creation through R&D, adding a financial intermediary to investigate and compare the finance-productivity nexus over the business cycles for China and the US. By doing this we can study how TFP is explained using financial and other shocks. One concern for our research is the question of whether Chinese TFP can be modeled using a endogenous technology creation mechanism. To help justify this framework we rely on empirical evidence that Chinese TFP is driven mainly by improvements in technology (see e.g Zheng et al. (2009)) and that historically we have witnessed the business sector as the main contributor of R&D in China since 1995; with the share of business R&D[2] around 60% to 75% in 2000s.

We augment the model by incorporating a stock market for R&D firms who, in turn, determine the optimal level of debt and equity in the economy. The inclusion of this market allows us to capture the key differences in financial systems for both countries. Furthermore, credit and risk (or equity) premium shocks are differentiated in order to disentangle their individual effects. This is helpful to address the issue of whether the volatility of TFP can be stablised by a diverse financial system. Finally, Bayesian estimation techniques are exploited to identify shocks and structural parameters for China and the US separately over 1995Q1 to 2016Q4. Eight shocks are added in this study including a credit premium shock, risk (or equity) premium shock, exogenous TFP shock, investment efficiency shock, price mark-up shock, wage mark-up shock, monetary policy shock and exogenous demand (or government spending) shock.

Our results show that various shocks play different roles for Chinese and US business cycles. The majority of shocks in China have larger variance but are less persistent compared with the case for the US. We find a hedging pattern between shocks in the shock decompositions for China; these shocks, especially the government expenditure shock, successfully reduce the fluctuation of Chinese output but not that of TFP. Based on the impulse response functions, we further 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 result for our policy implication is a need for the cautious development of equity markets in China.

This study contributes to the business cycle literature in three different ways. Firstly in terms of en-

This sector accounts for about 40% to 60% of GDP in 2000s and despite this large share, net exports account for only 3% to 7% of Chinese GDP.

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

dogenous TFP mechanisms in business cycles such as (Comin & Gertler 2006, Comin et al. 2014, Jinnai 2015, Kung & Schmid 2015, Anzoategui et al. 2016) who use endogenous innovation to show short-, mid- and long-run productivity dynamics in response to various shocks. Our framework is similar to these studies, though we explicitly incorporate financial shocks in the framework. Anzoategui et al. (2016) implicitly model a credit premium shock but do not distinguish between different sources of finance, with no financial sector in their model. Kung & Schmid (2015) and Jinnai (2015) include a stock market in a bid to address the asset price puzzle, though they normalise equity and do not address how equity-financing affects productivity dynamics in business cycles. By ustilising a Bayesian estimation for both countires our analysis can also provide a comparison between the two largest single economies worldwide.

Our study is closely related to Bianchi et al. (forthcoming) who firstly estimate a model with a finance-innovation-TFP nexus within a business cycle framework and distinguish debt and equity as different sources of finance. Our approach differs with Bianchi et al. (forthcoming) in four ways. Firstly, our study is a cross-country comparison and our attention goes beyond the US. Secondly, and perhaps most importantly, we address the effect of financial development on macroeconomic volatility. Thirdly, we focus on the variation of risks in the credit and equity markets while Bianchi et al. (forthcoming) focus on change in the quantity of credit and equity. Hence, we address a different aspect or role for the financial sectors in business cycle profiles. Lastly, they use a vertical innovation so that entrepreneurs can carry out production and innovation together. Such a framework can not be used for our purpose, as we have a need to investigate the effect of financial development on technological firms. A horizontal innovation framework allows us to separate technology and non-tech firms.

The second strand of literature to which we contribute is within the area of financial development, particularly on the debate over the relationship between financial development and macroeconomic stability. Does financial structure matter for macroeconomic volatility? While some studies, such as (Easterly et al. 2001, da Silva 2002, 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 (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.

With the shock decompositions signposting the transmission channels for each economy, we further provide evidence on how equity markets can stablise TFP for the US and China separately. Furthermore, our discussion of the relationship between financial development and macroeconomic volatility is linked with our differentiation of the risk premium shocks (Gilchrist et al. 2014, Caldara et al. 2016). Specifically, we distinguish the risk premium shock into a credit premium shock and an equity premium shock; motivated by the empirical facts presented in (Caldara et al. 2016), that the former captures risks in the financial condition of firms while the latter captures investor's uncertainty towards equity markets. Moreover, (Caldara et al. 2016) suggest these two are independent shock processes.

Lastly, we contribute to the literature on Chinese business cycle analysis based around the DSGE modelling framework. Authors such as; (Le et al. 2014, Dai et al. 2015, Ma & Li 2015) apply the Smets & Wouters (2007)-based workhorse to empirically examine the business cycle fluctuations of China, albeit without the limitation presented by the scarcity of quarterly observations of key macroeconomic variables for China. We extend this literature by utilizing an endogenous technology creation mechanism to examine 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 we know, 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.

The rest of the paper is organized as follows. Section 2 presents some empirical evidence and descriptive analysis of the cyclical behavior of the Chinese and US macroeconomic variable profiles. Section 3 presents the DSGE model with extended financial markets and endogenous technology creation. Section 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 4 makes further analysis of the cyclical behaviour of TFP between China and US. Finally, section 5 concludes with comments.

# 2 Empirical Evidence: China vs US

## 2.1 Economic and Productivity Performance

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

Figure 1: Output comparison: China vs US

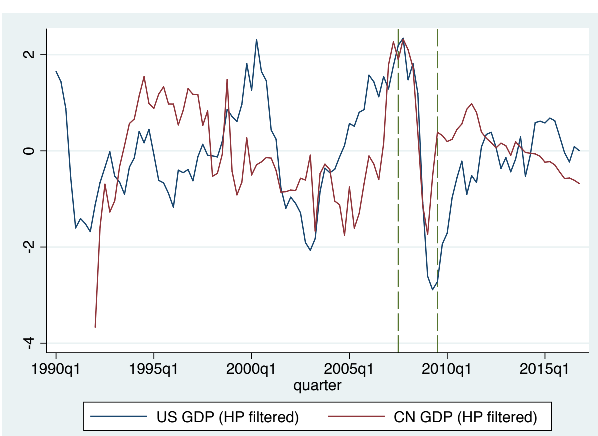
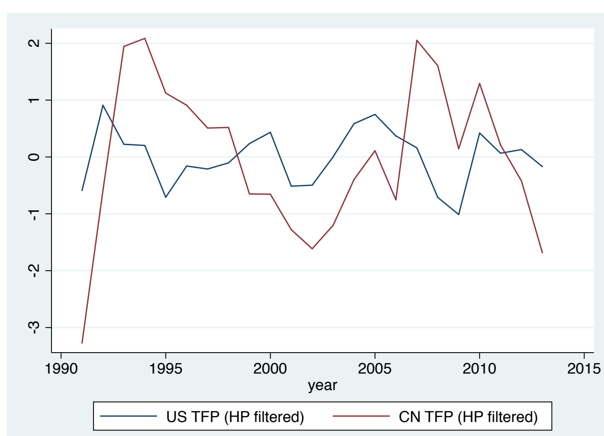



Figure 2: TFP comparison: China vs US



The profile of Chinese output in Figure 1, appears relatively smooth when we make a direct comparison with the same profile for the US. Output reached a peak of around 2% in both countries shortly before the global financial crisis, though during the crisis period, output in China and the US slumped by 4% and 4.5% respectively. Although both China and US were negatively affected by the global financial crisis, the decline of output for China is less significant than that for the US. Table 1 confirms the above findings and further shows that the standard deviation of output for China and the US are of similar magnitude. Moreover, China's output is very stable compared with the average level of developed and emerging economies separately. In this sense, China shares features one might associate with more developed countries.

Turning to TFP[3], we can see from Figure 2 that the fluctuations of Chinese TFP are of larger magnitude than that of the US. These findings are confirmed in Panel (a) of Table 1 based on our measure for high-frequency volatility. Panel (a) 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 Chinese TFP is marginally above average.

Considering Aguiar & Gopinath (2007)'s argument that cycles in emerging economies are mainly driven by variations in the stochastic trend, we also report low-frequency volatility of output and TFP for China and US separately. Briefly speaking, there is no fundamental difference in our findings; the pattern based on high-frequency data is similar to that based on low-frequency data. Hence, some justification for our focus on high-frequency volatility. Although low frequency volatility is interesting, we leave this for future research.

Table 1: Output and TFP Comparisons

(a) High-frequency volatility

| | China | US | Emerging Economies (average) | Developed Economies (average) |
|---|---|---|---|---|
| $\sigma(Y)$ | 0.973 | 1.066 | 2.150 | 1.307 |
| $\sigma(A)$ | 1.661 | 0.787 | 1.624 | 0.841 |

(b) Low-frequency volatility

| | China | US |
|---|---|---|
| $\sigma(Y)$ | 2.886 | 3.437 |
| $\sigma(A)$ | 3.427 | 1.482 |

Note: output refers to per capita GDP and is in quarter frequency. Due to data availability, TFP data are in annual frequency.

Calculations are based on HP filtered data. Smooth parameter is 1600 for quarter data and 6.25 for annual data (Ravn & Uhlig 2002). High-frequency data refer to cyclical components from HP filter. Low-frequency data refers to difference between stochastic trend from HP filter and linear trend.

Summing up, we can say that our descriptive analysis suggests that Chinese output is more stable but TFP is more volatile. Conversely, output and TFP in the US are similarly stable. Our data shows that China is a special case and one worthy of investigation, in that it displays mixed features of both developed and emerging economies. For the following analysis, we focus on the volatility of TFP and that of output between China and US. We provide evidence to direct our investigations into the differences between Chinese and US business cycle behaviours.

[3]The definition of total factor productivity (TFP) in Figure 2 and Table 1 is derived as defined by the Solow residual. For later analysis, we consider multiple and more comprehensive definitions.

Table 2: Macroeconomic volatility: further comparison

| | $\sigma(C)$ | $\sigma(I)$ | $\sigma(Emp)$ | $\sigma(RD)$ | $\sigma(BusinessRD)$ | $\sigma(C)/\sigma(Y)$ | $\sigma(I)/\sigma(Y)$ |
|---|---|---|---|---|---|---|---|
| China | 1.549 | 6.206 | 0.070 | 3.593 | 6.082 | 1.584 | 6.345 |
| US | 0.921 | 4.937 | 1.083 | 1.784 | 2.892 | 0.863 | 4.631 |

Note: All calculation are based on HP filtered data. Smooth parameter as above. Gross R&D and business R&D are in annual frequency. Other variables are in quarter frequency.

In Table 2 we present some measures of volatility for both the US and China in terms of selected key indicators. Table 2 shows that the relative volatility for Chinese consumption and investment are significantly higher than that for the US. The most striking comparison from Table 2 is that given for the volatility of employed labour, China being much less volatile than the US. This follows the pattern found in other studies, 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. Finally, in terms of innovation, the standard deviation of gross expenditure on R&D and that of business R&D suggests that Chinese R&D is more than twice as volatile than that found in the US. This finding is critical for our purposes, as it provides some empirical evidence for our proposition, that Chinese TFP volatility might be explained by R&D, reflected in our choice of theoretical framework.

