On the Macroeconomic Effects of Shadow Banking Development

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Abstract

We build and estimate a dynamic stochastic general equilibrium model with risky innovation and shadow credits to study the macroeconomic implications of shadow banking (SB), particularly on productivity. Our analysis is motivated by negative relationships between SB development and innovation outcome or total factor productivity (TFP) growth. In our model, information asymmetry associated with technology utilization leads to an agency problem in which shadow intermediation reduces banks' incentives to screen project quality. An SB boom crowd-out traditional financial services, decreases innovation quality and technology efficiency, and thereby reduces TFP. In the light of model mechanisms, we analyse cross-country differences and deliver important implications of SB. SB development mainly driven by financial factors (e.g., the US case) leads to significant loss on TFP while that relatively prompted by real-sided factors (e.g., China and the EA cases), could be less harmful.

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1 Introduction

A pronounced economic phenomenon over the last two decades or so is the fast development of shadow banking[1] in the world. It has many far-reaching consequences that economists have begun to appreciate recently, including stimulating credits and investment for the positive side and destabilizing business cycles for the negative side (Ferrante 2018, Fève et al. 2019, Moreira & Savov 2017, Ordonez 2018). Despite efforts in the literature, macroeconomic implications of shadow banking, particularly on productivity, are not well recognized yet. Interestingly, during shadow banking boom periods, there is a declining pattern in total factor productivity (TFP), a problem associated with unsustainable growth and development. In this study, we argue that accounting for a shadow banking (SB)-innovation relationship has important implications on the TFP slowdown and provides new insights into macroeconomic consequences of shadow banking.

The goal of our study is twofold. First, we provide new empirical evidence to understand the role of shadow banking in an innovation-growth relationship. Based on both panel data estimation and time series evidence, we document (i) a negative relationship between shadow banking and innovation outcome, (ii) a weak innovation-growth relationship when shadow banking is present, and (iii) diminished TFP following an expansionary shadow credit shock despite slight increase in output. These results imply shadow credits as an unfavourable funding source for delivering effective innovation to promote productivity.

Our second goal is to develop a theoretical framework to rationalize our empirical findings and further quantitatively evaluate its implications. To this end, we build a Dynamic Stochastic General Equilibrium (DSGE) model, incorporating two different types of capital (knowledge[2] and physical capital) and two sources of finance (traditional and shadow credits). In line with existing literature (e.g., Bianchi et al. (2019)), our model features two-step knowledge accumulation including technology creation and utilization which endogenously determine TFP.

Our model provides two essential departures compared with the literature. First, we introduce a finance-innovation-TFP nexus with shadow banking. In particular, we distinguish the two types of capital and financing. Compared with physical capital, knowledge is riskier in utilization (Anzoategui et al. 2019) with uncertain and unobservable outcome. The information asymmetry leads to an agency problem whereas traditional banks can mitigate it by costly screening and monitoring (see Christiano & Ikeda (2016) among others). On the contrary, shadow banks are less effective to engage in these services due to the nature of off-balance-sheet lending (Ferrante 2018). In addition, as the major form of shadow lending is market-based finance, shadow banks are disadvantageous than traditional banks to acquire private information (Gertler et al. 2016) which, however, is critical to evaluate innovation projects.[3] As a result, shadow banks fail to

[1] Following the definition of FSB (2019), shadow banking is defined as "credit intermediation involving entities and activities outside the regular banking system".

[2] In this paper, we use knowledge (capital) and technology interchangeably. Knowledge can be interpreted as intangible capital such as patents.

[3] Existing literature suggests that traditional banks can develop long-term relationship with firms, through which mitigates the information asymmetry issue (e.g., Levine (2005)).

overcome the agency problem, albeit a more cost-effective intermediation process is provided[4].

Second, we distinguish between financial and real-sided drivers of shadow banking, and investigate their different implications. On one hand, the spur of shadow credits can be owing to a shadow banking shock which affects efficiency of shadow intermediation. This captures a financial innovation or regulation arbitrage motive[5] in which shadow credits lead economic activities. On the other hand, our model also characterizes passive movement of shadow credits driven by real-sided shocks; the presence of shadow credits provides an extra channel for firms to raise funds when business opportunities arise. We label this as a credit demand motive[6]. Accounting for the two motives is important for understanding macroeconomic implications of shadow banking and to explain cross-country differences.

To quantitatively evaluate implications of our model, we conduct structural estimation using Bayesian techniques over standard macroeconomic series and financial flows (i.e., shadow credits). Following impulse response analysis, we identify a trade-off between output and TFP due to the presence of shadow credits. Shadow banking development shifts bank business away from traditional services, exacerbating the agency problem, and decreasing efficiency of technology utilization. Knowledge becomes less productive and firms shift their production choices toward physical capital. Consequently, TFP declines but investment is boosted which leads to slight increase in output. Comparing the two motives of shadow banking development, the SB shock significantly exacerbates the agency problem by crowding out traditional services, leading to larger TFP loss and steeper trade-off; whilst the extra propagation due to the presence of shadow lending only dampens the increase of traditional services, implying smaller TFP loss and milder trade-off.

In light of model mechanisms, we proceed to assess consequences of shadow banking development for the United States (US), China and the Euro area (EA), three major economies over the world which have experienced sharp expansion in shadow banking during the past two decades. We identify the most long-lasting effects of shadow banking for the US which is mainly driven by the financial innovation or regulation arbitrage motive. Consequently, the US shows the steepest trade-off and the largest TFP loss among the three economies. On the contrary, in the EA credit demand motive is relatively more important, thereby leading to modest loss in TFP. In terms of China, it receives the largest boosting effect on output which provides a cushion during the global financial crisis periods. The last finding implies relatively larger benefits of shadow banking for a developing country where capital deepening plays a more significant role than productivity in the economy.

This study provides a crossroad to two strands of growing literature, namely interactions between growth and business cycles, and macroeconomic consequences of shadow banking. For the former area, the bulk of literature analyses TFP dynamics both theoretically and practically with particular focus on the post-crisis period for the US (Anzoategui et al. 2019, Bianchi et al. 2019, Ikeda & Kurozumi 2019, Moran & Queralto

[4]In our framework, lack of engagement in traditional services and free of regulatory costs lead to low SB intermediation cost.

[5]Existing literature suggests that financial innovation and regulation arbitrage are key engines facilitating growth of shadow banking (see Adrian & Jones (2018) among others).

[6]For example, the presence of shadow credits may help relax financial constraint and provide alternative sources of finance.

2018). Within the area of shadow banking, its impacts are examined with particular focus on the demand-side activities, macroeconomic volatility, and government policies (Chang et al. 2019, Ferrante 2018, Fève et al. 2019, Moreira & Savov 2017, Ordonez 2018). To the best of our knowledge, this study is the first one to develop and estimate a shadow banking model under the unified framework with growth and business cycles. In particular, our study is related to Anzoategui et al. (2019) and Bianchi et al. (2019), both of which study how adverse conditions in the traditional financial markets cause productivity slowdown. Departing from traditional finance and recessionary periods, we show how a shadow banking boom leads to a vulnerable economy in the sense of weak productivity; growth gradually becomes unsustainable during the shadow banking boom period. By doing so, we trace the cause of the slow recovery back to normal time, implying a boom-bust link due to shadow banking.

