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Mitigating economic volatility: When building efficient financial markets should supersede conventional economic policy

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ABSTRACT

The choice of instruments for mitigating economic volatility is a serious consideration for policymakers and important question in government and economics. Using a DSGE model with endogenous technology creation, we show that efficient financial markets are more effective than conventional economic policies, such as fiscal interventions, in reducing economic volatility. Our findings are consistent with data from the Chinese and the US economies who contrast in structure perfectly for the purpose of our comparison. The implication is that rather than focusing on conventional economic policies, a government should help establish efficient financial markets to allow producers a hedge into equity finance during times of financial stress.

1. Introduction

In times of financial instability, the availability of alternative streams of finance are vital for maintaining the cash flows of producers. The successful development of equity markets as part of a financial system becomes a key consideration for policymakers concerned not only with the health of firms, but economic volatility more generally. This study considers the macroeconomic consequences of stock market development, especially useful for developing economies where markets tend to be in the earlier stages. We construct a dynamic stochastic general equilibrium (DSGE) model with financial markets, endogenous technology creation and a rich transmission for financial shocks.

After a preliminary data analysis, we build and nest a model that can capture the characteristics of two economies, the US and China, noting the profiles for economic activity and total factor productivity (TFP) for both countries; whilst the profiles of economic activity might be described as consistent, this is where the similarities end. China suffers from much higher volatility in TFP, a problem often associated with the misallocation of capital (Asker et al., 2014) and less consistent with what one might expect from an emerging economy where volatility in TFP comes 'hand in hand' with volatility in output (Aguiar and Gopinath, 2007; Comin et al., 2014). Following Bayesian estimation and analysis of the shock process decompositions, we suggest that the most likely factors driving higher volatility in TFP for China are intervention and volatile shocks alongside an underdeveloped market for equity finance. This contrasts to the case of the US where access to a well developed stock market enables firms to hedge away from credit markets in times of financial stress.

We extend the Smets and Wouters (2007) model with Comin and Gertler (2006) and Anzoategui et al. (2019) type endogenous technology creation through R&D and a financial intermediary to investigate and compare the finance-productivity nexus over the business cycles for China and the US. We also incorporate a stock market for R&D firms who, in turn, determine the optimal level of debt and equity in the economy; credit and risk (or equity) premium shocks are differentiated to disentangle their individual effects, motivated by Caldara et al. (2016), who suggest that these two processes are independent. Our contribution to the finance-innovation-TFP nexus is two fold; firstly by considering the underlying and competing channels for the propagation of financial shocks, and secondly using a two pronged estimation covering the economies of China and US to facilitate a comparison of two economies at different stages of financial development.

Our study is also related to Bianchi et al. (2019) who estimate a model with a finance-innovation-TFP nexus and distinguish the levels of debt and equity as different sources of firm finance using vertical innovation. We focus specifically on the variation of risks in the debt and equity markets making use of a horizontal innovation framework to allow the separation of tech and non-tech firms; this helps us to identify the effects of financial development on tech firms specifically.

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Our results highlight the role that economic policy plays in an economy with a less developed equity market. The policymaker becomes reliant upon demand side interventions to combat the volatility arising during a financial crisis from insufficient access to equity finance. This finding is reinforced by the visual inspections of the data in our case study; the majority of shocks that hit the Chinese economy have larger variance compared with the case for the US, this variance is often driven by international disturbances and requires the heavy and sporadic use of counteracting fiscal policy and other indirect investment interventions.

The smoothing of output for China comes at the cost of higher volatility in TFP, at times exacerbating the effects of shocks already in effect. For the US, shocks are more muted, following a more cyclical fashion as one might expect, resulting in less disturbance upon TFP. Based on the impulse response functions from our model, we show that the presence of a stock market has a dual effect on the volatility of TFP; the stock market can dampen the effect of a credit premium shock, but in doing so, magnifies the risk (or equity) premium shock. Finally, based on counter-factual experiments, we find that the accumulated dampening effect dominates the magnification effect on the volatility of US TFP. The US experience is in contrast to the case of China, because the magnification effect only dominates the dampening effect if the Chinese innovator has access to the stock market; an important implication of our research is a need for the cautious development of equity markets in developing economies. This key finding leads us to question which characteristics are causing the different reactions from the credit premium and risk premium shocks, so that the overall TFP effects for both countries are opposite to one another? In an analysis that focuses on the characteristics driving this different response we find that higher steady state growth rates do indeed play a role and to a lesser extent the level of R&D intensity.

The rest of the paper is organized as follows. Section 2 presents an exploratory discussion of the data for the cases of the US and China. Section 3 presents the model with extended financial markets and endogenous technology creation. Section 4 describes the Bayesian econometric methodology and presents our estimation results and shock decompositions that help us to understand the drivers behind movements in output under two levels of equity market development. We then make use of the estimated model parameters for an impulse response exercise that helps us to identify the magnification and dampening effect presented by the presence of equity markets. Section 5 concludes with some comments.

2. Exploratory data analysis: China vs US

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

2.1. Economic and productivity performance

From a simple visual inspection of the data presented in Fig. 1, we can see that the profiles of output for both China and the US are similar in magnitude. The further comparisons in Table 1 seem to confirm this observation; that the standard deviations of output for China and the US are of similar magnitude. Moreover, output in China is relatively stable compared with that of other developing and emerging economies. In this sense, China shares features that one might associate with more developed countries. Turning to total factor productivity (TFP), we can see from Fig. 2 that the fluctuations of both first-differenced and linearly-detrended TFP in China are of a larger magnitude than those of the US. Further, Table 1 confirms that TFP for China is significantly more volatile than that of the US and other developed economies; compared with emerging economies, the volatility of TFP in China is above average. Summing up, our descriptive analysis suggests that Chinese output is relatively more stable, but TFP is more volatile. Our data shows that China is an interesting case, in that it displays

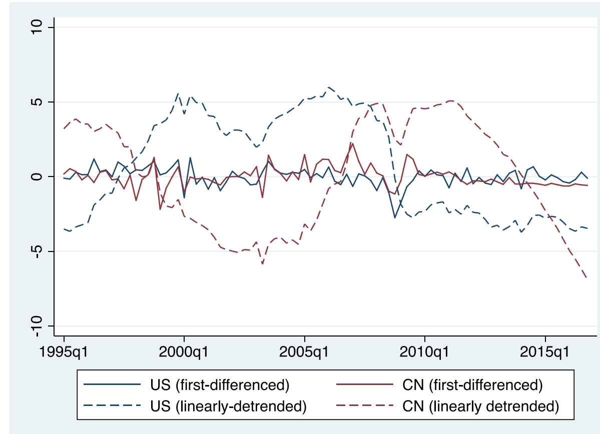

Fig. 1. Output comparison: China vs US.

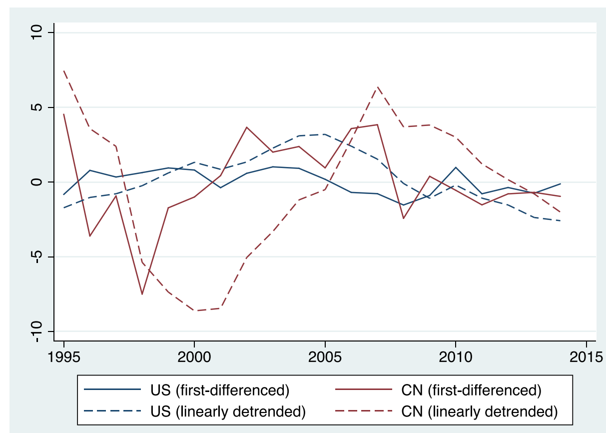

Fig. 2. TFP comparison: China vs US.