## 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 has only existed since 2012. Another problem for Chinese equity markets is that of stability in regulation, with the Chinese Security and Regulation Committee suspending initial public 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 & Den Haan 2012, Jermann & Quadrini 2012), suggest that debt and equity finance are alternative

[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).

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 3: Credit premium: China vs US

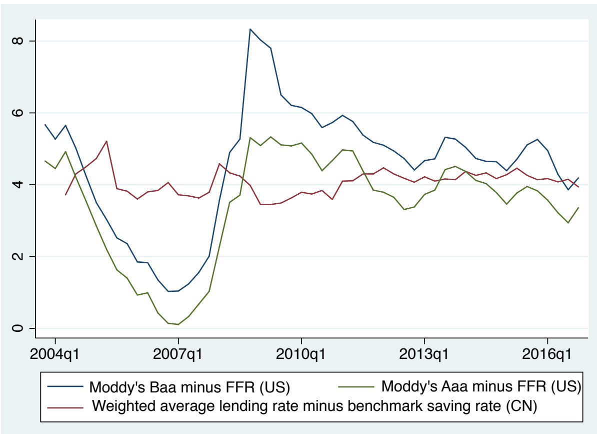
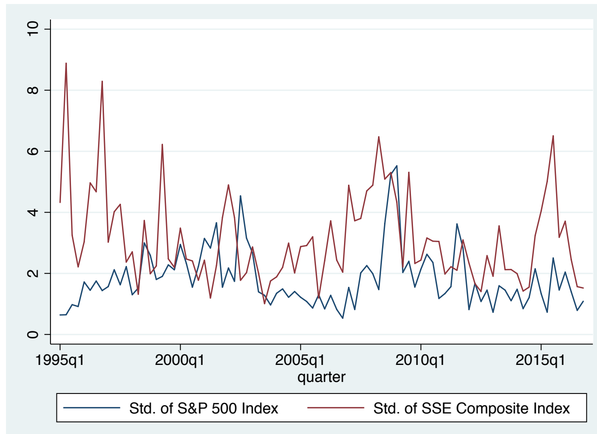



Figure 4: Stock market volatility: China vs US




With regards to financial volatility, the data can highlight some distinguishing features between China and the US. In Figure 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. We present the credit premium from 2004 because credit premium data at the quarterly frequency is only available from this date. In that year, the Chinese banking sector started a corporatisation reform and the upper ceiling for the lending rate was removed. Before 2004, there were upper and lower ceilings for the lending rate and saving rate separately. Hence, it is reasonable to believe that the credit premium before 2004 is even flatter. [7] For the US the credit premium 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 the credit premium provides evidence that the Chinese credit market is relatively stable while that of the US is much more volatile.

In Figure 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 of 2005-2009 and the 2015 stock market disaster period. The difference in volatility most probably reflects the

[5]The Chinese corporate bond market was established in 2007 but 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.

[7]The lower ceilings for the lending rate and two-side ceilings for the saving rate were removed in 2013 and 2015 receptively.

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 5: quarterly risk premium

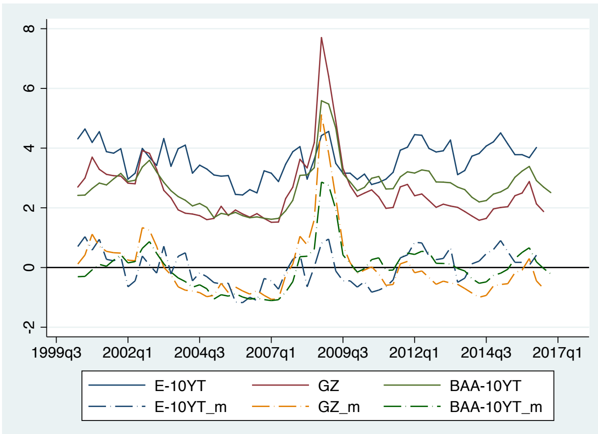
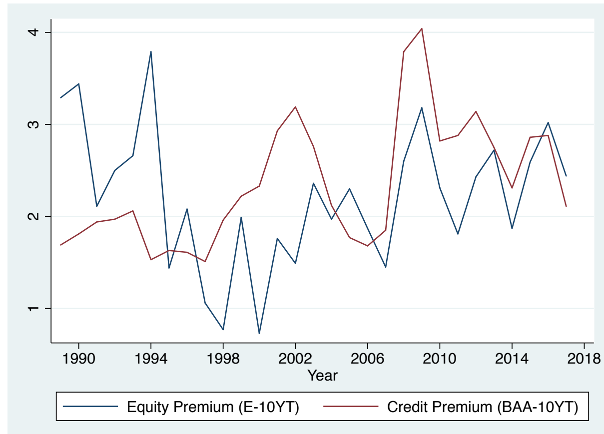



Figure 6: annual risk premium




Note: 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 & 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.

Shifting our attention to the US, we make use of Figures 5 and 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 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 another words, credit tends to be more expensive than equity in a recession or financial crisis. This pattern can also be found in Figure 6, based on annual data. In addition, the lower part of Figure 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. Although we are not concerned with why the costs of debt and equity change over time, it is still important to visually inspect the co-movements in the context of our research, and to see how the data highlights the differences in behaviour between those that hold debt and those that use equity for financing production.

Furthermore, Figures 5 and 6 show another interesting characteristic; that movement of the credit premium is more persistent than the equity premium. We find the auto-correlation 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 can 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 maybe helpful to smooth out US TFP volatility.

# 3 The Model

We expand Smets & Wouters (2007)'s model, incorporating a financial intermediary and endogenous technology creation via R&D, in a similar way to Comin & Gertler (2006) and Anzoategui et al. (2016). The financial intermediary supplies credit to both intermediary goods producers and innovators. There are two channels for the propagation of shocks into innovation via the financial intermediary: 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 is corresponds to the case of the US.

In both the benchmark and the augmented model, there are 5 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 create R&D with which to produce new technologies, sold 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 on equity issued from innovators.

## 3.1 Final Goods Producer

The final goods sector is very similar to Anzoategui et al. (2016). 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 to as an input to produce output. The production technology is as follows:

$$Y_{it} = Y_{it}^m \tag{1}$$

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

$$Y_t = (\int_0^1 Y_{it}^{1/\varepsilon_t^s} di)^{\varepsilon_t^s} \tag{2}$$

where $\varepsilon_t^s$ 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 $\eta_t^s$ follows an i.i.d $N(0, \sigma_S^2)$ process. The demand schedule for the final good producer is:

$$Y_{it} = Y_t(\frac{P_{it}}{P_t})^{\varepsilon_t^s/(1-\varepsilon_t^s)} \tag{3}$$

where the price index is given by

$$P_t = (\int_0^1 P_{it}^{1/(1-\varepsilon_t^s)})^{1-\varepsilon_t^s} \tag{4}$$

We follow Anzoategui et al. (2016) 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 $\pi$ is steady state inflation and $\iota_p$ 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[8], to obtain the optimally chosen reset price:

$$\sum_{l=0}^{\infty} \epsilon_p^l \Lambda_{t,t+l}[\frac{P_t^*(\pi_{t-1}^{t+l-1})^{\iota_p}\pi^{1-\iota_p}}{P_{t+l}} - \varepsilon_t^s MC_{t+l}^f]Y_{i,t+l} = 0 \tag{5}$$

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

## 3.2 Intermediate Goods Producer

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

$$Y_{jt}^m = \varepsilon_t^a(u_t K_{jt})^\alpha (H_{jt})^{1-\alpha} \tag{6}$$

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

The following CES technology is used to aggregate differentiated intermediate goods into an intermediate goods composite:

$$Y_t^m = (\int_0^{A_t} (Y_{jt}^m)^{1/\lambda_m} dj)^{\lambda_m} \tag{7}$$

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

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[9] (from a financial intermediary). The cost function is written

$$Cost_{jt} = (W_t H_{jt} + R_t^k u_t K_{jt}) R_t^b \tag{8}$$

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

$$W_t R_t^b = (1-\alpha) MC_t^M Y_{jt}^m / H_{jt} \tag{9}$$

$$R_t^k R_t^b = \alpha MC_t^M Y_{jt}^m / (u_t K_{jt}) \tag{10}$$

The nominal marginal cost $MC_{jt}^m$ for intermediate goods producer is as follows:

$$MC_{jt}^m = \frac{(R_t^k)^\alpha W_t^{1-\alpha} R_t^b}{(1-\alpha)^{(1-\alpha)} \alpha^\alpha \varepsilon_t^a} \tag{11}$$

Equation (11) suggests that marginal cost is the same across all intermediate goods firms. Hence, $MC_{jt}^m = MC_t^m$. Dividing $MC_t^m$ by price $P_t$ we can get real marginal cost

$$mc_t^m = \frac{(r_t^k)^\alpha w_t^{1-\alpha} R_t^b}{(1-\alpha)^{(1-\alpha)} \alpha^\alpha \varepsilon_t^a}$$

where $r_t^k$ and $w_t$ are the real capital rental rate and real wage separately.
Following Anzoategui et al. (2016), we assume the intermediate goods producer can set prices flexibly, so that each intermediate goods producer sets price $P_{jt}^m$ as a constant markup ($\lambda_m$) times its expected marginal cost.

$$P_t^m = P_{jt}^m = \lambda_m MC_t^m \tag{12}$$

where $\lambda_m > 1$. (12) suggests $MC_t^f = P_t^m = \lambda_m MC_t^m$. Nominal profits ($\Pi_t^m$) for individual intermediate goods producer can be calculated as follows, using (9)-(12).

$$\Pi_t^m = \frac{P_t^m Y_t^m - (W_t H_t + R_t^k u_t K_t) R_t^b}{A_t} = (\lambda_m - 1) \frac{W_t H_t R_t^b}{(1-\alpha) A_t} \tag{13}$$

Dividing two sides by $P_t$ yields real expected profit $\pi_t^m$ which is critical to link the intermediate goods producer's performance with innovation.

[9] 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.