In terms of shadow banking literature, our study relates to Ferrante (2018), Fève et al. (2019), Ordonez (2018), all of which analyse benefits and drawbacks of shadow banking, such as destabilizing business cycles. Moreover, Ferrante (2018) illustrates an SB-productivity relation running through an asset quality channel based on a calibrated model. Focusing on the endogenous technology mechanism, we complement the literature by showing negative implications of shadow banking on productivity in addition to the macroeconomic fluctuation. Furthermore, we distinguish drivers of shadow banking development, assess their quantitative importance, and provide cross-country implications.

This study is also broadly related to the financial development area (Greenwood et al. 2010, Levine 2005, Morganti & Garofalo 2019, Zhu et al. 2020). We show how the effects of shadow banking differ with that of traditional finance both empirically and theoretically. Our investigation is useful to address the puzzle of why financial development may fail to promote innovation-led growth (e.g., Arcand et al. (2015)).

The rest of the paper is organized as follows. Section 2 presents some empirical evidence about macroeconomic impacts of shadow banking. Section 3 presents the DSGE model with endogenous technology creation and extended financial markets. Section 4 presents our estimation results. In Section 5, we make use of the estimated model parameters for steady-state and impulse response analyses. Section 6 interpret shadow banking booming periods for the US, China and EA in light of our model. Section 7 concludes with comments.

2 Empirical Evidence

In this section, we provide empirical evidence to investigate the relationship between shadow banking and productivity, with particular emphasis on the innovation channels. We also provide a brief description about features of shadow banking in the Appendix A.

2.1 Cross-country Evidence

In this subsection, we examine the shadow banking (SB)-innovation relationship and the role of shadow banking in an innovation-driven growth based on a panel of 28 developed and developing economies[7] for the period 2002 to 2017. We start from examining the SB-innovation relationship, followed by innovation-growth relationship with presence of shadow banking. To examine the former relationship, we consider the following specification.

$$Innovation_{it} = \alpha_0 + \alpha_1 SB_{it} + \alpha_2 \mathbf{X}_{it} + \epsilon_{it} \tag{1}$$

where $Innovation_{it}$ denotes growth rate of innovation outcome, measured by either patent applications or journal article counts[8], SB_{it} denotes other financial intermediaries assets to GDP as a measure of shadow banking development, and $\mathbf{X}_{it}$ is a set of control variables including population, GDP per capita, FDI, averaged years of education, regulatory quality, country fixed effects and time dummies[9].

Table 1: Innovation and Shadow Banking

Variables	Patent	Journal
Shadow Banking	**-0.0203*** **	**-0.0184*** **
	(0.0076)	(0.0033)
Population	0.4545	0.1977
	(0.3275)	(0.1398)
GDP Per Capita	-0.0744	0.0150
	(0.1225)	(0.0505)
FDI	0.0016	0.0000
	(0.0010)	(0.0004)
Schooling	-0.0367	-0.0062
	(0.0442)	(0.0178)
Regulatory Quality	0.0363	0.0390
	(0.0769)	(0.0325)
Constant	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes
Observations	386	399
R^2	0.0823	0.1864

Note: ***, **, and * represent 1%, 5%, and 10%. All regressions include time and country fixed effects.

Table 1 shows the result of the SB-innovation relationship. The results present that shadow banking and innovation have a negative relationship, which implies that shadow banking could hinder innovation outcomes.

Next, we examine the role of shadow banking in the innovation-driven growth using both interaction analysis and sub-sample regressions based on the following specifications.

[7]See the list of countries in Table 8 in Appendix A1

[8]The patent application and the number of journal articles have been used to adjust for variation in the quality of innovation.

[9]Detailed descriptions about variables can be found from Table 8 in Appendix A1.

$$Growth_{it} = \beta_0 + \beta_1 Innovation_{it} + \beta_2 SB_{it} + \beta_3 Innovation_{it} * SB_{it} + \beta_4 \mathbf{Z}_{it} + \epsilon_{it} \quad (2)$$

$$Growth_{it} = \beta_0 + \beta_1 Innovation_{it} + \beta_2 SB_{it} + \beta_3 \mathbf{Z}_{it} + \epsilon_{it} \quad (3)$$

where $Growth_{it}$ is either growth rate of GDP per capita or TFP, $\mathbf{Z}_{it}$ is a set of control variables including initial GDP, investment-to-GDP ratio, openness ratio, government spending-to-GDP ratio, averages years of education, FDI, inflation, country fixed effects and time dummies. Following Zhu et al. (2020), we use Equation (2) to conduct an interaction analysis. We test the hypothesis that the relationship between innovation and growth varies in terms of different levels of shadow banking. The unique effect of innovation is captured by all that is multiplied by innovation: $\beta_1 + \beta_3 SB_{it}$. Equation (3) is used to examine the innovation-growth relationship using different sub-groups by country's level of development and the size of shadow banking. This provides an alternative way to examine whether the innovation-growth relationship varies across income groups or the degree of shadow banking advancement attained.

Table 2: Innovation, Shadow Banking and TFP growth

Variables	TFP growth				
	[1] Full	[2] Developed	[3] Developing	[4] High SB	[5] Low SB
Inno	**0.7217***	**-0.3575**	**0.8059**	**-0.0519**	**1.2825***
	(0.387)	(0.394)	(0.671)	(0.436)	(0.735)
SB	-1.8689**				
	(0.728)				
SB*Inno	**-0.1485****				
	(0.074)				
Initial GDP	-7.0962***	-9.4705**	-7.9124***	-6.6848***	-9.4697***
	(1.575)	(3.749)	(2.706)	(1.717)	(3.016)
Inv	0.7938	1.6503	4.7637*	0.6613	5.2794*
	(1.190)	(1.400)	(2.583)	(1.290)	(3.094)
Openness	0.1248	-1.8064	0.4455	-0.5240	1.2181
	(0.973)	(1.246)	(1.555)	(1.145)	(2.131)
Gov	-3.9869**	0.5251	-1.4810	-1.4972	-6.2324*
	(1.719)	(2.404)	(2.639)	(2.250)	(3.621)
Schooling	2.1329	5.8356	0.6971	0.2167	2.2176
	(3.558)	(4.803)	(5.915)	(5.229)	(7.210)
FDI	-0.1109	-0.0897	-0.2757	-0.1466	-0.0311
	(0.123)	(0.095)	(0.365)	(0.117)	(0.403)
Inf	0.0778***	-0.0331	0.0840**	-0.1420***	0.1436***
	(0.029)	(0.075)	(0.042)	(0.053)	(0.046)
Constant	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	356	187	177	237	127
R^2	0.38	0.45	0.32	0.42	0.31

Note: the same as above.