Table 1
Macroeconomic volatility comparisons.

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

Note: gY is annualized 4-quarter growth in output. $gTFP$ is TFP growth in annual frequency due to data availability. $\sigma(Y)$ and $\sigma(TFP)$ are calculated based on linearly detrended output and TFP. See the online Appendix A for more details, including data description, sources and country classifications.

mixed features, normally associated with both developed and emerging economies. For the following analysis, we will focus on the volatility of our four key variables including output, TFP and growth, between China and the US.

In Table 2, we present some measures of volatility for both the US and China in terms of selected key indicators. One striking comparison, is the volatility of the productivity-related variable for China, given the similar and more subdued profiles for output for both countries. The standard deviation of both gross R&D growth and business R&D growth suggests that Chinese R&D is more than twice as volatile than that for the US.

It is possible that the volatility of R&D might be subject to measurement errors, and for this reason also consider the volatility of patents, another reasonable proxy for innovation as a robustness check. The growth rate of triadic patent applications in China is more volatile than

Table 2
Macroeconomic volatility: further comparison.

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

Note: gI is 4-quarter investment growth, $gR\&D$ growth of overall R&D expenditure, $gBusinessR\&D$ growth of business R&D expenditure, $gPatent$ growth rate of number of triadic patent applications scaled by population. $gR\&D$, $gbusinessR\&D$ and $gPatent$ are in annual frequency due to data availability. Other variables are in quarter frequency; further details can be found in the online Appendix A.

that for the US. The volatility of growth in R&D and patents suggests that both inputs and outputs of technology creation in China are substantially more volatile than their US counterparts. This finding is critical for our purpose, in that it provides some empirical justification for our proposition that Chinese TFP volatility might be explained by technology creation through R&D, as reflected in our choice of theoretical framework. Finally, the correlation between TFP growth and growth in investment is positive for the US but weakly negative for China. This could be explained by the significant capital misallocation in China.

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.

On the other hand, the US financial system is more diverse and features a banking sector, a corporate bond market as well as a stock market. The technology-based NASDAQ stock market allows US innovative firms to get access to equity finance relatively easy. Contrasting this to the Chinese approval-based IPO process, the registration-based IPO process in the US provides a fast track for hi-tech firms to raise equity finance. Studies in the area of the relationship between financial structure and economic activity, such as (Covas and Den Haan, 2012; Jermann and Quadrini, 2012), suggest that debt and equity finance are alternative sources of finance over different phases of the business cycle. It is likely that a diverse financial system enables US firms, especially innovative ones, to smooth their activities more easily and successfully over the business cycle.

With regards to financial volatility, the data can highlight some distinguishing features between China and the US. In Fig. 3, we provide some time-series on credit premiums, a well known proxy for risk in credit markets 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, the profile of which is noticeably smooth, probably due to restrictive regulations in the Chinese banking sector. Note that the one-year weighted average lending rate can be thought of as an effective lending rate, capturing the lending cost of firms on average. For the US the credit premium which is measured by either Moody's BAA yield minus the Federal Reserve Fund rate or Moody's AAA yield minus the Federal Reserve Fund rate, the profile shows pronounced variation in both the pre-crisis and post-crisis periods. The dramatic difference in profiles for the credit premium provides evidence that the Chinese credit market is relatively stable while that of the US is much more volatile.

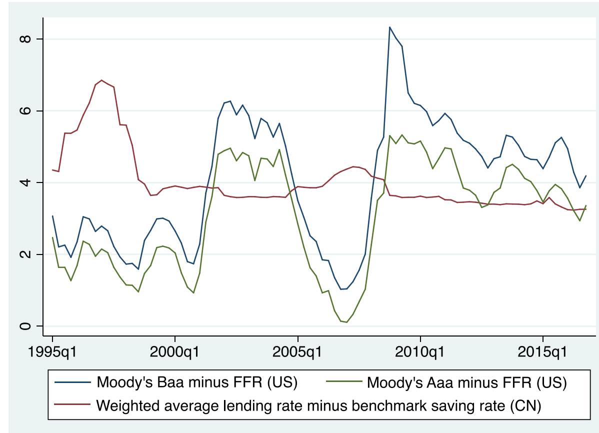

Fig. 3. Credit premium: China vs US.

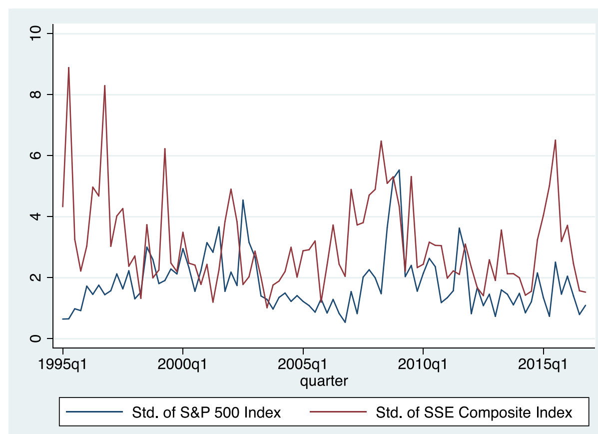

Fig. 4. Stock market volatility: China vs US.

In Fig. 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 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.

Shifting our attention to the US, we make use of Figs. 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, Fig. 5 shows a different magnitude in movement and change in the relative position of the credit premium and equity premium. When the US slips into recession, the credit premium moves closer to the equity premium and even surpasses the latter. In other words, credit tends to be more expensive than equity in a recession or financial crisis. This pattern can also be found in Fig. 6, based on annual data. In addition, the lower part of Fig. 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

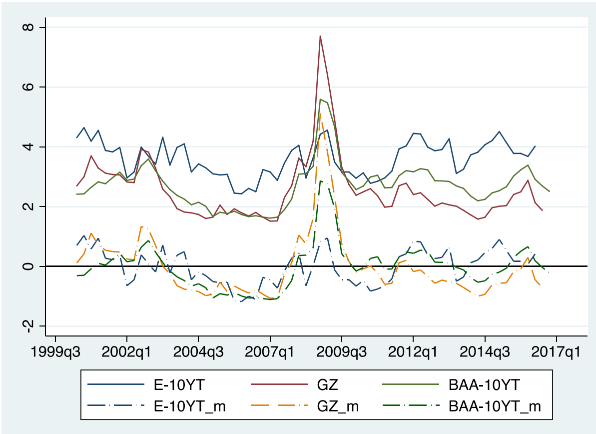

Fig. 5. Quarterly risk premium. Note: E-10YT is difference between equity risk premium and ten-year treasury bond yield, a measure of equity premium. GZ is the GZ spread (Gilchrist and Zakrajšek, 2012). BAA-10YT is difference between Moody BAA corporate bond yield and ten-year treasury bond yield. Quarterly equity risk premium data are from Duke CFO-Survey; Annual equity risk premium data are from NYU Stern Business School. Variables with _m refers deviation from mean value.