### 3.3 Innovator

We first layout 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 intermediate goods, 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 $\varphi_t$ 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 $\varphi_t$ amount of new technologies at the end of period $t$, and then sell them to a new intermediate goods producer at the beginning of period $t+1$. The technology coefficient is determinated based on Comin & Gertler (2006) and Anzoategui et al. (2016) but we have modified it. $\varphi_t$ is given by

$$\varphi_t = \chi(\frac{A_t}{RD_t})^{1-\mu} \tag{14}$$

where $\chi$ 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. $\mu$ is assumed to lie between 0 and 1 to maintain a 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 $\phi$ is the survival rate of a technology. Then, we follow Comin & Gertler (2006) and Anzoategui et al. (2016) to construct the endogenous part of technology growth, $G_t^A$, as:

$$G_{t+1}^A = \frac{A_{t+1}}{A_t} = \chi(\frac{RD_t}{A_t})^{\mu} + \phi \tag{15}$$

#### 3.3.1 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:

$$E_t\pi_t^I = E_t(\Lambda_{t,t+1}V_{t+1})\varphi_t RD_t - R_t^b RD_t \tag{16}$$

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 (before expiry) to produce a new intermediate good, the price of a new technology is equal to expected value of profits from producing this intermediate good.

$$V_t = E_t(\pi_t^m + \phi \Lambda_{t,t+1} V_{t+1}) \tag{17}$$

where $\phi$ is the survival rate of technology. Due to the free-entry condition, innovators will compete until they break-even so that

$$E_t(\Lambda_{t,t+1} V_{t+1} \varphi_t) = R_t^b \tag{18}$$

Equation (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 $RD_t$.

$$RD_t = [\frac{\chi A_t^{1-\mu} E_t(\Lambda_{t,t+1} V_{t+1})}{R_t^b}]^{1/(1-\mu)} \tag{19}$$

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 (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.

### 3.3.2 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 profit (20)

$$E_t \pi_t^I = E_t(\Lambda_{t,t+1} V_{t+1}) \varphi_t RD_t - R_t^b B_t - R_t^e E_t^I - \frac{\zeta}{2} \frac{(E_t^I - E_{t-1}^I)^2}{A_t} \tag{20}$$

where $B_t$ is the amount of borrowing, $E_t^I$ is the amount of equity, $R_t^e$ 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, $\zeta$ 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 & Den Haan 2012) and empirical evidence (Altınkılıç & Hansen 2000) that equity issuance exhibits an increasing marginal cost[10]. With access to the stock market, the total cost of innovation can be separated into three components: $R_t^b B_t$ being the cost of debt, $R_t^e E_t^I$ the cost of equity and equity adjustment

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

cost. All variables are expressed in real terms.

The forward-looking representative innovator maximizes expected profit to yield

$$R_t^b = R_t^e + \zeta \frac{E_t^I - E_{t-1}^I}{A_t} - E_t(\Lambda_{t,t+1}\zeta \frac{E_{t+1}^I - E_t^I}{A_{t+1}}) \tag{21}$$

Equation (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[11]. Using the break-even condition (20) 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 R&D.

$$\begin{aligned} E_t(\Lambda_{t,t+1}V_{t+1})\varphi_t RD_t &= R_t^b B_t + R_t^e E_t^I + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t} \\ &= R_t^b(1-\theta_t^e)RD_t + R_t^e\theta_t^e RD_t + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t} \end{aligned} \tag{22}$$

The right hand side of (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 (14), we can obtain an equilibrium level of R&D in a comparable form with (19)

$$RD_t = [\frac{\chi A_t^{1-\mu} E_t(\Lambda_{t,t+1}V_{t+1})}{R_t^b - (R_t^b - R_t^e)\theta_t^e + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{RD_t A_t}}]^{1/(1-\mu)} \tag{23}$$

Compared with equation (19), the denominator of the right hand side of (23) has an extra term $-(R_t^b - R_t^e)\theta_t^e + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{RD_t A_t}$.[12]

Compared to equity, debt is a less favourable sources of finance for R&D as it is more 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 stock market should lead to more R&D.

Furthermore, we assume that $R_t^b$ and $R_t^e$ are linked to risks in both the credit sector and stock market separately. If a sizable financial shock occurs, $R_t^b$ is much larger than $R_t^e$ and the stock market should mitigate such an adverse effect. If the stock market crashes this could magnify its own adverse effect.

## 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

[11]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

[12]It is uncertain whether this extra term is positive or negative so that we do not have analytic solution. However, we are able to show that there would be lower denominator and higher level of R&D in (23) if $R_t^b > R_t^e$ and access to equity market is not too costly ($\zeta$ not too high).

the innovator. We assume financial intermediaries acquire information about their borrowers and monitor their activities at the intermediation cost, $\varepsilon_t^f$, and that the intermediation cost is common for both types of borrowers. Since $\varepsilon_t^f$ creates a wedge between the borrowing and savings rate, $\varepsilon_t^f$ can be treated as the credit premium. We assume $\varepsilon_t^f$ 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 $\eta_t^f$ 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, prefect competition implies that each financial intermediary must break-even in equilibrium.

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

$$R_t^b L_t = (R_t \varepsilon_t^f) L_t \tag{24}$$

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

$$R_t^b = R_t \varepsilon_t^f \tag{25}$$

Equation (33) means that the borrowing rate is equal to the savings rate times the credit premium.

## 3.5 Household

We first specify the most common elements of the household sector, which are irrelevant to the stock market. Then, 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:

$$\max_{C_t, D_t, I_t, K_t, H_t} E_t \sum_{l=0}^{\infty} \beta^l [log(C_{t+l}) - \psi \frac{H_{t+l}^{1+\eta}}{1+\eta}] \tag{26}$$

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

$$P_t C_t + \frac{1}{\varepsilon_t^b} D_t = R_{t-1} D_{t-1} + W_t H_t + R_t^k u_t K_t - a(u_t) P_t K_t + \Pi_t^f - P_t I_t \tag{27}$$

$$K_{t+1} = (1-\delta) K_t + \varepsilon_t^i [1 - S(\frac{I_t}{(1+g^y) I_{t-1}})] I_t \tag{28}$$

where $C_t$ denotes consumption, $D_t$ saving, $K_t$ capital stock, $I_t$ investment, $a(u_t)$ is the capital utilization function with $a(1) = 0$, $\Pi_t^f$ are profits from the ownership of monopolistic competitive firms, $1 + g^y$ 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. (2016)). $\varepsilon_t^i$ is an investment efficiency shock following an AR(1) process: $ln\varepsilon_t^i = \rho_b ln\varepsilon_{t-1}^i + \eta_t^i$ and $\eta_t^i$ follows an i.i.d $N(0, \sigma_I^2)$. $\varepsilon_t^b$ 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 $\eta_t^b$ follows an i.i.d $N(0, \sigma_B^2)$. This risk premium shock is similar to that in Smets & Wouters (2007) and induces a precautionary saving effect when the household is worried about the economy ($\varepsilon_t^b$ increases). Utility maximisation yields the following first order conditions:

$$\frac{\partial L}{\partial C_t} = MU_{c,t} - \lambda_t P_t = \frac{1}{C_t - bC_{t-1}} - \lambda_t P_t = 0 \tag{29}$$

$$\frac{\partial L}{\partial D_t} = -\lambda_t + E_t \lambda_{t+1} \beta R_t \varepsilon_t^b = 0 \tag{30}$$

$$\begin{aligned} \frac{\partial L}{\partial I_t} = -\lambda_t P_t + \lambda_t^k P_t \varepsilon_t^i [(1 - S(\frac{I_t}{(1+g^y)I_{t-1}})) - S'(\frac{I_t}{(1+g^y)I_{t-1}})\frac{I_t}{(1+g^y)I_{t-1}}] \\ +E_t[\beta \lambda_{t+1}^k P_{t+1} \varepsilon_t^i S'(\frac{I_{t+1}}{(1+g^y)I_t})(\frac{I_t}{(1+g^y)I_t})^2] = 0 \end{aligned} \tag{31}$$

$$\frac{\partial L}{\partial K_{t+1}} = \beta E_t\{\lambda_{t+1}[R_{t+1}^k u_{t+1} - a(u_{t+1})P_t]\} + \beta E_t\{\lambda_{t+1}^k P_{t+1}(1-\delta)\} - \lambda_t^k P_t = 0 \tag{32}$$

$$\frac{\partial L}{\partial u_t} = -\lambda_t (R_t^k - a'(u_t)P_t)K_t = 0 \tag{33}$$

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-$\epsilon_w$ in each period. With probability $\epsilon_w$ households cannot re-optimise and index past inflation to adjust the wage, $W_t = W_{t-1}\pi^{1-\iota_p}\pi_{t-1}^{\iota_p}(1 + gy)$, where $\iota_w$ is the degree of wage indexation. The first order condition for the wage is:

$$\sum_{l=0}^{\infty} \epsilon_p^l \Lambda_{t,t+l}[\frac{W_t^*(\pi_{t-1}^{t+l-1})^{\iota_p}\pi^{1-\iota_p}}{P_t} - \varepsilon_t^w \psi \frac{H_t^\eta}{MU_{c,t}}]H_t = 0 \tag{34}$$

where $\varepsilon_t^w$ 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 $\eta_t^w$ 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 spent on equity. With equity, (27) becomes

$$P_t C_t + \frac{1}{\varepsilon_t^b} D_t + P_t E_t^I = R_{t-1} D_{t-1} + R_{t-1}^e P_{t-1} E_{t-1}^I + W_t H_t + R_t^k u_t K_t - a(u_t) P_t K_t + \Pi_t^f - P_t I_t \tag{35}$$

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

$$\frac{\partial L}{\partial E_t^I} = -\lambda_t P_t + E_t \lambda_{t+1} P_t \beta R_t^e = 0 \tag{36}$$

Combining (30) and (36) yields us

$$R_t^e = R_t \varepsilon_t^b = 0 \tag{37}$$

Therefore, with the stock market added, $\varepsilon_t^b$ not only affects the inter-temporal decisions of households but also affects the required return to equity. An increase in $\varepsilon_t^b$ rises up the required return to equity $R_t^e$. In this sense, $\varepsilon_t^b$ is not only a demand shock but also an equity premium shock.

Critical for our analysis, $\varepsilon_t^b$ has a distinct propagation mechanism compared with the credit premium shock $\varepsilon_t^f$. A rise in $\varepsilon_t^b$ leads to a decrease in aggregate demand and prices so that inflation declines, (see Smets & Wouters (2007) for more details). While a rise of $\varepsilon_t^f$ increases marginal cost and hence pushes up inflation. The differences in propagation are helpful to identify $\varepsilon_t^b$ and $\varepsilon_t^f$ 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 5.

## 3.6 Aggregation and Equilibrium

Aggregate output

$$\begin{aligned}
Y_t^m =& (\int_0^{A_t} (Y_{jt}^m)^{1/\lambda_m} dj)^{\lambda_m} = (\int_0^{A_t} (\varepsilon_t^a (u_t K_{jt})^\alpha H_{jt}^{1-\alpha})^{1/\lambda_m} dj)^{\lambda_m} \\
=& (\int_0^{A_t} [((u_t K_t)/H_t)^\alpha (H_t/A_t)]^{1/\lambda_m} \varepsilon_t^a dj)^{\lambda_m} \\
=& \varepsilon_t^a ((u_t K_t)/H_t)^\alpha [A_t (H_t/A_t)^{1/\lambda_m}]^{\lambda_m} \\
=& \varepsilon_t^a A_t^{\lambda_m - 1} (u_t K_t)^\alpha H_t^{1-\alpha}
\end{aligned}$$

Owing to symmetric equilibrium, $Y_t = Y_t^m$, we obtain:

$$Y_t = \varepsilon_t^a A_t^{\lambda_m - 1} (u_t K_t)_t^\alpha H_t^{1-\alpha} \tag{38}$$

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 $\varepsilon_t^a$ is an exogenous shock, the second $A_t^{\lambda_m - 1}$ technology and the third $u_t^\alpha$ utilization of capital.