Table 2 shows shadow banking's role in the relationship between TFP growth and innovation. In column [1], the significant negative coefficient of the interaction term suggests that TFP growth is lower for a country with larger shadow banking markets, given the level of innovation; an increase in the size of shadow banks will shift the innovation-TFP relationship downward. In column [4] and [5], we consider the relationship between innovation and TFP growth as the size of shadow banks changes.[10] Innovation is positively related to TFP growth for countries with a smaller size of shadow banks, while the relationship is negative and insignificant for countries with a larger size of shadow banks. Moreover, we find the relationship between innovation and TFP growth for different economic development groups as shown in column [2] and [3] are insignificant but the relationship is more likely to be larger for developing countries.

Table 3: Innovation, Shadow Banking and per capita GDP growth

Variables	per capita GDP growth					
	[1] Full	[2] Developed	[3] Developing	[4] High SB	[5] Low SB	[6] Full
Inno	**1.1591*** **	**-0.5624**	**1.3725** **	**0.7435***	**1.5075** **	
	(0.361)	(0.400)	(0.623)	(0.423)	(0.695)	
SB	-2.2612***					0.0570
	(0.677)					(0.158)
SB*Inno	**-0.1748** **					
	(0.070)					
TFPg						0.7137***
						(0.046)
SB*TFPg						**-0.0279** **
						(0.013)
Initial GDP	-8.0008***	-21.1830***	-7.8706***	-7.2261***	-11.2829***	-4.8542***
	(1.460)	(4.037)	(2.407)	(1.683)	(2.844)	(1.190)
Inv	2.3339**	3.9458***	5.2107**	1.7181	2.5368	4.1698***
	(1.167)	(1.481)	(2.444)	(1.408)	(2.898)	(0.897)
Openness	1.0685	2.4552*	-0.4310	3.2042***	-1.1023	1.1512
	(0.924)	(1.321)	(1.481)	(1.197)	(1.870)	(0.776)
Gov	-10.2376***	-10.5579***	-4.3637	-11.0454***	-10.2372***	-7.6390***
	(1.692)	(2.597)	(2.650)	(2.269)	(3.489)	(1.328)
Schooling	3.5081	0.5950	5.0761	11.9826**	12.9828**	4.3297*
	(3.463)	(5.239)	(5.350)	(5.723)	(6.402)	(2.481)
FDI	0.1875	0.0356	0.3848	-0.0604	1.1001***	0.2109**
	(0.127)	(0.103)	(0.331)	(0.132)	(0.376)	(0.097)
Inf	-0.0066	-0.0394	0.0004	-0.2004***	0.0206	-0.0297
	(0.026)	(0.080)	(0.039)	(0.052)	(0.043)	(0.020)
Constant	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	399	192	216	262	146	377
R^2	0.58	0.71	0.45	0.61	0.48	0.77

Note: the same as above.

[10]The split is based on the sample mean of SB_t

Table 3 presents how shadow banking affects the innovation-growth relationship. The significant and negative coefficient of the interaction terms in column [1] and [6] reflect an important role of shadow banking in influencing the innovation-growth relationship. The slopes of the regression lines between innovation and GDP growth vary depending on the different size of shadow banking markets. Countries with a larger size of shadow banks may hinder innovation, which leads to lower GDP growth. In column [4] and [5], both coefficients of innovation are positive and significant, but countries with a smaller size of shadow banks are found to have a larger magnitude. Innovation is significantly positively related to GDP growth in developing countries while the relationship is negative in developed countries.

In summary, cross-country evidence delivers two important implications. First, unlike traditional finance (De la Fuente & Marin 1996, Zhu et al. 2020) which can boost innovation outcomes by selecting the most promising projects and scrutinizing their performance (Levine 2005), shadow banking development does not appear to achieve the same target. Second, the presence of shadow banking weakens the innovation-growth relationship. Both of them indicate a possibility that shadow banking may encourage speculation, resulting in over-investment and a misallocation of resources, which we find similar cases during the 2008–09 global financial crisis (Law & Singh 2014). Therefore, this finding suggests that more shadow credits are not always favourable and that it can lead to a detriment of innovation performance.

2.2 Time series Evidence: The US and China

Although analyses in subsection 2.1 establishes the SB-innovation-growth relationship in a general term, yet speciality of shadow banking system is not explored. The typical shadow banking system in developed countries is market-based with the US as an representative. An essential feature is heavy involvement of securitization in credit origination. We also consider a bank-like system such as the Chinese one which features dominant roles of commercial banks (Ehlers et al. 2018). It is possible that macroeconomic implication of shadow banking, especially on productivity, might be conditional on structures of shadow banking system.

To investigate this possibility, we estimate and compare the impact of a SB shock on GDP, TFP and R&D based on the US and Chinese quarterly time-series data. Specifically, we estimate a small Bayesian SVAR model for both US and China. The data details are given in the Appendix A2. We use a typical Choleski decomposition assuming that a shock in GDP affects contemporaneously all the variables, while a TFP shock affects only the proxies of shadow banking and innovation. Finally, we insert the shadow banking variable as third variable assuming that affects innovation contemporaneously. Overall, the ordering does not seem to play any role as the results are robust to several alternative schemes. Figure 1 shows the impulse responses from a 1% increase in the shadow banking for the US assuming a Minnesota prior. The output responds with a small but statistically significant increase for about four quarters. Interestingly, the TFP is significantly reduced. Figure 2 presents the corresponding impulse responses for the case of China. Despite the different proxies for the measure of shadow banking, the results are qualitatively and quantitative very similar; the positive shock in shadow banking causes a short-run and quantitatively small increase of output and at the same time a decrease of TFP.