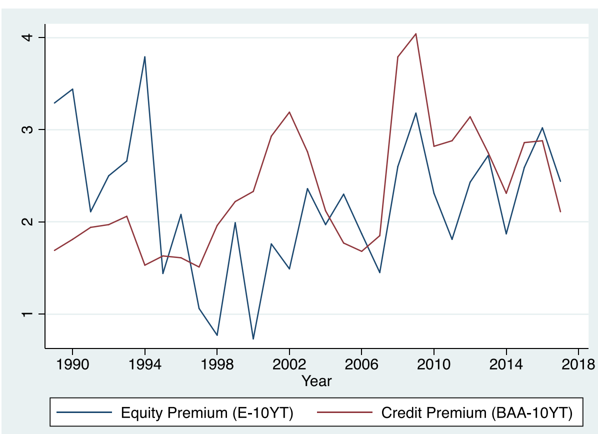

Fig. 6. Annual risk premium. Note: E-10YT is difference between equity risk premium and ten-year treasury bond yield, a measure of equity premium. GZ is the GZ spread (Gilchrist and Zakrajšek, 2012). BAA-10YT is difference between Moody BAA corporate bond yield and ten-year treasury bond yield. Quarterly equity risk premium data are from Duke CFO-Survey; Annual equity risk premium data are from NYU Stern Business School. Variables with _m refers deviation from mean value.

differences in behaviour between those that hold debt and those that use equity for financing production.

Furthermore, Figs. 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 upon the Smets and Wouters (2007) model by incorporating a financial intermediary, a stock market, and endogenous technology creation via R&D, in a similar way to Comin and Gertler (2006) and Anzoategui et al. (2019). The financial intermediary supplies credit to both intermediary goods producers and innovators. In the model, the endogenous component of TFP is determined by technology innovation. There are two channels for the propagation of shocks into innovation: the incentive channel and the cost channel. The former 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. With the presence of the stock market, innovators are able to use equity to smooth their R&D (e.g., a cushion to a credit premium shock) but are subjected to an extra source of fluctuations in doing so (e.g., extra transmission of a risk premium shock), through the cost channel. Hence, the presence of the stock market has a dual effect on the volatility of TFP through the technology innovation. The benchmark model without a stock market is corresponding to the case for China while the full model corresponds to the case of the US.

3.1. Innovator

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

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

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

The evolution of technology is expressed as follows:

$$A_{t+1} = \varphi_t RD_t + \phi A_t = \chi A_t(\frac{RD_t}{A_t})^{\mu} + \phi A_t \tag{2}$$

where ϕ is the survival rate of a technology.

The representative innovator will choose an optimal level of equity to maximize expected profit

$$E_t\pi_t^I = E_t(\Lambda_{t,t+1}V_{t+1})\varphi_t RD_t - R_t^b B_t - R_t^e E_t^I - \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t} \tag{3}$$

where B_t is the amount of borrowing, E_t^I is 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, ζ governs the magnitude of the adjustment cost. V_t is the value or real price of a new technology, which can be in the form of a patent. 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. $V_t = E_t(\pi_t^m + \phi\Lambda_{t,t+1}V_{t+1})$. The optimization yields

$$R_t^b = R_t^e + \zeta\frac{E_t^I - E_{t-1}^I}{A_t} - E_t(\Lambda_{t,t+1}\zeta\frac{E_{t+1}^I - E_t^I}{A_{t+1}}) \tag{4}$$

Eq. (4) implies that the marginal cost of debt is equal to that for equity. Using the break-even condition $E_t\pi_t^I = 0$ and defining $\theta_t^e = \frac{E_t^I}{RD_t}$ as a proportion of R&D financed by equity, we can derive the equilibrium level of R&D.

$$RD_t = [\frac{\chi A_t^{1-\mu}E_t(\Lambda_{t,t+1}V_{t+1})}{R_t^b - (R_t^b - R_t^e)\theta_t^e + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{RD_t A_t}}]^{1/(1-\mu)} \tag{5}$$

In equilibrium, R_t^b and R_t^e are linked to risks in both the credit sector and stock market separately. If a sizeable financial shock occurs, R_t^b becomes 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.

3.2. Financial intermediary

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, the competitive financial intermediary collects deposits and originates loans to innovators and intermediate goods producers. The perfect competition implies that each financial intermediary must break even in equilibrium. Hence, the borrowing rate R_t^b is equal to the savings rate times the credit premium, $R_t^b = R_t\varepsilon_t^f$. ε_t^f is a credit premium shock following an AR(1) process.

We also consider that many innovators in China are private firms who are subject to more severe financial frictions compared with the US. In an extended model, we further account for this difference by incorporating extra credit premium in the lending rate.

$$R_t^b = R_t(\frac{L_t^r}{Y^t})^{\nu}\varepsilon_t^f, \ \nu > 0 \tag{6}$$

where $(\frac{L_t}{Y^t})^{\nu}$ is the extra financial premium positively related to the total real lending amount L_t^r and scaled by output to ensure a balanced growth path. $L_t^r = w_t H_t + r_t^k K_t + (1-\theta_t^e)RD_t$. The way we model the financial premium is consistent with other business cycle models for developing countries (for example Özbilgin (2010) who suggest specific structures aimed at countries exposed to higher volatilities).

3.3. Households

The representative household derives utility from consumption and leisure, consumes and saves money with the financial intermediaries, and experiences external habit formation in consumption, b. As is standard in the New Keynesian literature, the household sets wages subject to nominal rigidities based on the Calvo scheme. The household faces the following problem:

$$\max_{C_t,D_t,I_t,K_t,H_t} E_t\sum_{l=0}^{\infty}\beta^l[log(C_{t+l}-bC_{t+l-1})-\psi\frac{H_{t+l}^{1+\eta}}{1+\eta}] \tag{7}$$

subject to the budget constraint and accumulation of capital.

$$P_tC_t + \frac{1}{\varepsilon_t^b}D_t + P_tE_t^I = R_{t-1}D_{t-1} + R_{t-1}^eP_{t-1}E_{t-1}^I + W_tH_t + R_t^ku_tK_t - a(u_t)P_tK_t + \Pi_t^f - P_tI_t \tag{8}$$

$$K_{t+1} = (1-\delta)K_t + \varepsilon_t^i[1-S(\frac{I_t}{(1+g^y)I_{t-1}})]I_t \tag{9}$$

where C_t denotes consumption, D_t saving, E_t^I equity, H_t labour, K_t capital stock, I_t investment, $a(u_t)$ is the capital utilization function with $a(1)=0$, Π_t^f are profits from the ownership of monopolistic competitive firms, $1+g^y$ 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 $S''()>0$. ε_t^i is an investment efficiency shock and ε_t^b is a risk premium shock, both following an AR(1) process.

With the inclusion of an equity market, ε_t^b affects not only the intertemporal decisions of households as in Smets and Wouters (2007) but also the required return to equity $R_t^e = R_t\varepsilon_t^b$. In this sense, ε_t^b is not only a demand shock but also an equity premium shock. Critical for our analysis, ε_t^b could lead to positive comovement between output and inflation, implying a distinct propagation mechanism compared with the credit premium shock ε_t^f. While the latter (ε_t^f) increases marginal cost, pushes up inflation, and generates tightening effects on output. The differences in propagation are helpful to identify ε_t^b and ε_t^f and to distinguish the credit premium and equity premium.