Another definition we can consider is utilization-adjusted TFP $\varepsilon_t^a A_t^{\lambda_m - 1}$ which excludes utilization. Equations (9) and (10) can be rewritten as

$$W_t R_t^b = (1-\alpha) MC_t^M (u_t K_t / H_t)^{\alpha} \tag{9'}$$

$$R_t^k R_t^b = \alpha MC_t^M (u_t K_t / H_t)^{\alpha - 1} \tag{10'}$$

The resource constraint

$$Y_t = C_t + I_t + RD_t + G_t + a(u_t)K_t + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t} \tag{39}$$

$G_t$[13] is an exogenous demand shock following AR(1) process: $ln\varepsilon_t^g = (1-\rho_g)g + \rho_g ln\varepsilon_{t-1}^g + \eta_t^g$ and $\eta_t^g$ follows i.i.d $N(0, \sigma_G^2)$. The financial market clears in (in real term): $D_t^r = L_t^r = w_t H_t + r_t^k K_t + RD_t$ 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 growth Taylor rule

$$R_t = R_{t-1}^{\rho_r} [R(\frac{\pi_t}{\overline{\pi}})^{\rho_\pi} (\frac{Y_t}{Y_{t-1}})^{\rho_y}]^{1-\rho_r} \varepsilon_t^m \tag{40}$$

where $\varepsilon_t^m$ is a monetary policy shock following an AR(1) process: $ln\varepsilon_t^m = \rho_m ln\varepsilon_{t-1}^m + \eta_t^m$ and $\eta_t^m$ follows an i.i.d $N(0, \sigma_M^2)$. Equation (5), (9'), (10'), (13)-(15), (17)-(19), (25), (28)-(34) and (38)-(40) are equilibrium conditions for the benchmark case. When adding a stock market, (23) replaces (19) and there are two more conditions required, (22) and (37).

# 4 Bayesian Estimation and Simulation

In this section we report our results for the Bayesian estimation 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 paprameters to measure the different responses from the economies to financial shocks.

## 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 are notoriously rare, with availability beginning in the mid-1990s. Secondly, in terms of economic structure, China becomes a more market-oriented economy since the mid-1990s, with significant growth in the private sector since. Thirdly, we prefer to keep

[13]For later analysis, we focus on the efficiency unit of $G_t$ which is defined as $\varepsilon_t^g = G_t/(1+g^y)^t$. Exogenous demand embodies government expenditure and net exports (Kollmann 2013). This shock is anchored with output so that it is unnecessary to specify government expenditure separately.

the sample period consistent across US and China to facilitate comparison. We use eight macroeconomic variables as observables for estimation: real per capita GDP, real per capita consumption, real per capita investment, hours worked, wages, GDP deflator inflation, the policy interest rate and lending rate [14].

In terms of lending rate, Moody BAA corporate bond yield is used as proxy for US while the weighted averaged lending rate[15] 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 quantitatively incomparable with the banking sector. Finally, all variables are HP filter detrended.

## 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 3: Calibrated parameters

| Parameters | Description | US | China |
|---|---|---|---|
| $\alpha$ | capital share | 0.36 | 0.5 |
| $\beta$ | discount factor | 0.995 | 0.995 |
| $\delta$ | capital depreciation | 0.02 | 0.025 |
| $\mu$ | technology elasticity | 0.8 | 0.7 |
| $\phi$ | technology survival rate | 0.965 | 0.95 |
| $\eta$ | labour elasticity | 2 | 2 |
| $\lambda_m$ | intermediate goods mark-up | 1.64 | 1.5 |
| $\zeta$ | 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 | 0.18 | 0.18 |
| $\overline{H}$ | ss working time | 0.3 | 0.3 |
| $\varepsilon_f$ | ss credit premium | 0.0075 | 0.0075 |
| $\theta^e$ | ss percentage of equity finance | 0.55 | / |

Table 3 shows calibrated parameters for China and the US together. These parameters are well identified

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

[15] This variable is only available after 2004Q2. One reason is that the upper ceiling of the lending rate was removed in 2004. Before 2004, the Chinese lending rate was not allowed to deviate too much from the official policy lending rate.

in existing literature, for example (Chang et al. 2015, Dai et al. 2015, Anzoategui et al. 2016, Smets & Villa 2016). Hsieh & Klenow (2009) find that labour income share accounts for about half of GDP in china, which implies a capital share $\alpha$ of 0.5. For the US this is calibrated as 0.36, in line with other US-based DSGE studies. The technology elasticity with respect to R&D $\mu$ is calibrated based on the patent-R&D or R&D stock-R&D flow relationship. Following Comin & Gertler (2006), we choose $\mu$ as 0.8 for US. Its counterpart for China is set to 0.7 in order to match business cycle moments of Chinese business R&D. This value also implies the efficiency of Chinese R&D is lower than that in the US.

We follow Kung & Schmid (2015) and Jinnai (2015) to calibrate the quarterly technology obsolescence rate 1-$\phi$ for the US as 3.75%. 1-$\phi$ for China is calibrated as 5% which is consistent with a 20% annual obsoletion rate of Chinese invention patents (SIPO 2014). Following Kung & Schmid (2015) and Jinnai (2015), we calibrate the intermediate goods mark-up $\lambda_m$ as 1.64 for the US, and 1.5 for China to ensure a balanced growth path[16]. Following (Covas & Den Haan 2012), we calibrate $\zeta$ such that the equity issuance cost accounts for about 5.7% of equity issuance. Other parameters do not differ significantly between China and US in existing literature. Hence, we give them the same value.

The lower part of Table 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 loan to total finance ratio for the innovator is calibrated as 0.45 based on loan, debt and equity issuance data for hi-tech firms[17] between 1995 and 2016.

### 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 methods of estimating these types of structural models.
The posterior distribution is obtained by employing the Bayes rule:

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

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

[16]Kung & Schmid (2015), Jinnai (2015) calibrate $\lambda_m$ such that $\lambda_m$-1+$\alpha$=1. This is to ensure a constant returns to scale for the aggregate production function, critical for a balanced growth path.
[17]Source: Thomson One Database. Classification of hi-tech firms can be found from the Thomson One website.

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.

The posterior distributions are then optimized using Monte-Carlo Markov Chain (MCMC) simulation techniques. Under the Bayesian perspective, both the posterior distribution and the likelihood function can be utilized to obtain a probabilistic interpretation of the estimated parameters. Another advantage of this methodology is the ability to make model comparisons, even where the models are not nested, using posterior odds analysis, conveying relative probabilities to competing models. Table 4 shows prior and posterior distribution of structural parameters and shock processes. The choice of prior distributions follow standard values reported in the related literature (Dai et al. 2015, Anzoategui et al. 2016, Smets & Villa 2016).

Our estimation results suggest that Chinese consumers are more habitual than their US counterparts; consumption habit for China is (0.72) and the US (0.56). There is a higher level of stickiness in both prices and wages in the US (0.86 and 0.87) than in China (0.7 and 0.58). Chinese goods producers index more on lagged prices and lagged wages respectively (0.43 and 0.49) than producers in the US (0.17 and 0.44). The Chinese capital utilization elasticity is estimated as 0.82, slightly higher than that in the US (0.76). The investment adjustment cost parameter is higher in China (5.05) than in the US (3.34). The Taylor parameters suggest that the Chinese policy rate is more sticky ($\rho_r$=0.94 for China and $\rho_r$=0.81 for US) and the Chinese central bank appears to react less aggressively to both inflation ($\rho_\pi$=1.52 for China and $\rho_\pi$=1.62 for the US) and output growth ($\rho_y$=0.26 for China and $\rho_y$=0.46 for the US).

With regards to the shock process, we find the most remarkable differences between China and the US, in terms of both depth and persistence. In terms of standard deviation, which reflects the depth of the shocks' effect on the economy. The risk premium shock, exogenous TFP shock, both mark-up shocks, investment efficiency shock and exogenous demand shocks 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, the overall finding is that shock processes in China are less persistent except for the two mark-up shocks. Particularly, persistence of the investment efficiency shock in China is only 0.06 which is close to what you might expect from a random walk. The credit premium shock in China shares about two-thirds of the persistence of its US counterpart. This relative low persistence, plus low variance, implies that the Chinese credit market is less likely to suffer from exogenous disturbances and can recovery relatively quickly when this does happen.

Furthermore, our estimates suggest that the persistence of other shocks in China are lower (exogenous TFP shock, risk premium shock and exogenous demand shock) or similar (monetary policy shock) to the US counterparts. Finally, we find that the persistence parameters of the exogenous TFP shock in both China and US are lower than in existing literature. This is may well be owing to the fact that the persistence of TFP is