Figure 1: Shadow Banking Shock: the US

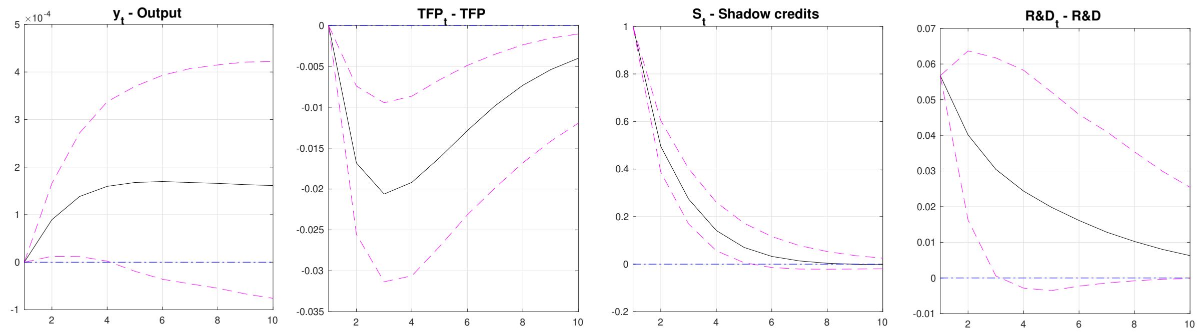
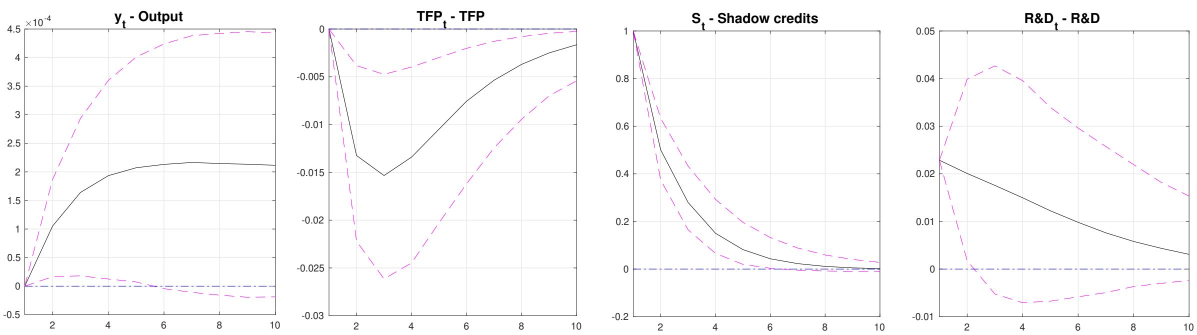


Figure 2: Shadow Banking Shock: China



The macro evidence based on the above SVAR, alongside with the cross-country evidence, provides further empirical support to the main mechanism of our model. Particularly, consistent with the model prediction, the presence of shadow banking weakens the effects of innovation, through which slowdowns TFP and renders growth to be less innovation-driven.

3 The Model

We expand Smets & Wouters (2007)'s model, incorporating a traditional bank, a shadow bank and two-stage technology innovation in a similar way to Bianchi et al. (2019). There are several options in modelling financing of innovation. One typical choice is a financial constraint framework such as Jermann & Quadrini (2012) in which financial sectors are exogenous. Instead of following this stream, we choose a shadow banking framework, e.g., Gertler & Karadi (2011), which enables us to model banking behavior endogenously. Particularly, we build a finance-innovation nexus with shadow banking. Compared with physical capital, knowledge capital is riskier but traditional banks can reduce the risks by costly screening. Such traditional services are not provided by shadow banks though their intermediation process is more cost-effective.

Shadow banking development shifts banks business away from traditional finance which is more important for delivering successful innovation outcome. Such a shift undermines innovation quality, decreases efficiency of technology utilization, and makes knowledge capital less attractive in production. Consequently, firms shift their production choices toward physical capital. The reallocation of credits and capital leads an economy away from innovation-driven growth and results in deviated movement between output and TFP.

3.1 Final Goods Producer

There are a continuum of monopolistic competitive final goods producers i, each of which is like a retailer, who buys intermediate goods Y_{it}^m and transfers them into differentiated final goods Y_{it} in a linear way. 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.

The final goods producer maximizes expected profit from which we obtain the optimally chosen reset price:

$$E_t \sum_{l=0}^{\infty} \epsilon_p^l \Lambda_{t,t+l} [\frac{P_t^*(\pi_{t-1}^{t+l-1})^{\iota_p}\pi^{1-\iota_p}}{P_{t+l}} - \varepsilon_t^s MC_{t+l}^f] Y_{i,t+l} = 0 \tag{4}$$

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

3.2 Intermediate Goods Producer

The representative firm, indexed by j, produces the intermediate goods Y_{jt}^m using labour H_{jt}, capital services $u_t K_{jt}$ and effective technology or knowledge $\tilde{A}_{jt}$ (e.g., patents). Following Bianchi et al. (2019), we interpret the use of knowledge capital in production as utilization or adoption of technology. The production function is as the follows.

$$Y_t^m = \varepsilon_t^a \tilde{A}_t^{\zeta} (u_t K_t)^{\alpha} (H_t)^{1-\alpha-\zeta} \tag{5}$$

where $\tilde{A}_t = \phi_t A_t$ is the product of raw technology A_t and utilization efficiency of technology ϕ_t, K_t is physical capital, u_t is the utilization rate of the physical capital and ε_t^a is an exogenous TFP shock following an AR(1) process.

Compared with physical capital, knowledge capital is riskier in utilization (Anzoategui et al. 2019) with uncertain and unobservable outcome. We incorporate a binomial distribution to capture utilization outcomes, in a similar spirit to Ferrante (2018). With probability pr_t the project succeeds and a high realization θ^G is achieved; otherwise the project fails and obtain a low realization θ^B.

$$\text{project productivity} = \begin{cases} \theta^G & \text{w.p. } pr_t \\ \theta^B & \text{w.p. } 1 - pr_t \end{cases} \tag{6}$$

Although the uncertain outcome introduces an agency problem, banks can exert efforts to increase successful probability by screening and selecting project with better potential. Following Christiano & Ikeda (2016) and Ferrante (2018), we assume that the successful probability depends on bank's efforts in a linear way $pr_t = \xi_t$. Efficiency of technology utilization ϕ_t which also reflects project quality can be derived by taking weighted average of project outcomes.

$$\phi_t = \theta^G pr_t + \theta^B(1 - pr_t) = \theta^B + (\theta^G - \theta^B)\xi_t \tag{7}$$

Given $\theta^G > \theta^B$, The last equality of equation (7) suggests a positive relationship between bank efforts, project quality and utilization efficiency.

At the end of period t, an intermediate goods producer acquires technology and capital for use in production in the subsequent period. After production in period t+1, the firm has the option of selling the capital on the open market.

The firm j maximize expected profits

$$\max_{A_t, K_t, H_t, u_t} E_t \sum_{l=0}^{\infty} \Lambda_{t,t+l} \Pi^m_{t+l}$$

$$\Pi^m_t = P^m_t Y^m_t + (Q^k_t - \delta^k(u_t))K_t - R^b_t Q^k_{t-1} K_t + (Q^a_t - \delta^a)A_t - R^b_t Q^a_{t-1} A_t - W_t H_t \tag{8}$$

where P^m_t is the price of the intermediate good, Q^k_t and Q^a_t are prices of the physical capital and the knowledge capital respectively, δ^k_t and δ^a depreciation rates of the two types of capital, R^b_t is the lending rate and W_t the wage. Profit maximization yields

$$E_t \Lambda_{t,t+1} R^b_{t+1} = \frac{E_t \Lambda_{t,t+1}[\zeta P^m_{t+1} Y^m_{t+1}/A_{t+1} + (Q^a_{t+1} - \delta^a)]\phi_{t+1}}{Q^a_t} \tag{9}$$

$$E_t \Lambda_{t,t+1} R^b_{t+1} = \frac{E_t \Lambda_{t,t+1} \alpha P^m_{t+1} Y^m_{t+1}/K_{t+1} + (Q^k_{t+1} - \delta^k(u_t))}{Q^k_t} \tag{10}$$

$$W_t = (1 - \zeta - \alpha) P^m_t Y^m_t / H_t \tag{11}$$

$$\delta^{k'}(u_t) = \alpha P^m_t Y^m_t / u_t \tag{12}$$

Equation (9) implies that the aggregate demand positively affects marginal return of technology, inducing a procyclical force on the utilization of technology. Such a mechanism is consistent with Anzoategui et al. (2019)

and Bianchi et al. (2019). In addition to the aggregate demand channel, we introduce another mechanism through technology quality ϕ_t. Combining (9) and (10) yields the optimal choice between knowledge and physical capital.