3.4. Final goods producer

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

3.5. Intermediate goods producer

The intermediate goods sector is similar to Smets and Wouters (2007) but we introduce financing for working capital. There exists a continuum A_t of monopolistic competitors indexed by j, using labour and capital services to produce intermediate goods.

$$Y_{jt}^m = \varepsilon_t^a(u_tK_{jt})^{\alpha}(H_{jt})^{1-\alpha} \tag{10}$$

where ε_t^a is an aggregate productivity shock following an AR(1) process.

3.6. Aggregation and equilibrium

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

$$Y_t = \varepsilon_t^aA_t^{\lambda_m-1}(u_tK_t)^{\alpha}H_t^{1-\alpha} \tag{11}$$

We consider two definitions of TFP. The first is the Solow residual $\varepsilon_t^aA_t^{\lambda_m-1}u_t^{\alpha}$. The second is the utilization adjusted TFP which excludes u_t^{α} utilization of capital from the Solow residual. The resource constraint is:

$$Y_t = C_t + I_t + RD_t + G_t + NX_t + a(u_t)K_t + \frac{\zeta}{2}\frac{(E_t^I - E_{t-1}^I)^2}{A_t} \tag{12}$$

G_t and NX_t are government spending shock and exogenous demand shock respectively following AR(1) processes. The financial market clears: $D_t = L_t$. The policy rate is given by the Taylor rule:

$$R_t = R_{t-1}^{\rho_r}[R(\frac{\pi_t}{\pi})^{\rho_\pi}(\frac{Y_t}{(1+g^y)^t})^{\rho_y}(\frac{Y_t}{Y_{t-1}})^{\rho_{\Delta y}}]^{1-\rho_r}\varepsilon_t^m \tag{13}$$

where ε_t^m is a monetary policy shock following an AR(1) process.

We also consider that China follows a quantity-based monetary policy (Chen et al., 2018; Chang et al., 2019). In an extended model, we introduce a money growth rule as follows:

$$\frac{M_t^s}{M_{t-1}^s(1+g^y)} = (\frac{\pi_t}{\pi})^{\psi^m}(\frac{Y_t}{Y_{t-1}(1+g^y)})^{\psi^y} \tag{14}$$

where M_t^s is broad money supply, equal to the sum of cash[1] M_t and deposit D_t.

$$M_t^s = M_t + D_t \tag{15}$$

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. In particular, we first report and compare business cycle patterns including empirical features for China and the US in Section 4.3. This comparison is also useful to highlight the importance of technology activities in the business cycles for both economies, allowing further investigation into the finance-innovation relationship. After measuring the ability of the model to match the business cycle behaviours, we proceed to Section 4.4 to understand the macroeconomic consequences of financial development via an impulse response function exercise.

[1] We also incorporate a real balance in the household utility function, following Chang et al. (2019).

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 has become a more market-oriented economy since the mid-1990s, with significant growth in the private sector since. Thirdly, we prefer to keep the sample period consistent across US and China to facilitate comparison. We use nine macroeconomic variables as observables for estimation: GDP, consumption, investment, government spending, hours worked, real wages, GDP deflator inflation, the policy interest rate and lending rate. Following Anzoategui et al. (2019) and Bianchi et al. (2019), we do not use TFP data directly in estimation.

In terms of lending rate, Moody BAA corporate bond yield is used as a proxy for US while the weighted averaged lending rate is that proxy for China. 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. We transform the data as follows. GDP, consumption, investment and government spending are expressed as real per capita, logarithmic first difference; the real wage is logarithmic first difference; labour hours are measured as per capita employment times hours worked. Following Christiano et al. (2014), all variables are demeaned separately.

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

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 shows calibrated parameters for China and the US together. These parameters are well identified in existing literature, for example (Chang et al., 2015; Dai et al., 2015; Anzoategui et al., 2019; Smets and Villa, 2016). Hsieh and Klenow (2009) find that labour income share accounts for about half of GDP in China, which implies a capital share α of 0.5. For the US this is calibrated as 0.36, in line with other US-based DSGE studies. The discount factor β is calibrated as 0.995 to match quarterly interest rate for the US (0.65%) and China (2.75%) separately. The technology elasticity with respect to R&D μ is calibrated based on the patent-R&D or R&D stock-R&D flow relationship. Following Comin and Gertler (2006), we choose μ as 0.8 for US. Its counterpart for China is set to 0.7 in order to match moments of Chinese business R&D growth. This value also implies the efficiency of Chinese R&D is lower than that in the US.

Table 3
Calibrated parameters.

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

We follow Kung and Schmid (2015) and Jinnai (2015) to calibrate the quarterly technology obsolescence rate 1-ϕ for the US as 3.75%. 1-ϕ for China is calibrated as 5% which is consistent with a 20% annual obsoletion rate of Chinese invention patents (SIPO, 2014). Following Kung and Schmid (2015) and Jinnai (2015), we calibrate the intermediate goods mark-up λ_m as 1.64 for the US, and 1.5 for China to ensure a balanced growth path. Following (Covas and Den Haan, 2012), we calibrate ζ 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 4 shows the calibrated value of steady-state parameters for the US and China. The annual per capita GDP growth rates are 1.9% and 8.8% for the US and China respectively between 1995 and 2016. Hence we calibrate g^y as 0.48% and 2.2% for the US and China separately. ξ is calibrated as 2.59% for the US and 1.21% for China to match the R&D to GDP ratio (R&D intensity). The steady-state debt to total finance ratio for the innovator is calibrated as 0.45 based on debt and equity issuance data[2] for hi-tech firms between 1995 and 2016.

4.3. Estimation

Bayesian estimation offers a useful tool to estimate and evaluate 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 Bayesian updating:

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

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

Our estimation results, presented in Table 4 provide us with some interesting insights into the characteristics of the two economies; US consumers are slightly more habitual than their Chinese counterparts;

[2] Source: Thomson One Database

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

Note: 90% HPD in bracket.

habit in consumption for the US is 0.61 and China 0.56. There is a similar level of stickiness in both prices and wages for the US (both 0.93) and China (0.93 and 0.92). Chinese goods producers index more on lagged prices and lagged wages respectively (0.29 and 0.44) than producers in the US (0.23 and 0.40). The Chinese capital utilization elasticity is estimated at 0.83, higher than that in the US (0.75). The investment adjustment cost parameter is higher in China (6.53) than in the US (4.10). The Taylor parameters suggest that the Chinese policy rate is more sticky (ρ_r = 0.97 for China and ρ_r = 0.89 for US) and the Chinese central bank appears to react less aggressively to inflation (ρ_π = 1.22 for China and ρ_π = 1.76 for the US). With regards to the shock process, we find the most notable differences between China and the US, in terms of both depth and persistence. In terms of standard deviations, which reflect the depth of the shocks' effecting on the economy, the majority of shocks in China are significantly larger.

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

We find that the persistence parameters of the exogenous TFP shock in both China and US are lower than in existing literature. This may well be owing to the fact that the persistence of TFP is generated from an endogenous technology channel. Next we show the relative importance of each shock in China and the 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. The investment and exogenous demand shocks are two major driving factors for output growth variance in China (35% and 30%), followed by the risk premium and government spending shocks (19% and 8%). In terms of output, its variance is mainly explained by risk premium and investment shocks (40% and 27%).