Table 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 | 0.56 [0.48, 0.64] | 0.72 [0.65, 0.80] |
| $\epsilon_p$ calvo price | Beta | 0.8 | 0.15 | 0.86 [0.84, 0.89] | 0.70 [0.63, 0.76] |
| $\iota_p$ price indexation | Beta | 0.5 | 0.1 | 0.17 [0.04, 0.31] | 0.43 [0.27, 0.58] |
| $\epsilon_w$ calvo wage | Beta | 0.8 | 0.15 | 0.87 [0.82, 0.91] | 0.58 [0.44, 0.72] |
| $\iota_w$ wage indexation | Beta | 0.5 | 0.1 | 0.44 [0.12, 0.75] | 0.49 [0.34, 0.66] |
| s" invest. adj. cost | Gamma | 5 | 2 | 3.34 [2.15, 4.47] | 5.05 [3.55, 6.48] |
| $\xi$ elasticity of K utilization | Beta | 0.5 | 0.1 | 0.76 [0.67, 0.86] | 0.82 [0.75, 0.89] |
| $\rho_r$ taylor smoothing | Beta | 0.7 | 0.15 | 0.81 [0.77, 0.85] | 0.94 [0.93, 0.96] |
| $\rho_\pi$ taylor parameter | Normal | 1.5 | 0.25 | 1.62 [1.30, 1.94] | 1.52 [1.13, 1.87] |
| $\rho_y$ taylor parameter | Normal | 0.3 | 0.1 | 0.46 [0.31, 0.62] | 0.26 [0.13, 0.39] |
| | | | | | |
| $\rho_f$ per. of credit premium | Beta | 0.5 | 0.2 | 0.91 [0.85, 0.97] | 0.60 [0.43, 0.76] |
| $\rho_b$ per. of risk premium | Beta | 0.5 | 0.2 | 0.78 [0.71, 0.86] | 0.57 [0.42, 0.73] |
| $\rho_a$ per. of exo. TFP | Beta | 0.5 | 0.2 | 0.68 [0.56, 0.79] | 0.60 [0.47, 0.73] |
| $\rho_i$ per. of inv. efficiency | Beta | 0.5 | 0.2 | 0.46 [0.32, 0.61] | 0.06 [0.01, 0.11] |
| $\rho_m$ per. of mon. policy | Beta | 0.5 | 0.2 | 0.23 [0.11, 0.35] | 0.31 [0.18, 0.45] |
| $\rho_s$ per. of price mark-up | Beta | 0.5 | 0.2 | 0.17 [0.03, 0.30] | 0.52 [0.33, 0.73] |
| $\rho_w$ per. of wage mark-up | Beta | 0.5 | 0.2 | 0.08 [0.01, 0.15] | 0.30 [0.12, 0.49] |
| $\rho_g$ per. of exo. demand | Beta | 0.5 | 0.2 | 0.92 [0.84, 0.99] | 0.82 [0.77, 0.87] |
| | | | | | |
| $\sigma_f$ std. of credit premium | Inv_Gamma | 0.1 | 2 | 0.16 [0.14, 0.17] | 0.07 [0.06, 0.08] |
| $\sigma_b$ std. of risk premium | Inv_Gamma | 0.1 | 2 | 0.24 [0.15, 0.32] | 1.20 [0.55, 1.87] |
| $\sigma_a$ std. of exo. TFP | Inv_Gamma | 0.1 | 2 | 0.49 [0.43, 0.55] | 0.60 [0.51, 0.67] |
| $\sigma_i$ std. of inv. efficiency | Inv_Gamma | 0.1 | 2 | 0.41 [0.31, 0.49] | 2.15 [1.87, 2.43] |
| $\sigma_m$ std. of mon. policy | Inv_Gamma | 0.1 | 2 | 0.09 [0.08, 0.11] | 0.06 [0.05, 0.07] |
| $\sigma_s$ std. of price mark-up | Inv_Gamma | 0.1 | 2 | 0.14 [0.12, 0.16] | 0.39 [0.31, 0.47] |
| $\sigma_s$ std. of wage mark-up | Inv_Gamma | 0.1 | 2 | 0.54 [0.46, 0.62] | 1.47 [1.02, 1.90] |
| $\sigma_g$ std. of exo. demand | Inv_Gamma | 0.1 | 2 | 0.45 [0.39, 0.51] | 1.46 [1.28, 1.64] |

Note: 90% confidence intervals in bracket.

generated from an endogenous technology channel (Anzoategui et al. 2016). Next we show relative importance of each shock in China and US respectively, starting with the unconditional variance decomposition for China, in Table 5.

Not surprisingly, the credit premium is quantitatively less important in terms of explanatory power for Chinese macroeconomic fluctuations. Investment efficiency shocks and exogenous demand shocks are two major driving factors for Chinese output, consumption and investment. These two shocks together account for 70% of the variance for output, 73% variance for consumption and 90% variance for investment. In terms of productivity-related variables including R&D, technology, technology growth and TFP variables, the exogenous demand shock is the dominant driving force accounting for 51% of technology variance, 45% of utilization-adjusted TFP variance and 38% of Solow residual variance.

Table 5: Unconditional Variance Decomposition (%): China

| Variables | Structural Shocks | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Credit Premium | Risk premium | TFP (exo.) | Invest. Efficiency | Mon. policy | Price mark-up | Wage mark-up | Demand (exo.) |
| $y$ Output | 0.03 | 9.39 | 3.51 | 28.55 | 2.96 | 11.69 | 2.84 | 41.04 |
| $c$ Consumption | 0.04 | 8.57 | 3.70 | 10.82 | 2.77 | 10.00 | 3.08 | 61.04 |
| $i$ Investment | 0.01 | 1.80 | 1.83 | 64.35 | 0.84 | 4.26 | 1.43 | 25.48 |
| $\pi$ Inflation | 0.01 | 17.95 | 4.00 | 29.31 | 11.58 | 14.18 | 4.25 | 18.72 |
| $r$ Policy rate | 0.01 | 19.35 | 2.32 | 35.37 | 2.16 | 5.64 | 2.21 | 32.94 |
| $v$ value of tech. | 0.01 | 47.47 | 1.89 | 12.46 | 6.87 | 15.08 | 2.17 | 14.06 |
| $rd$ R&D | 0.07 | 39.62 | 2.51 | 17.99 | 6.28 | 12.28 | 2.71 | 18.55 |
| $a$ Technology | 0.08 | 9.11 | 3.90 | 14.76 | 3.76 | 14.38 | 3.60 | 50.41 |
| $ga$ Tech. growth | 0.06 | 46.48 | 2.19 | 18.71 | 6.85 | 11.81 | 2.52 | 11.38 |
| $tfpu$ Uti-adj TFP | 0.07 | 7.92 | 16.45 | 12.84 | 3.27 | 12.50 | 3.13 | 43.83 |
| Solow residual | 0.07 | 9.53 | 13.27 | 17.95 | 3.70 | 14.97 | 3.19 | 37.33 |

Investment efficiency shocks and price mark-up shocks contribute 10% to 20% of the variance for all five productivity-related variables. The risk premium shock is the critical force behind the variation of R&D (33%) and technology growth (40%). Furthermore, Table 5 suggests that the variation of Chinese TFP is primarily driven by endogenous channels. Endogenous channels contributes to more than 84% and 87% of the variance for utilization-adjusted TFP and Solow residual respectively.

Table 6: Variance Decomposition (%): US

| Variables | Structural Shocks | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Credit Premium | Risk/ Equity premium | TFP (exo.) | Invest. Efficiency | Mon. policy | Price mark-up | Wage mark-up | Demand (exo.) |
| $y$ Output | 9.28 / 11.82 | 38.35 / 33.31 | 3.72 / 3.90 | 5.95 / 6.06 | 17.99 / 18.88 | 7.15 / 7.51 | 6.57 / 6.90 | 10.98 / 11.62 |
| $c$ Consumption | 11.84 / 13.75 | 30.58 / 26.00 | 3.60 / 3.79 | 3.07 / 3.05 | 15.49 / 16.38 | 5.96 / 6.30 | 6.36 / 6.69 | 23.09 / 24.05 |
| $i$ Investment | 2.38 / 1.72 | 19.12 / 19.47 | 2.72 / 2.73 | 49.15 / 49.38 | 9.13 / 9.21 | 3.65 / 3.68 | 4.79 / 4.80 | 9.06 / 9.02 |
| $\pi$ Inflation | 0.34 / 0.20 | 30.27 / 29.85 | 3.63 / 3.67 | 6.14 / 6.26 | 11.51 / 11.45 | 36.28 / 36.58 | 5.46 / 5.52 | 6.37 / 6.47 |
| $r$ Policy rate | 0.55 / 0.67 | 60.01 / 58.64 | 1.06 / 1.10 | 11.67 / 12.00 | 8.60 / 8.91 | 4.14 / 4.27 | 1.63 / 1.69 | 12.34 / 12.71 |
| $v$ Value of tech. | 0.79 / 0.61 | 62.76 / 63.49 | 1.54 / 1.51 | 0.76 / 0.71 | 20.86 / 20.63 | 8.48 / 8.39 | 2.65 / 2.59 | 2.17 / 2.08 |
| $rd$ R&D | 6.01 / 9.09 | 53.56 / 45.85 | 1.95 / 2.17 | 1.41 / 1.58 | 21.48 / 23.88 | 8.54 / 9.48 | 3.28 / 3.66 | 3.78 / 4.29 |
| $a$ Technology | 17.00 / 22.80 | 33.21 / 24.61 | 3.50 / 3.69 | 1.90 / 1.93 | 18.22 / 19.25 | 7.24 / 7.64 | 6.12 / 6.46 | 12.82 / 13.63 |
| $ga$ Tech. growth | 3.10 / 5.13 | 58.94 / 51.98 | 1.54 / 1.74 | 1.28 / 1.48 | 22.34 / 25.21 | 8.88 / 10.01 | 2.52 / 2.85 | 1.39 / 1.60 |
| $tfpu$ Uti-adj TFP | 14.82 / 19.92 | 28.95 / 21.50 | 15.87 / 15.84 | 1.66 / 1.69 | 15.89 / 16.82 | 6.31 / 6.67 | 5.34 / 5.64 | 11.17 / 11.91 |
| Solow residual | 14.94 / 20.40 | 31.09 / 23.43 | 14.15 / 14.13 | 1.63 / 1.67 | 16.73 / 17.61 | 6.85 / 7.20 | 5.09 / 5.37 | 9.51 / 10.20 |

For the US, we report the variance decomposition for both the benchmark case and our extended model with stock market. Table 6 shows that variance of US output is mostly explained by the two premium shocks (together 48%), followed by the monetary policy shock (20%) and exogenous demand shock (10%). The variance of US consumption and investment can be largely explained by the risk premium shock, exogenous demand shock and investment efficiency shock together.

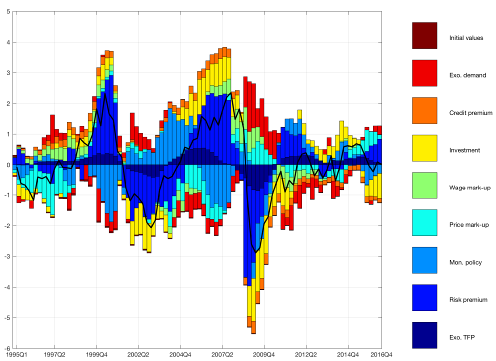
With regards to the productivity-related variables, the two premium shocks account for 60% of the variance for R&D, 49% of the variance for technology, 62% for technology growth, 43% for utilization-adjusted TFP and 46% for the Solow residual. Monetary policy shocks are important for productivity-related variables with the contributions ranging from 15%-25% separately. The exogenous TFP shock has the second largest single contribution (16%) to utilization-adjusted TFP and is moderately important in explaining the variance (14%) of the Solow residual. Turning to the benchmark case without a stock market, the credit premium shock's contributions increase dramatically. It is noteworthy that the credit premium shock would have the second largest single contribution to technology (23%), utilization-adjusted TFP (20%) and Solow residual

(20%) if stock market is absent.

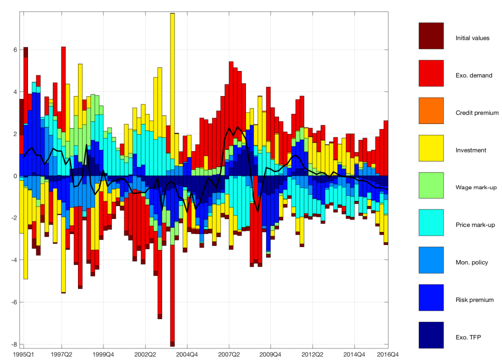
Comparing China and the US, we find that the credit premium shock is important for the US model, especially for productivity-related variables, but not for China; investment efficiency and exogenous demand shocks are much more important in this case. The latter finding is consistent with the fact that Chinese output is largely affected by investment, government expenditure. 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 Chinese output is relatively stable but TFP is more volatile?