$$\frac{A_t}{K_t} = \frac{\zeta}{\alpha} \frac{R_t^b Q_{t-1}^k - (Q_t^k - \delta_k)}{R_t^b Q_{t-1}^a - (Q_t^a - \delta_a)\phi_t} \tag{13}$$

Equation (13) suggests a negative relationship between the knowledge-to-capital ratio $\frac{A_t}{K_t}$ and technology quality. A decrease in technology quality would discourage firms from adopting technology, as it becomes less profitable, and hence leading to a less technology-intensive production.

3.3 Traditional Bank

There are a continuum of traditional banks receiving deposit D_t from the household and originating loans to either intermediate goods producers, denoted by L_t, or shadow banks, denoted by S_t^a. The budget constraint for the bank verifies

$$D_t = L_t + S_t^a \tag{14}$$

We incorporate three differences between traditional banking and shadow banking as well-documented in the literature. First, the traditional bank provides financial services such as screening to ensure project quality alongside the intermediation process (Ferrante 2018), whereas shadow loans does not.[11] Secondly, traditional loans are subject to costly banking regulations, whereas shadow loans are not (Ordonez 2018). Thirdly, shadow lending often involve liquidity transformation from short-term to long-term assets, which can be modelled as a portfolio adjustment cost (Fève et al. 2019).

The representative traditional banks maximize expected profits .

$$\max_{L_t, S_t^a, \xi_t} E_t \sum_{l=0}^{\infty} \Lambda_{t,t+l} \Pi_{t+l}^b$$

$$\Pi_t^b = [R_t^b(\xi_t) L_{t-1} + R_t^s S_{t-1}^a - \underbrace{\frac{\gamma_1}{2}(\frac{S_t^a}{L_t} - \theta) S_t^a}_{\text{liquidity transformation cost}} - \underbrace{\frac{\gamma_2}{2} \frac{L_t^2}{(1+g^y)^t}}_{\text{regulation cost}} - \underbrace{\frac{\gamma_3}{2} \xi_t^2 (1+g^y)^t}_{\text{traditional service cost}} - R_{t-1} D_{t-1}] \tag{15}$$

where R_t^s is the shadow lending rate, θ the steady state share of shadow assets and ξ_t reflects the intensity of bank efforts in screening. γ_1, γ_2 and γ_3 are parameters governing magnitude of three types of financial costs respectively, including liquidity transformation cost, regulation cost and traditional service cost. Later we also consider to vary γ_3 to capture a traditional banking shock. We include a scaling factor $(1+g^y)^t$ in the regulation and the traditional service costs to ensure balanced growth path. Profit maximization yields

$$E_t \Lambda_{t,t+1}(R_{t+1}^b - R_t) = \gamma_2 \frac{L_t}{(1+g^y)^t} - \gamma_1 (\frac{S_t^a}{L_t} - \theta)(\frac{S_t^a}{L_t})^2 \tag{16}$$

[11] Ferrante (2018) shows that shadow banks are less likely to screen project quality compared with traditional banks.

$$R_t^{b'} L_{t-1} = \gamma_3 \xi_t (1+g^y)^t \tag{17}$$

$$E_t \Lambda_{t,t+1}(R^s_{t+1} - R_t) = \gamma_1 (\frac{S_t^a}{L_t} - \theta)(\frac{S_t^a}{L_t}) \tag{18}$$

Equation (17) suggest a positive relationship between bank efforts and amount of traditional loan. This is consistent with the fact that banks tend to be cautious when more assets are held on the balance sheet. Consequently, the bank has more incentives to ensure project quality.

3.4 Shadow Bank

The representative shadow bank purchases off-balance-sheet assets S_t^a from traditional banks using funds raised by issuing shadow credits S_t to intermediate goods producers. One can view the shadow bank in our framework as a special purpose vehicle (SPV) which facilitates off-balance-sheet lending.[12]

The effective shadow credits is expressed as follows.

$$S_t = (1 - \varepsilon_t^s) S_t^a \tag{19}$$

Following Fève et al. (2019), we include a stochastic management cost or a shadow banking shock ε_t^s to capture efficiency of the shadow banking intermediation. ε_t^s follows an AR(1) process: $ln\varepsilon_t^s = (1-\rho_s)\varepsilon^s + \rho_s ln\varepsilon_{t-1}^s + \eta_t^s$ and η_t^s follows i.i.d $N(0, \sigma_S^2)$.

The representative shadow bank maximizes expected profits

$$\max_{S_t} E_t \sum_{l=0}^{\infty} \Lambda_{t,t+l} \Pi_{t+l}^s$$

$$\Pi_t^s = R_t^b S_{t-1} - R_t^s S_{t-1}^a \tag{20}$$

Profit maximization yields

$$E_t \Lambda_{t,t+1} R_{t+1}^b = E_t \Lambda_{t,t+1} R_{t+1}^s / (1 - \varepsilon_t^s) \tag{21}$$

Equation (17), (18), (19) and (21) together suggest how the shadow banking development may affect technology quality. A decrease in shadow banking cost ε_t^s would increase efficiency of shadow intermediation (see (19)) and hence stimulate shadow credits. Based on (21), shadow assets return R_t^s would increase in order to hold the equilibrium condition. Following the higher shadow return, traditional banks would shift away from traditional business to shadow business, suggested by (18). As a result, L_t could be crowded out and banks pay less attentions to screen project quality (see (17)).

[12] In the case of China, the shadow bank can be viewed as trust and wealth management companies.

3.5 Household

The representative household derives utility from consumption and leisure, consumes and saves money with the financial intermediaries. Households supply labour measured in hours H_t, used for the production of intermediate goods.

The household faces the following problem:

$$\max E_t \sum_{l=0}^{\infty} \beta^l \varepsilon_{t+l}^p [log(C_{t+l} - bC_{t+l-1}) - \frac{\psi(H_{t+l})^{1+\eta}}{1+\eta}] \tag{22}$$

subject to the budget constraint

$$P_t C_t + D_t = R_{t-1} D_{t-1} + W_t H_t + \Pi_t^f \tag{23}$$

where C_t denotes consumption, D_t saving, R_t interest rate, and Π_t^f profits from the ownership of both non-financial and financial firms, b measures degree of external habits in consumption and η measures the elasticity of labour supply with respect to wage. ε_t^p is a preference shock following an AR(1) process: $ln\varepsilon_t^p = \rho_p ln\varepsilon_{t-1}^p + \eta_t^p$ and η_t^p follows an i.i.d $N(0, \sigma_P^2)$.