In terms of productivity-related variables including R&D, technology and TFP variables, the risk premium shock has the largest contribution, ranging from 38% to 53%. In addition, the investment shock, TFP shock and monetary policy shock are also important in explaining the variance of productivity related variables, with contributions between 8% to 23%. Furthermore, Table 5 suggests that non-TFP shocks together have a 77% and 87% contribution to utilization-adjusted TFP and Solow residual respectively. This finding implies that Chinese TFP is primarily explained by the technology creation channel.

For the US, Table 6 shows that variance of US output and growth are mostly explained by the risk premium shock (50%–55%), followed by the monetary policy shock (20%). With regards to the productivity-related variables, the two premium shocks account for 63% of R&D variance, 68% of technology variance, 67% of utilization-adjusted TFP variance and 65% of the Solow residual variance. The monetary policy shock is also an important driving force for productivity-related variables, with the contributions ranging from 10%–20% separately. The exogenous TFP shock has a non-negligible contribution to utilization-adjusted TFP (6%) and the Solow residual (5%). Comparing China and the US, we find that the credit premium shock is important for the US model, especially for productivity-related variables, but not for China; investment, government spending and exogenous demand shocks are much more important in this case. The latter finding is consistent with the fact that Chinese output is largely affected by investment, government expenditure and net exports.

After establishing the relative importance of the individual shocks, we now turn our investigation to how these contributions might help answer our research question: how do the underlying driving factors of the short run fluctuations compare across two economies that differ in terms of equity market development? What lessons can we draw from these shock decompositions?

Table 5
Unconditional variance decomposition (%): China.

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

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

Table 6
Unconditional variance decomposition (%): US.

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

(a) China (b) US

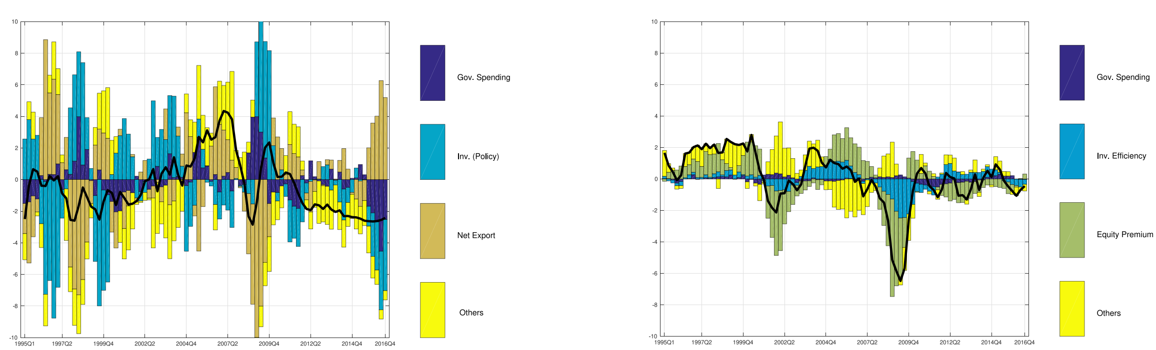

Fig. 7. Output growth historical decomposition. Note: the two figures are expressed as percentage deviation from steady state.

Fig. 5 shows the historical variance decomposition of 4-quarter output growth for the US and China separately. We find a marked difference in terms of the contribution of the shocks for output growth. For China, the contribution of shocks shows a more counteracting pattern. Fig. 5(a) highlights a pattern in China that the investment shock and government spending shock together counteract effects from other shocks, particularly the exogenous demand shock, which we can think of as representing net exports. The latter hits the Chinese economy during several periods, such as the Asian and global financial crisis. For the US, however, there is no suggestion that the investment shock works strongly against the contribution from others (5(b)). We find that the government spending shock combats other shocks in the US, yet the effect of the former on output growth is small.

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 2.873, 2.016 and 1.907 respectively, whilst for China, the equivalent counterparts are 5.313, 6.365 and 6.057 respectively. In addition to this, the model generated standard deviation of technology growth, utilization–adjusted TFP growth and Solow residual growth are 1.052, 1.000 and 1.072 for the US, and 2.682, 3.262 and 2.827 for China respectively. It is clear that the model generates significantly larger fluctuations and variance of the three types of TFP for China, relative to the US and consistent with the empirical facts we have mentioned in Section 2. Fig. 6(a) shows that several non-TFP shocks, including the risk premium shock, monetary policy shock, price mark-up shock, and the investment shock, account for

(a) China (b) US

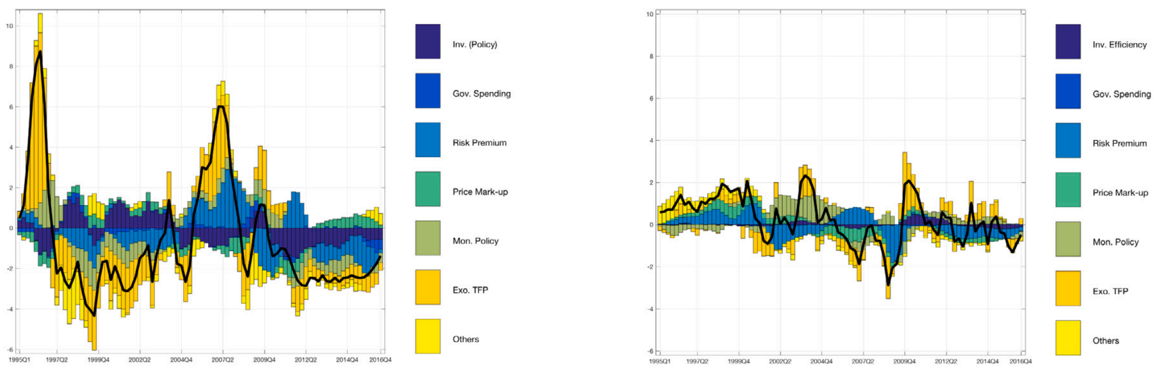

Fig. 8. TFP growth historical decomposition. Note: the same as above.

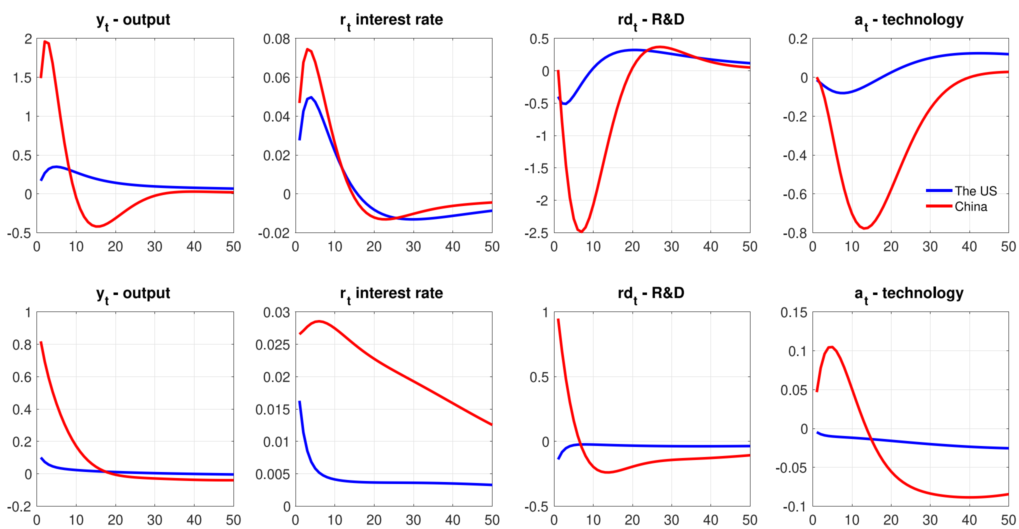

Fig. 9. Impulse responses to positive inv. and gov. spending shocks (1 std).