Figure 7: Output Historical Decomposition by Shocks (%)

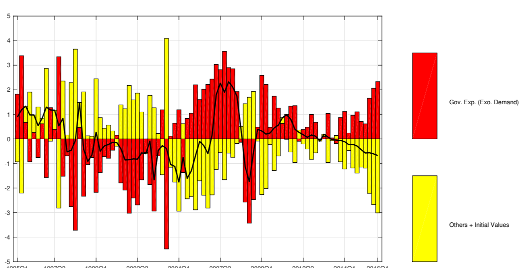
(a) US




(b) China




(c) China: government expenditure shocks vs others




(d) China: government espenditure

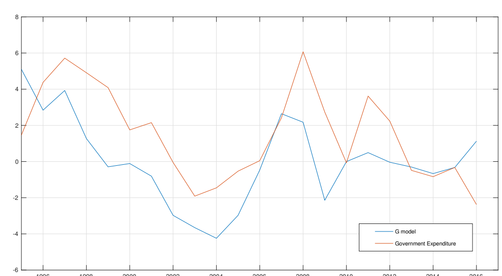



Figure 7 shows the historical variance decomposition of output for the US and China separately[18]. We find a striking difference in terms of the contribution of shocks for the profile of output. For the US, the contributions of the shocks (7(a)) are almost overlapped with the fluctuations in output, as we might expect under normal circumstances. For China, however, the contribution of the shocks (7(b)) have no such pattern. What we are seeing instead is a disconnect between exogenous demand shocks, which we might think of as government intervention, and the profile of output; output is stabilised by a combination of shocks, almost as if government intervention is applied liberally and has to work hard to counteract other shocks hitting the

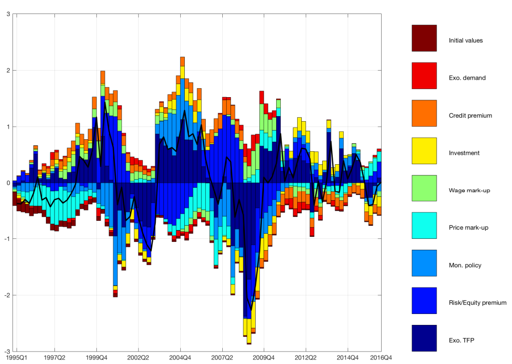
[18]Black lines in Figure 7 mark the profile of filtered output, with the initial value referring to factors not captured by the model.

economy, as suggested in Table 5.

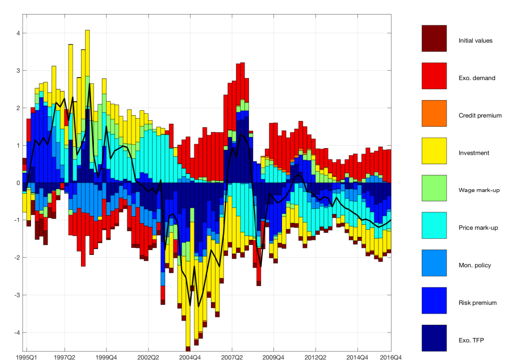
In figure 7(c), we highlight the contribution of the exogenous demand shock and the pool contributions from the other shocks as a whole. From this perspective, it seems more clear that the exogenous demand shock has the largest contribution and works against other shocks as a whole. A question remains at this stage as to whether we can reasonably assume that the exogenous demand shock is actually reflecting government intervention. We compare annualised exogenous demand, generated from the model, with data using Figure 7(d) and on visual inspection, it does appear that there is co-movement between the two series. Hence, it is approximately sensible to interpret the contribution of the exogenous demand shock as the effect of fiscal policy[19]. Hence, under our assumption that this is the case, we interpret that fiscal policy is successful in smoothing output in China. A question come very naturally is whether such a policy can smooth TFP?

Figure 8: TFP (Solow residual) Historical Decomposition by Shocks (%)

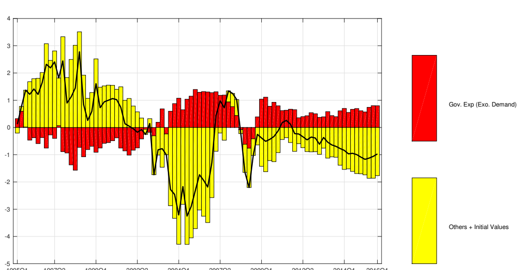
(a) US



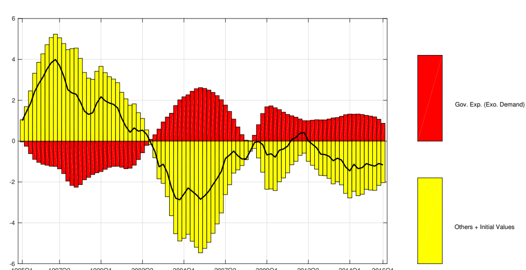

(b) China




(c) China: government expenditure shocks vs others




(d) Chinese Technology




Turning to TFP, we find that for the US, the standard deviation of technology, utilization–adjusted TFP and Solow residual generated from the model are 0.524, 0.632 and 0.677 respectively, whilst for China, the equivalent counterparts are 1.812, 1.23 and 1.295 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

[19]The Chinese government expenditure data are from Chinese Ministry of Finance and only available at an annual frequency. The difference between the two series is likely to be due to net exports and measurement error.

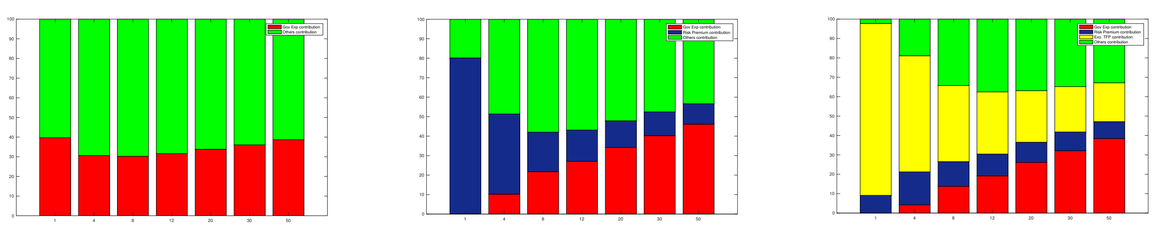
the empirical facts we have mentioned in Section 2.

Figure 8(b) shows that the TFP shock, itself, only accounts for a small contribution to the variation in TFP overall. Considering that Chinese technology is more than three times more volatile than in the US, it appears that the endogenous technology channel might be responsible for Chinese TFP volatility. We highlight the contribution of the exogenous demand shock for TFP and technology in figure 9(c) and 9(d) separately. What we see is a counteracting pattern between government intervention and other shocks, yet the contribution from the former is not sufficient enough to smooth technology and TFP. Thus, government intervention does not appear to be able to reduce TFP volatility in China. This finding seems to contradict Table 5, that the exogenous demand shock has a large contribution to productivity-related variables and that they are quantitatively similar to the contribution towards output. In order to investigate this puzzle, we resort to the conditional variance decomposition.

Figure 9(a) shows that contribution of the government expenditure shock to output does not change much over time. Specifically, the contribution remains in the range 30% to 40%. For productivity-related variables, such as technology and TFP, Figure 9(b) and 9(c) show that the contributions of a government expenditure shock vary substantially over different time horizons. A common pattern is that the government expenditure shock only has significant contributions in the medium- to long-run. This implies that fiscal policy is of only marginal importance to productivity-related variables in the short run. Furthermore, Figures 8(b) and 8(c) suggest that the risk premium shock and the TFP shock have a large impact on technology and TFP in the short run respectively. The time-variant pattern, in terms of the contribution from multiple shocks for TFP, creates the difficulty for fiscal policy in stabilising TFP.

Figure 9: Conditional Variance Decomposition (%): China

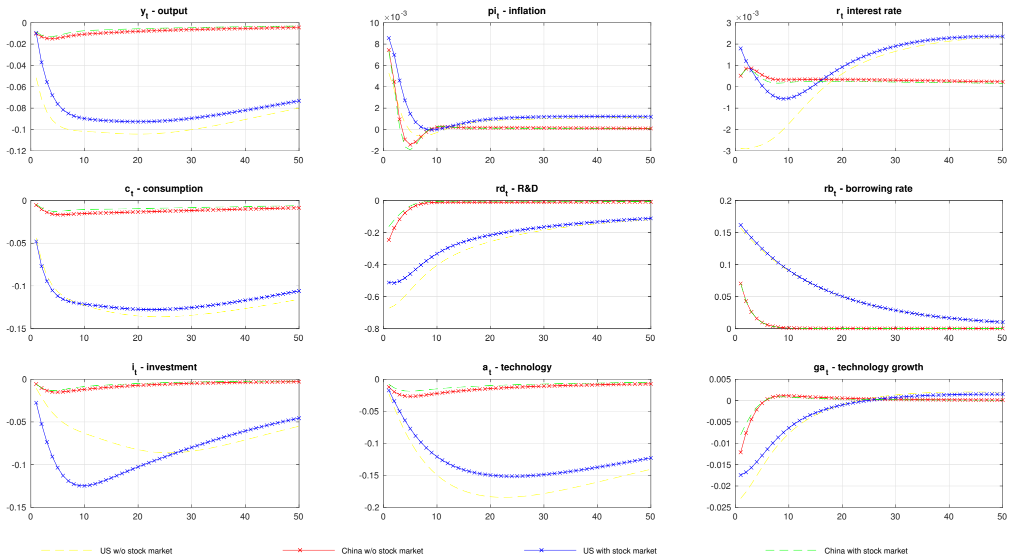
(a) Output (b) Technology (c) TFP



## 4.4 Financial Development and TFP Volatility

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

Figure 10: Impulse Response (%) to Credit Premium shock (one standard deviation)



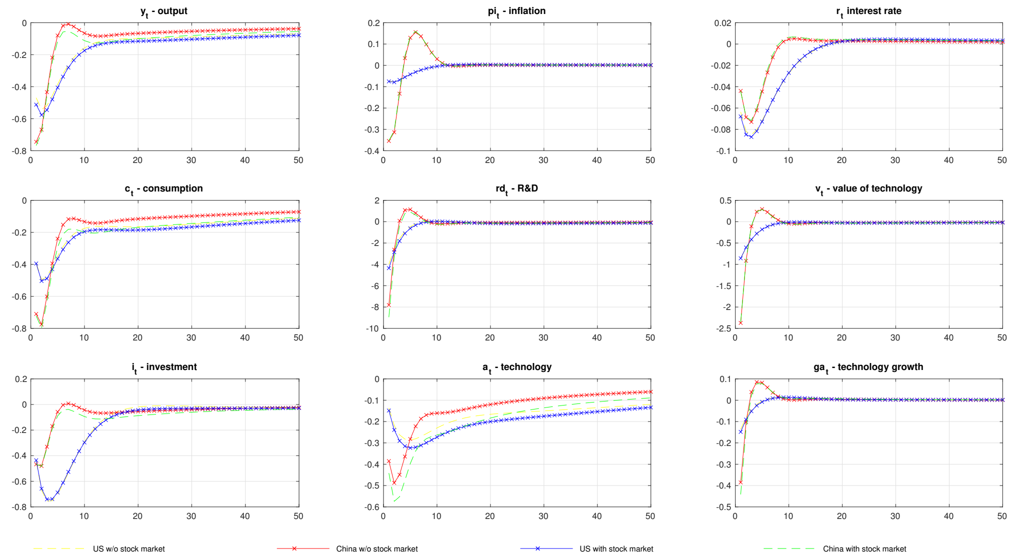

within those processes. The effect from the credit premium shock runs mainly through the cost channel[20] of R&D to affect technology before being transmitted to output.