3.6 Knowledge and Physical Capital Producers

Competitive capital producers buy capital from intermediate goods producers, then repair depreciated capital and build new capital. They then sell both the new and re-furbished capital. The physical capital producer chooses physical investment I_t to maximize expected profits

$$\max_{I_t} E_t \sum_{l=0}^{\infty} \Lambda_{t,t+l} \Pi_{t+l}^i$$

$$\Pi_t^i = Q_t^k I_t - \varepsilon_t^i([1 + s_k(\frac{I_t}{(1+g^y)I_{t-1}})]I_t \tag{24}$$

where $s_k()$ is an adjustment cost function with $s_k(1) = s_k'(1) = 0$ and $s_k"(1) = 0$. ε_t^i is an investment efficiency shock following an AR(1) process. Profit maximization yields

$$\frac{Q_t^k}{\varepsilon_t^i} = 1 + s_k(\frac{I_t}{(1+g^y)I_{t-1}}) + \frac{I_t}{(1+g^y)I_{t-1}} s_k'(\frac{I_t}{(1+g^y)I_{t-1}}) - E_t\Lambda_{t,t+1}[\frac{I_{t+1}}{(1+g^y)I_t}]^2 s_k'(\frac{I_{t+1}}{(1+g^y)I_t}) \tag{25}$$

Knowledge can be interpreted as intangible capital and evolves à la Bianchi et al. (2019) and Ikeda & Kurozumi (2019).[13] Competitive knowledge producers or innovators buy technology from intermediate goods producers, then depreciate obsoleted technology and develop new knowledge. They then sell both the new

[13] We abstract from a sophisticated technology creation process. The reason is twofold. First, existing literature suggests that the technology utilization substantially explains productivity fluctuation. Second, we later show that empirical performance of our model is as good as those with an explicit technology creation sector (e.g., Anzoategui et al. (2019)).

and existing technology. The knowledge producer chooses knowledge investment N_t to maximize expected profits

$$\max_{N_t} E_t \sum_{l=0}^{\infty} \Lambda_{t,t+l} \Pi^n_{t+l}$$

$$\Pi^n_t = Q^a_t N_t - \varepsilon^n_t([1 + s_a(\frac{N_t}{(1+g^y)N_{t-1}})]N_t \quad (26)$$

where $s_a()$ is an increasing and convex adjustment cost function similar to $s_k()$. ε^n_t is an knowledge efficiency shock in the spirit of Anzoategui et al. (2019) following an AR(1) process. Profit maximization yields

$$\frac{Q^a_t}{\varepsilon^n_t} = 1 + s_a(\frac{N_t}{(1+g^y)N_{t-1}}) + \frac{N_t}{(1+g^y)N_{t-1}} s'_a(\frac{N_t}{(1+g^y)N_{t-1}}) - E_t \Lambda_{t,t+1}[\frac{N_{t+1}}{(1+g^y)N_t}]^2 s'_a(\frac{N_{t+1}}{(1+g^y)N_t}) \quad (27)$$

3.7 Equilibrium

We consider two definitions of TFP. The first is the Solow residual $\varepsilon^a_t \tilde{A}^\zeta_t u^\alpha_t$ containing three components: the first ε^a_t is an exogenous shock, the second $\tilde{A}^\zeta_t = (\phi_t A_t)^\zeta$ effective technology and the third u^α_t utilization of capital. Another definition we can consider is utilization-adjusted TFP $\varepsilon^a_t \tilde{A}^\zeta_t$ which excludes capital utilization.

The law of motions for physical capital and knowledge capital (Lopez & Olivella 2018, Mitra 2019) are

$$K_{t+1} = (1-\delta^k)K_t + \varepsilon^i_t[1 - S_k(\frac{I_t}{(1+g^y)I_{t-1}})]I_t \quad (28)$$

$$A_{t+1} = (1-\delta^a)\tilde{A}_t + \varepsilon^n_t[1 - S_a(\frac{N_t}{(1+g^y)N_{t-1}})]N_t \quad (29)$$

The resource constraint

$$Y_t = C_t + \varepsilon^i_t[1 + s_k(\frac{I_t}{(1+g^y)I_{t-1}})]I_t + \varepsilon^n_t[1 + s_a(\frac{N_t}{(1+g^y)N_{t-1}})]N_t + G_t \quad (30)$$

$$GDP_t = C_t + \varepsilon^i_t I_t + \varepsilon^n_t N_t + G_t \quad (31)$$

G_t is a government spending shock following AR(1) process: $ln\varepsilon^g_t = (1-\rho_g)g + \rho_g ln\varepsilon^g_{t-1} + \eta^g_t$ and η^g_t follows i.i.d $N(0, \sigma^2_G)$.[14]

The financial market clears (in real terms): $K_t + A_t = L_t + S_t$. The policy rate is given by the Taylor rule

$$R_t = R^{\rho_r}_{t-1}[R(\frac{\pi_t}{\overline{\pi}})^{\rho_\pi}(\frac{Y_t}{Y_{t-1}})^{\rho_y}]^{1-\rho_r}\varepsilon^m_t \quad (32)$$

where ε^m_t is a monetary policy shock following an AR(1) process.

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

4 Estimation

4.1 Data

Our benchmark estimation is based on the US economy over the sample period from 1992Q1 to 2019Q4.[15] It includes a shadow banking boom period in which we are particularly interested. We use eight macroeconomic variables as observables for estimation: GDP growth, consumption growth, investment growth, R&D spending growth, hours worked, GDP deflator inflation, the policy interest rate and shadow banking credits growth. Our definitions of shadow banks are consistent with the literature, e.g., Meeks et al. (2017) and Fève et al. (2019), including security brokers and dealers and issuers of asset-backed securities. We also consider a broad measure of shadow credits for robustness check.[16]

We transform the data as follows. GDP, consumption, investment, R&D spending and shadow credits growth are expressed as real per capita, logarithmic first difference; labour hours are measured as per capita employment times hours worked. Following Christiano et al. (2014), all variables are demeaned separately.

4.2 Calibration

In this section we present our calibration of the structural parameters. Calibrated parameters are well-identified in the literature, for example Smets & Wouters (2007), Bianchi et al. (2019), Ferrante (2018), and kept fixed during estimation.

Table 4: Calibrated parameters

Parameters	Description	Value
α	physical capital share	0.35
ζ	knowledge share	0.1
β	discount factor	0.995
θ^G	high idiosyncratic realization	1.003
θ^B	low idiosyncratic realization	0.905
δ^k	capital depreciation	0.02
δ^a	knowledge depreciation	0.0375
λ^m	intermediate good mark-up	1.1
Steady-State		
$1+g^y$	ss per capita GDP growth	1.005
G/Y	ss exo. demand share	0.15
H	ss labour hour worked	1/3
θ	ss shadow credit share	0.25
ε^s	ss shadow credit cost	0.026

Table 4 presents calibrated parameters. Capital share α is set as 0.35, in line with other US-based DSGE studies. Knowledge share ζ is calibrated as 0.1, which is the mean level as found in the literature (Lopez

[15] We observe large swing of ABS data at the end of the 1980s. In order to avoid potential outlier issues, we do not include data before 1992 in our estimation.