the significant variation in TFP growth overall in China; aside from investment, these shocks are major driven forces for US TFP growth. Considering that Chinese technology is about twice as volatile as that in the US, it appears that the endogenous technology channel could be responsible for Chinese TFP volatility. This pattern is also identified based on a historical decomposition of utilization-adjusted TFP. See the online Appendix E for more details. The importance of the endogenous technology channel in driving TFP for both economies provides us with a foundation to analyse the implications of financial development in the next section.

Before exploring the macroeconomic consequences of financial development, we further investigate the implications of government interventions for TFP volatility in China. This analysis is useful to highlight a policy trade-off in an economy with a less developed equity market. As shown in Fig. 7, positive investment shocks and government spending shocks increase output immediately. However, as the economy is expanding, the central bank will increase the interest rate which further increases the financing cost of R&D. Hence, R&D will be crowded out and technology levels will drop. Moreover, if we assume government intervention is counter-cyclical, these crowding-out effects are likely to magnify the volatility in technology and TFP. We can use the pathology of the global financial crisis as a further explanation. The investment stimulus during 2008–2009 recovers the economy rapidly. Though following this, the People's Bank of China increased interest rates 5 times between 2010 and 2011, leading to higher financing costs for innovative firms in China, as noted by Bleck and Liu (2018). Our explanation is consistent with Bai et al. (2016) and Zilibotti (2017) which document a crowding-out effect of the government intervention on innovative investment. Considering that the government intervention in China is discretionary, the impulse response analysis is not sufficient to provide the overall effect of the government intervention on TFP in China. Hence we proceed with the following counter-factual analysis for our sample period. Firstly, we re-estimate the model to allow the response of the investment shock and government spending shock to the net exports innovation. The investment and government spending shock equations, in linearized form, are rewritten as

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

We then calibrate these response parameters $\rho_{i,x}, \rho_{g,x}$ as zero and simulate the model once more. Our underlying assumption is that the government does not respond to net exports, neither directly nor through investment policies. Some essential findings are presented in Table 7. We find substantial differences in terms of volatility and correlation in two cases. Firstly, volatility in output increases significantly if the government does not respond to a change in net exports. In addition, the correlation between TFP and capital turns from negative to weakly positive. Such a change in correlation may signal less distortion in resource allocation. Furthermore, the volatility of three productivity

Table 7
Comparisons of volatility and correlation (with respect to feedback).

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

Table 8
Relative volatility in alternative models.

	US parameters and shocks (i)	US parameters, Chinese shocks (ii)	China, no feedback (iii)	China with extra financial premium, no feedback (iv)	China, monetary supply rule, no feedback (v)	China, with feedback (vi)
$\sigma(Y)$	106.664%	129.293%	125.028%	134.301%	113.851%	100%
$\sigma(gY)$	99.400%	199.289%	219.500%	246.661%	184.006%	100%
$\sigma(uTFP)$	34.731%	93.035%	91.484%	91.201%	89.289%	100%
$\sigma(TFP)$	34.747%	93.814%	89.657%	89.414%	89.830%	100%
$\sigma(guTFP)$	31.478%	104.065%	99.785%	96.704%	93.853%	100%
$\sigma(gTFP)$	38.840%	108.419%	99.752%	104.436%	102.140%	100%

Note: this table shows volatility of output and productivity variables relative to the Chinese case with feedback (the government intervention).

variables would decrease, although magnitudes are relatively small compared to the change in output volatility. These results suggest that the government intervention is very successful in smoothing output but that it is costly; volatility in TFP increases and risks misallocations (see Figs. 8 and 9).

To further understand factors in driving the differences of TFP volatility between the US and China, we proceed with a Shapley-value style decomposition exercise. Our starting point is the US case which is normally treated as a benchmark or standard business cycle model (column (i) in Table 8). Then we gradually add China-specific factors and simulate alternative models to explore the contributions of each factors to TFP volatility in China. In each case or model we compute model-implied volatility of output and productivity relative to the Chinese model.

When setting persistence and standard deviation of shocks for the US using the Chinese values, column (ii) in Table 8 shows that both output and TFP volatility increase significantly. Relative volatility of the two TFP variables increase from about 35% to 93%, indicating that the volatile shocks hitting China are major drivers of TFP volatility. This result is consistent with our finding based on the variance decomposition analysis. Based on (ii), we further change the parameter values to the Chinese ones. Compared to column (ii), column (iii) suggests slight changes in the relative volatility. This finding implies that structural parameters, e.g. the degree of price rigidity and adjustment costs, are unlikely to be the cause of the unique business cycle patterns of China. This is consistent with our estimation results as shown in Table 4; differences in structural parameters between the two economies are not pronounced. We further consider to add some China-specific factors to the model such as the extra financial premium or the quantity-based monetary policy. Column (iv) and (v) shows that adding these factors do not fundamentally change the relative volatility of TFP. Common to model (ii) to (v), the government intervention is shut down. Column (ii) to (v) together suggest that the side effects of government intervention accounts for about 10% of TFP volatility in China. Overall, the extra TFP volatility in China is jointly explained by high volatility in shocks and the side effects of government intervention.

4.4. Financial development and TFP volatility

Now that we have demonstrated the ability of the model to capture the business cycle characteristics of the two economies, we proceed to investigate how financial development can affect the profile of TFP after a shock. There are two specific questions we are addressing; firstly, does a diverse financial system contribute to the stabilization of TFP in the US? and secondly, whether such an experience can apply to the case of China? We start from the impulse response analysis to study the propagation mechanisms of shocks and the role of debt and equity within those processes.

When there is a positive credit premium shock, the borrowing rate will rise immediately, pushing up the cost of R&D. In order for the equilibrium condition to remain intact, the innovator has to cut back on R&D expenditure, which reduces technology and slows down technology growth. Hence, the marginal efficiency of labour and capital will be reduced separately, eventually dragging down output. If there is access to an equity market[3] 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 Fig. 10, we provide the impulse response functions (IRFs), which make use of the structural parameters obtained from the estimation. The reaction of our variables of interest to a credit premium shock captures the above propagation mechanism. If we compare the US and China, it is perhaps unsurprising to find that the credit premium shock has a larger and more persistent influence on the US than on China.