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 10, we provide the impulse response functions (IRF)s, 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. The only exception is the response of inflation, which is similar for both countries.

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 an acceleration or magnification effect. When there is a positive risk premium shock, households becomes worried

[20]We find the effect of the credit premium shock through the value of technology channel is incomparable with the effect through the cost channel as suggested by Table 5 and 6. For the reason of brevity, we do not report the impulse responses of $v_t$.

Figure 11: Impulse Response (%) to Risk (Equity) Premium shock (one standard deviation)




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 11, capture this propagation mechanism.

Figure 12 and 13 show the impulse responses of key variables to another six shocks; TFP, monetary policy, price and wage mark-ups, investment and exogenous demand. Comparing China and the US, we find the impulse responses to these six shocks are significantly larger for China than that of the US, but there is little qualitative difference. Furthermore, differences between the benchmark and augmented case are small. This is because the non-premium shocks do not trigger significant movements in equity. Despite this, we do find that the response of technology to non-premium shocks is marginally dampened with the presence of a stock market. The results related to output, inflation, interest rate, consumption and investment are in line with the existing literature. Specifically, a positive investment and exogenous demand shock will crowd-out R&D and hence the technology level drops. An increase in the exogenous part of TFP leads to lower interest and borrowing rates, encouraging innovators to spend more on R&D, as innovation becomes cheaper; as a result, more technology will be created. Positive mark-up shocks and tightening monetary policy raise both the interest rate and the borrowing rate; hence R&D becomes more expensive and is reduced, resulting in fewer

Figure 12: Impulse Response (%) to One Standard Deviation

(a) Exogenous TFP Shock (b) Monetary Policy Shock (c) Price Mark-up Shock

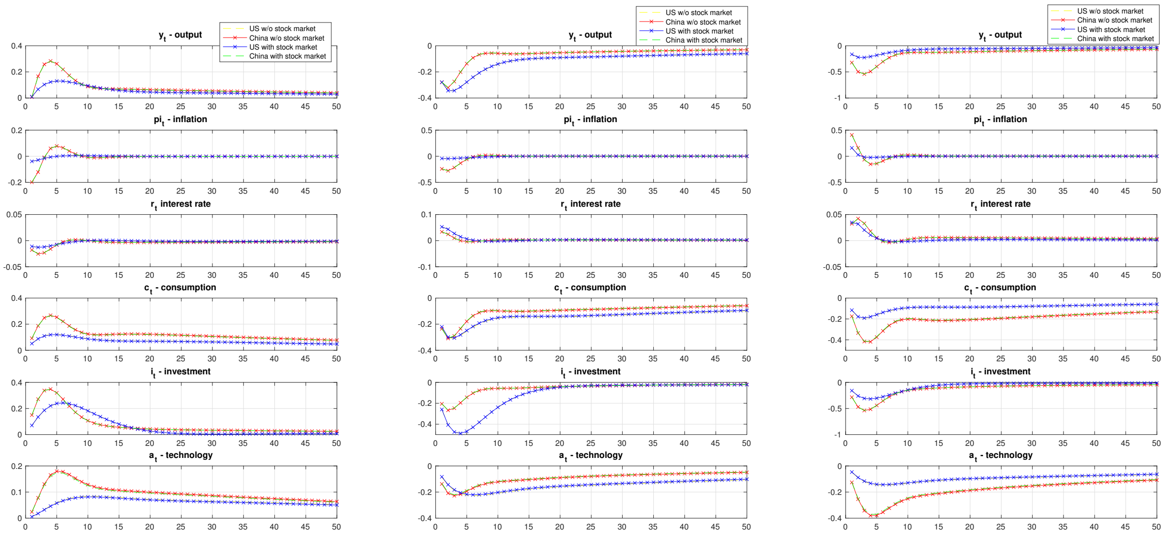



Table 7: Comparison of Dampening and Magnification Effects

| | Initial 8 quarters | Short run accumulation | Med-to-long run accumulation |
|---|---|---|---|
| Dampening on technology (US) | 0.138% | 0.995% | 2.215% |
| Magnification on technology (US) | 0.256% | 1.007% | 2.006% |
| Dampening on technology (China) | 0.058% | 0.176% | 0.461% |
| Magnification on technology (China) | 0.815% | 2.421% | 4.586% |

new technologies.

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 7. 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 difference between the two effects disappears for the US, though the magnification remains larger. Furthermore, when moving to the medium to long run, the accumulated magnification effect becomes smaller than the accumulated dampening 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 in the medium-to-long run. 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.

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

Figure 13: Impulse Response (%) to One Standard Deviation

(a) Wage mark-up Shock (b) Investment Shock (c) Exogenous Demand Shock

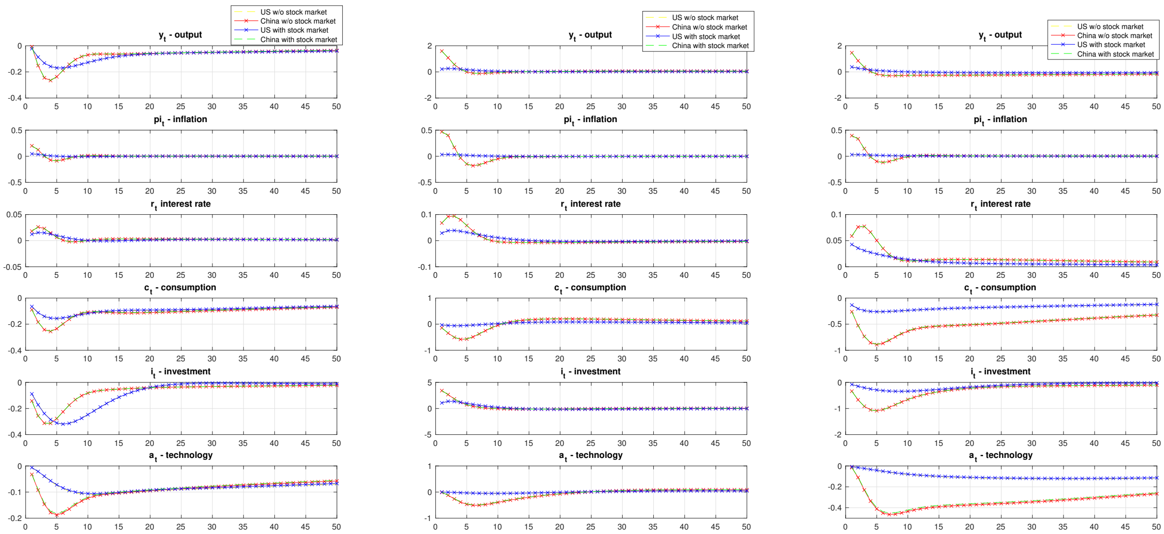



Table 8: Standard deviation of productivity-related variables generated from models

| Variables | US (without stock market) | US (with stock market) | China (without stock market) | China (with stock market) |
|---|---|---|---|---|
| endogenous TFP | 0.575 | 0.524 | 1.812 | 2.265 |
| utilization adjusted TFP | 0.692 | 0.632 | 1.230 | 1.404 |
| TFP (Solow Residual) | 0.706 | 0.677 | 1.295 | 1.477 |

cases: US without and with stock market (real case) and China without (real case) and with stock market. Table 8 shows the moments of the TFP-related variables including technology, utilization-adjusted TFP and 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-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 2.265 from 1.812. 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. Hence, we can suggest that the Chinese stock market is over volatile and the volatility which feeds through the equity premium channel dominates the potential gain from a diverse financial system.

# 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 framework that allows the comparison between two economies, both of which enjoy a good stock of new innovation, 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 that attempts to counteract the volatility of output in China, and this is likely to be due to the Chinese government's priority concern over economic activity. There are GDP growth targets in China each year and these targets are always achieved, despite a series of multiple and sizeable shocks hitting the economy. The cost of this intervention is an inability to smooth TFP for China, fueled by shocks transmitted through the endogenous technology creation channel.

Although the shock decompositions point to fiscal intervention as the cause of 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 dual effects. With access to a stock market, the US is better able to smooth out fluctuations in TFP since the dampening effect of a stock market option dominates the volatility magnification of TFP. However, the same benefits do not apply to China, where the magnification effect dominates with the addition of a stock market to the model.

Our findings have implications for policy currently aimed at the Chinese financial sector, which is undergoing deleveraging reform. Its purpose is to construct multiple-tiers of capital markets to expand funding sources for future innovative and technology based enterprises, and to reduce systemic risk associated with the financial sector as a whole. Our findings suggest that the deleveraging reform should be implemented cautiously and alongside stock market reforms to avoid magnifying fluctuations in TFP further. In order to exploit the advantages of equity finance, attention should be first paid to reducing the volatility of the Chinese stock market. Finally, in this study we have not considered the informal financial sector which is growing in importance and provides a new source of uncertainty, or how the interventions provided by the financial crisis might affect our results, or change the transmission of volatility from the shocks, as suggested by some literature including (Galvão et al. 2016). Whilst this is firmly on our research agenda, we leave this for future research.