[16] For more details of the observable variables used in our estimation, please refer to Appendix A2.

& Olivella 2018, Mitra 2019). The discount factor β is calibrated as 0.995 to match quarterly interest rate. The physical capital depreciation rate δ^k is calibrated as 0.02, consistent with existing literature. Following Kung & Schmid (2015) and Jinnai (2015), we choose the knowledge capital depreciation rate δ^a as 0.0375. The combination of α, ζ, δ^k and δ^a delivers knowledge investment-to-GDP (N/Y) ratio as 5% and knowledge investment share (N/(N+I)) as 27%, consistent with empirical evidence (Aghion et al. 2010, Lopez & Olivella 2018).[17]

In terms of the idiosyncratic realization parameters, our calibration strategy is similar to Ferrante (2018). That is, we choose θ^G and θ^B so as to match 3% loan default rate and normalized steady state technology quality ϕ_t to unity. This leads to 1.003 and 0.905 for the two idiosyncratic realization parameters. The intermediate good mark-up is set as 1.1, in line with existing literature.

The lower part of Table 4 shows the calibrated value of steady-state parameters. The average per capita GDP growth rate is about 0.5%, implying g^y as 0.005. The exogenous demand-to-output ratio is calibrated as 15%. The dis-utility parameter ψ is set to match 1/3 hour worked. Finally, we follow Fève et al. (2019) to calibrate steady state shadow credit share θ as 0.25 and shadow intermediation cost ϵ^s as 0.026.

4.3 Bayesian Estimation

The choice of prior distributions is similar to those used in Smets & Wouters (2007), Bianchi et al. (2019), Fève et al. (2019). Our estimation results (see Table 5) are similar to those in the literature. Particularly, the adjustment cost parameter is higher for knowledge than physical capital, capturing more rigid movement of R&D than physical investment in data. This result is consistent with Bianchi et al. (2019). In terms of the shock processes, the shadow banking shock is both volatile and persistent, implying potentially large and long-lasting effects on the economy. The AR(1) parameter of exogenous TFP shock is less persistent than in the literature, reflecting that persistent movement of TFP is captured by the endogenous components. Such a finding is consistent with Anzoategui et al. (2019).

Before analysing the macroeconomic effects of shadow banking, we use model-smoothed TFP and components to compare our results with data and existing literature. The comparisons serve as a first check of the empirical performance of the model.

Figure 3a and 3b compare model-implied Solow residual and utilization-adjusted TFP with data.[18] From visual inspection, the two smoothed series match TFP data well. The correlation coefficients is 0.85 between the two Solow residuals and 0.82 between the two utilization-adjusted TFP. Particularly, over the 2000-2007 period when the shadow banking development reached its peak, the two smoothed series almost perfectly match the data. We also compare our utilization-adjusted TFP with that estimated from Anzoategui et al. (2019). The two series (blue and green lines in Figure 3b) basically comove while our series is closer to the

[17] The knowledge in our framework is corresponding to intangible investment provided by National Income and Product Accounts (NIPA). Lopez & Olivella (2018) find the N/Y ratio as 5% and the N share as 29%. Aghion et al. (2010) suggest that the N share is between 11% to 47%.

[18] Note that labour productivity corresponds exactly to the data.

Table 5: Prior and posterior distribution of structural parameters and shock processes

Parameters	Prior			Posterior
	Distribution	Mean	St.Dev.	Mean [5, 95]
b habit	Beta	0.7	0.1	0.80 [0.72, 0.87]
η Inverse labour elasticity	Gamma	2	0.75	1.61 [0.68, 2.50]
γ_1 bank portfolio adj. cost	Gamma	0.2	0.1	0.06 [0.02, 0.11]
s_k" inv. adj. cost	Gamma	4	1	7.56 [5.72, 9.44]
s_a" tech. adj. cost	Gamma	4	1	8.04 [6.21, 9.90]
δ_u" capital util. elast.	Gamma	4	1	5.16 [3.57, 6.67]
ϵ_p calvo price	Beta	0.75	0.1	0.93 [0.92, 0.96]
ι_p price indexation	Beta	0.5	0.15	0.28 [0.06, 0.53]
ρ_r taylor smoothing	Beta	0.7	0.15	0.87 [0.85, 0.91]
ρ_π taylor parameter	Normal	1.5	0.25	1.91 [1.61, 2.22]
ρ_y taylor parameter	Normal	0.3	0.1	0.38 [0.25, 0.51]
ρ_a per. of exo. TFP	Beta	0.5	0.2	0.95 [0.91, 0.98]
ρ_d per. of preference	Beta	0.5	0.2	0.79 [0.68, 0.88]
ρ_s per. of shadow credit	Beta	0.5	0.2	0.98 [0.97, 0.99]
ρ_i per. of inv. efficiency	Beta	0.5	0.2	0.89 [0.83, 0.94]
ρ_n per. of tech. efficiency	Beta	0.5	0.2	0.96 [0.93, 0.98]
ρ_p per. of price mark-up	Beta	0.5	0.2	0.48 [0.12, 0.76]
ρ_m per. of mon. policy	Beta	0.5	0.2	0.49 [0.40, 0.59]
ρ_g per. of exo. demand	Beta	0.5	0.2	0.94 [0.89, 0.98]
σ_a std. of exo. TFP	Inv_Gamma	0.1	2	0.46 [0.41, 0.51]
σ_d std. of preference	Inv_Gamma	0.1	2	0.72 [0.21, 1.18]
σ_s std. of shadow credit	Inv_Gamma	0.1	2	1.62 [0.99, 2.25]
σ_i std. of inv. efficiency	Inv_Gamma	0.1	2	0.19 [0.15, 0.23]
σ_n std. of tech. efficiency	Inv_Gamma	0.1	2	0.27 [0.23, 0.33]
σ_p std. of price mark-up	Inv_Gamma	0.1	2	0.09 [0.07, 0.12]
σ_m std. of mon. policy	Inv_Gamma	0.1	2	0.08 [0.07, 0.09]
σ_g std. of exo. demand	Inv_Gamma	0.1	2	0.39 [0.35, 0.44]

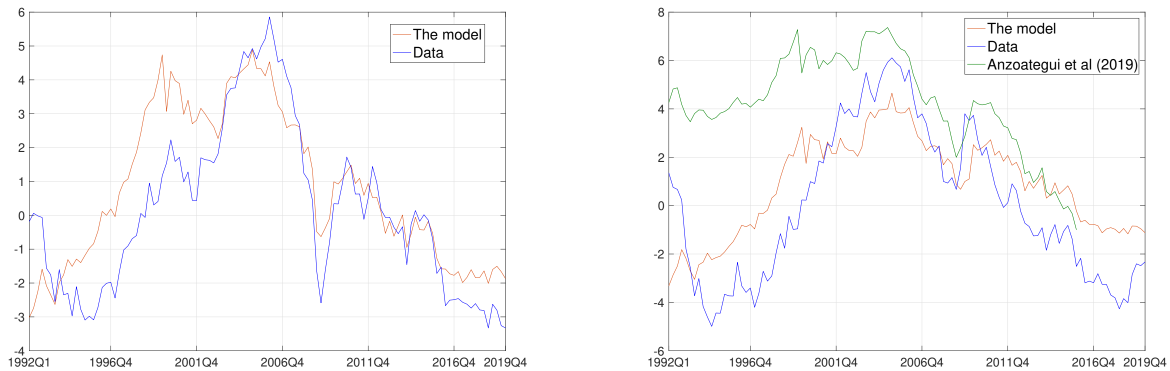
Note: 90% HPD in bracket.

data, especially in the 1990s period.