Whilst the presence of a stock market for the innovator will tend to dampen the effect of the credit premium shock, the impulse responses to a risk premium shock suggest the opposite; a stock market can provide a magnification effect. When there is a positive risk premium shock, households becomes worried about the economy and require higher returns on all types of assets that they hold. As a result, households will consume and invest less and demand a higher return from equities held; this leads to a decrease in aggregate demand and a higher equity cost; the former transmitting to the production sector resulting in a sharp decline in profits and depreciation of technology; the latter, to higher equity costs, discouraging the equity financing of new innovations. Both of these channels push down R&D expenditure. Compared with the benchmark case, access to the stock market will expose the innovator to an extra disturbance through the second channel, hence the fluctuation of R&D and technology will be exacerbated. In this sense, the stock market plays as an accelerator and the impulse response, from Fig. 11, capture this propagation mechanism.

To further understand the effects of the credit premium and risk premium shocks, we simulate the model based on two extra cases, using different parameter values and compare the IRFs with the benchmark case. In particular, we start from the benchmark calibration for the US and further set the growth rate or R&D intensity to the Chinese values. We set a higher growth rate (increasing g^y from 0.48% to 2.2%) in

[3] In the model, we conduct a counterfactual analysis via our settings in the parameterization, effectively switching the equity market on or off as required, by changing the steady-state debt to total finance ratio to unity.

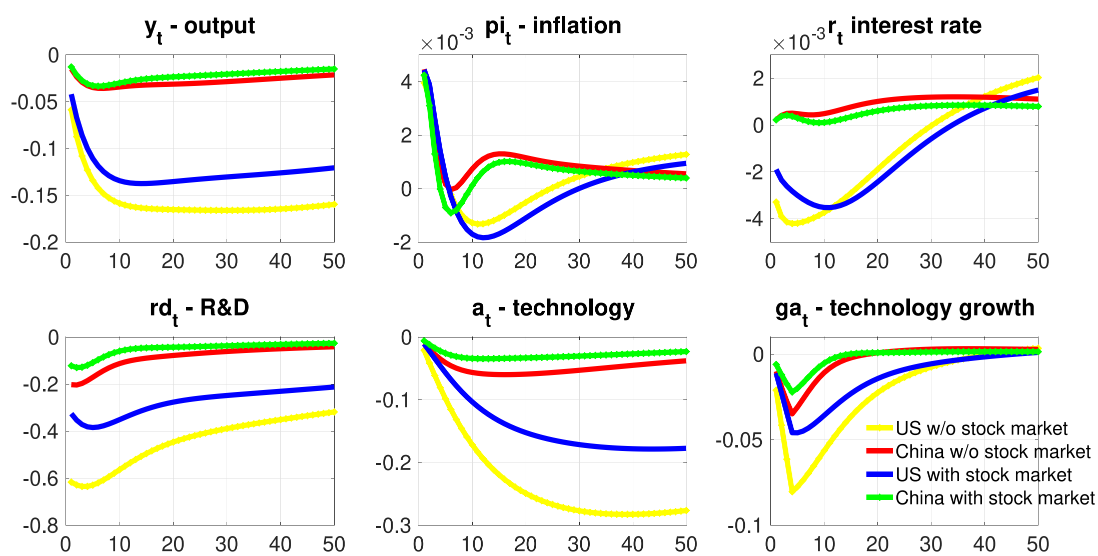

Fig. 10. Impulse responses to credit premium shock (1 std).

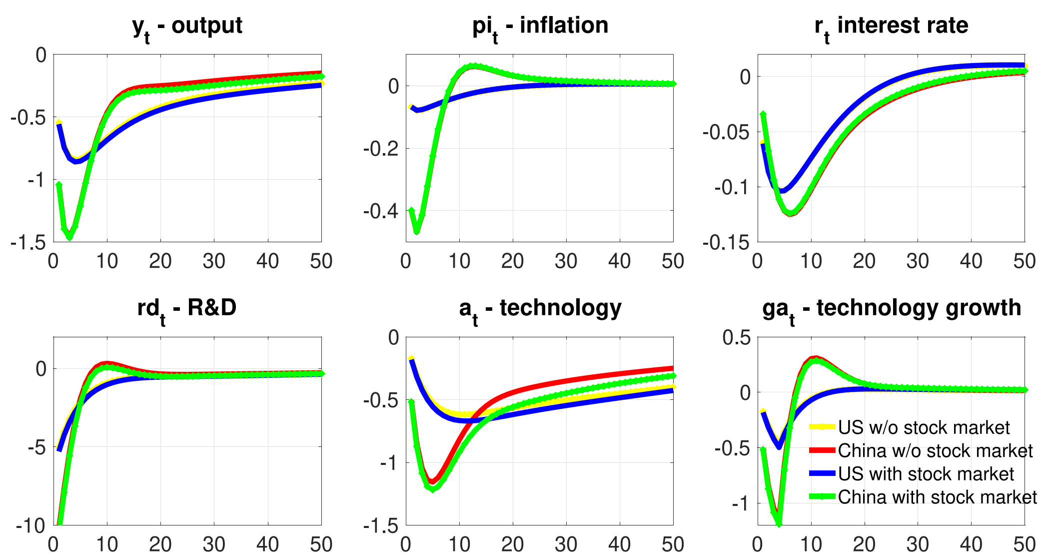

Fig. 11. Impulse responses to (equity) risk premium shock (1 std).

one additional case. In the other case, we use a lower R&D intensity (reducing RD/Y from 2.6% to 1.2%). These exercises are useful to show if the differences in the growth rate and R&D intensity lead to a different propagation of the two shocks between the US and China. Particular attention is paid to technology.

The upper panels in Fig. 12 compare the IRFs of technology to the credit premium shock (Fig. 12(a)) and the risk premium shock (Fig. 12(b)) in the three cases. Fig. 12 shows that the responses of technology are amplified when there is a higher growth rate. On the contrary, changing R&D intensity only has marginal impacts on the responses of technology to both shocks in our exercise.

The lower panels in Fig. 12 shows differences in the responses of technology between the equity case and the no-equity case. These differences show the dampening (or magnification) effects provided by the inclusion of equity. With a higher growth rate, both dampening and magnification effects are strengthened but the latter effect increases more. Results based on 12 are consistent with the traditional view that high growth is normally associated with high risks; it is not surprising to find magnified response of technology when the growth rate becomes high[4] . Furthermore, the analysis based on Figs. 11 and 12 together implies that both the size and the transmission of the risk premium shock contributes to the large variation of technology in China. Compared with the US, switching on the stock market would expose Chinese innovators to more volatile disturbances from the stock market.

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. These results are reported in Table 8. Notice that, within the first 8 quarters, for both the US and China, the magnification effect is larger than the dampening effect, and that the difference in China is more pronounced. When moving to about 32 quarters, the dampening effect becomes larger for the US. Furthermore, when moving to the medium to long run (up to 200 quarters), the accumulated

[4] The risk and uncertainty literature suggests that macroeconomic fluctuations tend to be larger in a riskier regime (see Lhuissier and Tripier (2021) amongst others).