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# Appendix A Data

Table 9: Data and sources for estimation

| Variables | Observables-China | Source | Observables-US | Source |
|---|---|---|---|---|
| *gdp* GDP | per capita real GDP | National Bureau of Statistics, China | per capita real GDP | Federal Reserve Bank of St. Louis |
| $c$ Consumption | per capita real household consumption expenditure | Federal Reserve Bank of St. Atlanta | per capita real personal consumption expenditure | Federal Reserve Bank of St. Louis |
| $i$ Investment | per capita real enterprise fixed Investment | National Bureau of Statistics | per capita real private fixed Investment | Federal Reserve Bank of St. Louis |
| $\pi$ Inflation | GDP Deflator | Federal Reserve Bank of St. Atlanta | GDP Deflator | Federal Reserve Bank of St. Louis |
| $r$ Interest rate | 3-month base policy saving rate | The Peoples Bank of China | effective federal fund rate | Federal Reserve Bank of St. Louis |
| $h$ hour | employment level | Federal Reserve Bank of St. Atlanta | total hour worked | Federal Reserve Bank of St. Louis |
| $w$ wage | aggregate nominal wage | Federal Reserve Bank of St. Atlanta | nonfarm business sector compensation | Federal Reserve Bank of St. Louis |
| *lending rate* | weighted averaged lending rate | The Peoples Bank of China | Moody's BAA corporate bond yield | Federal Reserve Bank of St. Louis |
| Population | total population | Federal Reserve Bank of St. Atlanta | civilian noninstitutional population | Federal Reserve Bank of St. Louis |

All nominal variables are adjusted by GDP deflator. We want to mention that our enterprise fixed investment data cover state-owned companies. Companies with state background are essential components in Chinese economy and this feature should not be excluded. Nevertheless, we also did estimation using fixed investment for only private-owned companies. Then we do not find fundamental change in our results as in section 4.3 and 4.4.

Hour worked data for China is not available so that we use employment level. This is the only quarterly data we have to proxy $h$ in the model. In order to keep consistency and comparability between China and US, we have used employment level for US as proxy of $h$. Then our results remain very similar as in section 4.3 and 4.4. Our selection of emerging and developed countries are taken consideration of data availability,

Table 10: Emerging economies and developed countries

| Emerging Economies | Developed Economies |
|---|---|
| Argentina | Australia |
| Brazil | Austria |
| Chile | Belgium |
| China | Canada |
| Colombia | Denmark |
| Czech Republic | Finland |
| Greece | Finance |
| Hungary | Germany |
| India | Italy |
| Indonesia | Japan |
| Israel | Luxemburg |
| Korea | Netherland |
| Mexico | New Zealand |
| Poland | Norway |
| Portugal | Spain |
| Russia | Sweden |
| Saudi Arabia | Switzerland |
| South Africa | United Kingdom |
| Turkey | United States |

classifications from (Aguiar & Gopinath 2007), IMF and MSCI Emerging Market Index. Quarterly GDP data are from OECD Quarterly National Account over 1991Q1 to 2016Q4. Annual TFP data are from PennWorld

Table 9.0 over 1991 to 2014. Gross R&D and business R&D data are from OECD MSTI database. Sock market index for China (Shanghai Stock Exchange Composite Index) and US (S&P 500 Index) are from China Stock Market and Accounting Research via its Wharton Business School supplier. We have taken log 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
$http://pages.stern.nyu.edu/\ adamodar/New_Home_Page/home.htm$.

# Appendix B Linearised equations

$$\hat{y}_t = \hat{\varepsilon}^a_t + (\lambda_m - 1)\hat{a}_t + \alpha(\hat{u}_t + \hat{k}_t) + (1-\alpha)\hat{h}_t \tag{L1}$$

$$\hat{y}_t = \frac{C}{Y}\hat{c}_t + \frac{I}{Y}\hat{i}_t + \frac{RD}{Y}\hat{rd}_t + r^k\frac{K}{Y}\hat{u}_t + \zeta\theta^e\frac{RD}{Y}\frac{e^I}{a}\frac{g^y}{1+g^y}(\hat{e}^I_t - \frac{1}{1+g^y}\hat{e}^I_{t-1} - \frac{1}{2}\frac{g^y}{1+g^y}\hat{a}_t) \tag{L2}$$

$$\hat{\pi}_t = \frac{1}{1+\epsilon_p\tilde{\beta}}\hat{\pi}_{t-1} + \frac{\epsilon_p\tilde{\beta}}{1+\epsilon_p\tilde{\beta}}E_t\hat{\pi}_{t+1} + \frac{(1+\epsilon_p\tilde{\beta})(1-\epsilon_p)}{(1+\epsilon_p\tilde{\beta})\epsilon_p}\hat{mc}^f_t + \hat{\varepsilon}^s_t \tag{L3}$$

$$\hat{r}^k_t + \hat{R}^b_t = \hat{mc}_t + \hat{\varepsilon}^a_t + \alpha(\hat{u}_t + \hat{k}_t - \hat{h}_t) \tag{L4}$$

$$\hat{w}_t + \hat{R}^b_t = \hat{mc}_t + \hat{\varepsilon}^a_t + (\alpha-1)(\hat{u}_t + \hat{k}_t - \hat{h}_t) \tag{L5}$$

$$\hat{\pi}^m_t = \hat{w}_t + \hat{h}_t + \hat{R}^b_t - \hat{a}_t \tag{L6}$$

$$\hat{V}_t = (1-\phi/R)\hat{\pi}^m_t + (\phi/R)E_t[(\hat{V}_{t+1} + \hat{\Lambda}_{t,t+1})] \tag{L7}$$

$$E_t(\hat{\Lambda}_{t,t+1} + \hat{V}_{t+1}) - (1-\mu)(\hat{rd}_t - \hat{a}_t) = \hat{R}^b_t \tag{L8}$$

$$E_t(\hat{\Lambda}_{t,t+1} + \hat{V}_{t+1}) - (1-\mu)(\hat{rd}_t - \hat{a}_t) = \frac{\theta^b\hat{R}^b_t + \theta^e\hat{R}^e_t + \zeta\theta^e\frac{e^I}{a}\frac{g^y}{1+g^y}(\hat{e}^I_t - \frac{1}{1+g^y}\hat{e}^I_{t-1} - \frac{1}{2}\frac{g^y}{1+g^y}(\hat{rd}_t + \hat{a}_t))}{R^b\theta^b + R^e\theta^e + \frac{\zeta\theta^e e^I}{2a}(\frac{g^y}{1+g^y})^2} \tag{L8-1}$$

$$\hat{\Lambda}_{t,t+1} = \hat{mu}_{c,t+1} - \hat{mu}_{c,t} \tag{L9}$$

$$(1+g^y)\hat{a}_{t+1} = (g^y - \phi)\mu rd_t + \phi\hat{a}_t \tag{L10}$$

$$\hat{g}^a_{t+1} = \hat{a}_{t+1} - \hat{a}_t \tag{L11}$$

$$\hat{R}^b_t = \hat{R}_t + \hat{\varepsilon}^f_t \tag{L12}$$

$$0 = \hat{mu}_{c,t+1} - \hat{mu}_{c,t} + \hat{R}_t - \hat{\pi}_{t+1} + \hat{\varepsilon}^b_t \tag{L13}$$

$$0 = \hat{mu}_{c,t+1} - \hat{mu}_{c,t} + \frac{r^k}{r^k + (1-\delta)} \hat{r^k}_{t+1} - \frac{(1-\delta)}{r^k + (1-\delta)} q_{t+1} - q_t \tag{L14}$$

$$\hat{mu}_{c,t} = -\frac{1+g^y}{(1+g^y) - b} \hat{c}_t + \frac{b}{(1+g^y) - b} \hat{c}_{t-1} \tag{L15}$$

$$\hat{i}_t = (\frac{\beta}{1+g^y+\beta}) \hat{i}_t + \frac{1+g^y}{1+g^y+\beta} \hat{i}_{t-1} + \frac{1+g^y}{(1+g^y+\beta)s"} q_t + \hat{\varepsilon}^i_t \tag{L16}$$

$$\hat{r}^k_t = \frac{\xi}{1-\xi} \hat{u}_t \tag{L17}$$

$$\begin{aligned} \hat{w}_t =& \frac{1}{1+\tilde{\beta}} (\hat{w}_{t-1} + \iota_w \hat{\pi}_{t-1} - (1+\iota_w \tilde{\beta}) \hat{\pi}_t) + \frac{\tilde{\beta}}{1+\tilde{\beta}} E_t(\hat{w}_{t+1} + \hat{\pi}_{t+1}) \\ &+ \frac{(1-\epsilon_w \tilde{\beta})(1-\epsilon_w)}{\epsilon_w (1+\tilde{\beta})(1+\eta(\epsilon_w - 1))} (\eta \hat{H}_t - \hat{w}_t - \hat{mu}_{c,t}) + \hat{\varepsilon}^w_t \end{aligned} \tag{L18}$$

$$\hat{k}_{t+1} = \frac{1-\delta}{1+g^y} \hat{k}_t + \frac{g^y + \delta}{1+g^y} (\hat{i}_t + \hat{\varepsilon}^i_t) \tag{L19}$$

$$\hat{R}_t = \rho_r \hat{R}_{t-1} + (1-\rho_r)(\rho_\pi \hat{\pi}_t + \rho_y (\hat{y}_t - \hat{y}_{t-1})) + \hat{\varepsilon}^m_t \tag{L20}$$

$$\hat{R}^e_t = \hat{R}_t + \hat{\varepsilon}^b_t \tag{L21}$$

$$R^b \hat{R}^b_t - R^e \hat{R}^e_t = \frac{(\hat{e}^I_t - \frac{1}{1+g^y} \hat{e}^I_{t-1} - \frac{g^y}{1+g^y} \hat{a}_t) - \frac{1}{R} (\hat{e}^I_{t+1} - \frac{1}{1+g^y} \hat{e}^I_t - \frac{g^y}{1+g^y} \hat{a}_{t+1}) - \frac{g^y}{R(1+g^y)} \hat{\Lambda}_{t,t+1}}{\frac{g^y}{1+g^y} \frac{R-1}{R}} \tag{L22}$$

$$\hat{\theta}^e_t = \hat{e}^I_t - \hat{rd}_t \tag{L23}$$

$$\hat{\varepsilon}^a_t = \rho_a \hat{\varepsilon}^a_{t-1} + \eta^a_t \tag{L24}$$

$$\hat{\varepsilon}^s_t = \rho_s \hat{\varepsilon}^s_{t-1} + \eta^s_t \tag{L25}$$

$$\hat{\varepsilon}^f_t = \rho_f \hat{\varepsilon}^f_{t-1} + \eta^f_t \tag{L26}$$

$$\hat{\varepsilon}^b_t = \rho_b \hat{\varepsilon}^b_{t-1} + \eta^b_t \tag{L27}$$

$$\hat{\varepsilon}^i_t = \rho_i \hat{\varepsilon}^i_{t-1} + \eta^i_t \tag{L28}$$

$$\hat{\varepsilon}^w_t = \rho_w \hat{\varepsilon}^w_{t-1} + \eta^w_t \tag{L29}$$

$$\hat{\varepsilon}^g_t = \rho_g \hat{\varepsilon}^g_{t-1} + \eta^g_t \tag{L30}$$

$$\hat{\varepsilon}^m_t = \rho_s \hat{\varepsilon}^m_{t-1} + \eta^m_t \tag{L31}$$

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. $s$ is steady state level of equity in efficient unit. $\theta^b = 1 - \theta^e$.