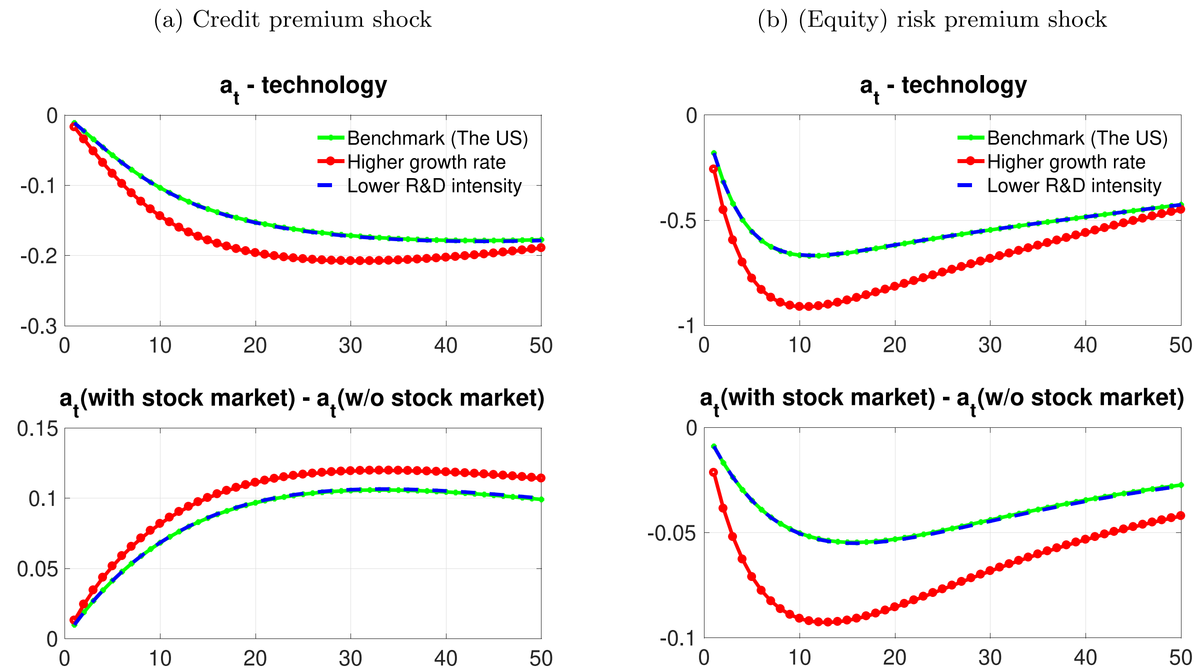

Fig. 12. Responses of technology in alternative cases.
Note: a positive value of $a_t(with\ stock\ market) - a_t(w/o\ stock\ market)$ indicates a dampening effect provided by equity. A negative effect indicates a magnification effect.

Table 9
Comparison of dampening and magnification effects on technology.

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

Table 10
Standard deviation of productivity-related variables.

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

dampening effect becomes much larger than the accumulated magnification effect in the US, whilst the reverse pattern persists in China. Therefore, only the US benefits more than suffers from the presence of a stock market, and that benefit dominates. To further confirm this finding, we proceed to show the moments of the productivity-related variables for the two countries with and without stock markets (see Table 10).

We investigate the overall effect of stock market development on productivity volatility. In order to address this question, we calculate the moments of the TFP-related variables for four cases: US without and with stock market and China without and with stock market. Table 9 shows the moments of the TFP-related variables including technology, utilization-adjusted TFP, the Solow residual. For the US, if we switch off the stock market, the volatility of all three TFP-related variables increases. Not surprisingly, the most substantial increase in volatility would be from technology which is directly affected by the two premium shocks. In which case, the dampening effect, especially in the medium to long run, outweighs the magnification effect and the presence of a stock market reduces volatility of TFP in the US.

For the case of China, we find the reverse pattern in the TFP-related variables; after switching on the stock market for the Chinese innovator, the standard deviation of three TFP-related variables would increase respectively. Similar to the US, the most significant change would come from technology, whose standard deviation would rise to 5.313 from 5.547. For China, the magnification effect outweighs the dampening effect and the presence of a stock market increases the volatility of TFP. This last finding is consistent with the empirical facts that we have presented in Section 2. Hence, we can suggest that the Chinese stock market is over volatile and that 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 investigated the more complex transmissions surrounding the propagation of financial shocks to better understand how producers react to financial disturbances, and to learn lessons for the successful development of equity markets. To achieve this, we have built a model that facilitates a comparison between two economies, both of which have access to a good stock of new innovation, but are distinguished in terms of financial development. We use Bayesian

Table 11
Descriptions and sources for variables used in estimation.

Variables	Description-China	Source
gdp GDP	Gross domestic product	NBS, China
c Consumption	Household consumption expenditure	Chang et al. (2016)
i Investment	Gross fixed capital formation excluding change of inventory, SOE and government investment	Chang et al. (2016)
π Inflation	GDP Deflator	Chang et al. (2016)
r Interest rate	3-month policy saving rate	PBC, China
h Labour	Hour worked times employed labour	Chang et al. (2016) and PBC, China
w Wage	Aggregate wage	Chang et al. (2016)
g Gov. spending	Government consumption, investment and SOE investment	Chang et al. (2016)
$Lending\ rate$	Weighted averaged lending rate	PBC, China
M^s money supply	Broad money supply (M2)	Chang et al. (2016)
Population	Total population	Chang et al. (2016)
Variables	**Description-US**	**Source**
gdp GDP	Gross domestic product	FRED
c Consumption	Personal consumption expenditure	FRED
i Investment	Private fixed investment	FRED
π Inflation	GDP Deflator	FRED
r Interest rate	Effective federal fund rate	FRED
h Labour	Hour worked times employed labour	FRED
w Wage	Nonfarm business sector compensation	FRED
g Gov. spending	Government consumption and gross investment	FRED
$Lending\ rate$	Moody's BAA corporate bond yield	FRED
Population	Civilian noninstitutional population	FRED

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

estimation techniques to capture the structural parameters of two economies, chosen by stage of development, to test the suitability of our model set up stylized to capture richer financial flows. We compare the two economies by making use of the shock decompositions obtained during the estimations. This method allows the information from the data and previous studies to contribute towards our findings, and draw lessons for equity market development.

The decomposition of the shock processes suggests that macroeconomic policies are responsible for conflicting observations from the macroeconomic profiles. Macroeconomic intervention, in terms of traditional fiscal policy and indirect financial interventions in investment, seems to counteract the volatility of output in China; likely due to the Chinese government's focus on economic activity as a priority. The cost of this intervention is volatility in TFP for China, fuelled by shocks transmitted through the endogenous technology creation channel, exacerbating the already volatile TFP movements. The presence of developed equity markets in the US seem to facilitate the positive connection between TFP and economic activity that we would expect, with producers enjoying the option to switch into equity markets during times of financial stress.

Based on the impulse response functions, we propose that the stock market provides both magnifying and dampening effects. With access to a stock market, the US is better able to smooth fluctuations in TFP since the dampening effect of a stock market option dominates the volatility magnification of TFP in the medium run. However, the same benefits do not apply to a less developed economy such as China, where the magnification effect dominates throughout, once firms have access to equity markets. Our study has implications for policy currently aimed at the development of the financial sector in emerging economies. Our findings suggest that deleveraging reform should be implemented cautiously to avoid the magnifying fluctuations in TFP that we predict will arise from rapid financial market reform.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Data

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

Chinese quarterly consumption, investment, GDP deflator, wage, employment level, government spending, money supply, and population data are from Chang et al. (2016). Details about construction of data can be refereed to Higgins and Zha (2015). Hour worked data for China is unavailable in Chang et al. (2016) and we obtain this data from the People's Bank of China in Table 11.

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