Next we compare our model-implied components of TFP with existing literature based on smoothed variables. Figure 4a and 4b suggests that our technology and adoption are comparable to those generated from Anzoategui et al. (2019). It is evident that a comovement pattern exists between our technology and that from Anzoategui et al. (2019) with correlation as 0.88. Similarly, we also find high correlation (0.84) between the two adoption variables. Interestingly, accounting for shadow lending renders our adoption moving opposite to their counterpart around the Great Recession period. It is likely that shadow banking had prolonged effects on technology utilization which are captured by our estimation. One may note that their model-implied technology and adoption are above our counterparts. This is probably due to the reason that their TFP is estimated tilted upward and hence components of TFP could also shift up. Furthermore,

Figure 3: Productivity comparison

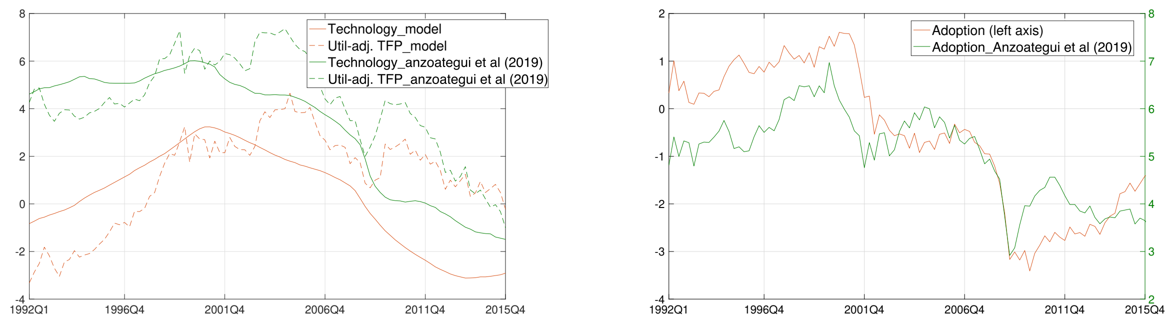
(a) Solow residual (b) Utilization-adjusted TFP



Note: Data about Solow residual and utilization-adjusted TFP are from http://www.frbsf.org/economic-research/total-factor-productivity-tfp/; see Fernald (2014) for details).

Figure 4: Productivity-related variable comparison

(a) Technology (b) Adoption/Utilization efficiency



Note: Smoothed variables are from the model estimated using data as described in Section 4.1 and Appendix A2.

we find that the model-implied endogenous component of TFP[19] and technology growth are consistent with Bianchi et al. (2019).

5 Results

5.1 Steady State Analysis

Given estimated and calibrated parameters, in Table 6 we report the implied steady-state values of some key variables for the benchmark economy together with two extended cases for comparison; one is the case with more efficient shadow banking system (SB case) and the other is the one with more efficient traditional

[19]The endogenous component of TFP is defined as utilization-adjusted TFP excluding the TFP shock.

banking system (TB case). In each case, we increase 10% of debt-to-output ratio by reducing either the shadow intermediation cost parameter ε^s (SB case) or the service cost γ_3 (TB case). We use the former to show effects of SB development while the latter shows effects of TB development.

Table 6: Steady-State Values

Variables	Benchmark	SB case	SB/Benchmark	TB case	TB/Benchmark
y output	1.0322	1.0614	2.83%	1.1235	8.85%
tfp TFP	1.0233	0.9987	-2.42%	1.0914	6.66%
a technology	1.2593	1.0485	-16.74%	2.0558	63.25%
k capital	5.7606	6.4784	12.46%	6.3504	10.24%

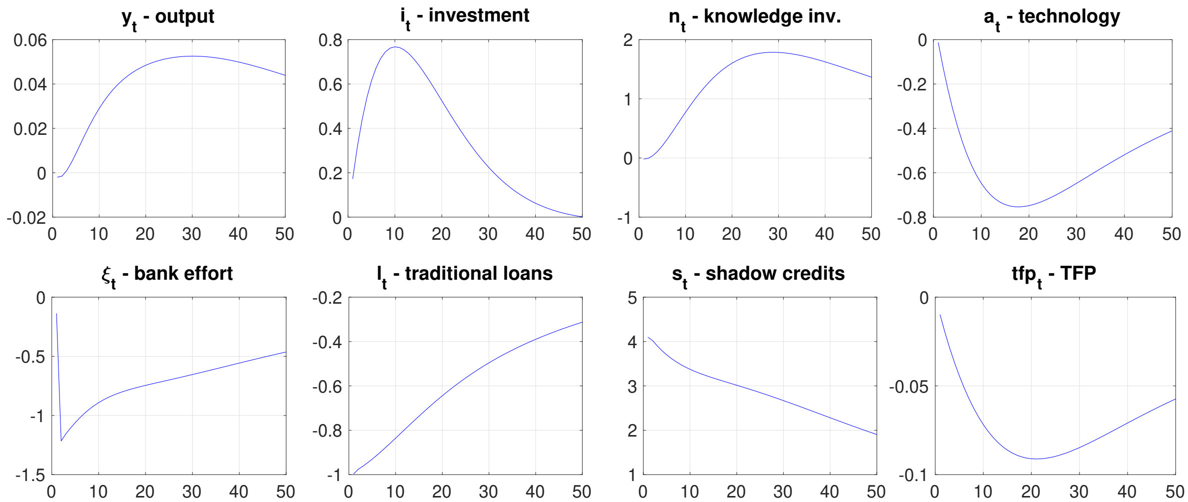
Table 6 shows significantly different impacts of SB development and TB development on the economy. Although increasing efficiency in both financial sectors promote output and capital accumulation, only TB development stimulates technology and TFP. As predicted form our theory, the expansionary effects of SB development come at the cost of technology and TFP, leading to a macroeconomic trade-off. Moreover, we find that the impacts of SB development on output is significantly smaller than that from TB development. This finding is in line with empirical evidence (Morganti & Garofalo 2019). We further explain this quantitative difference as the consequence of opposite movement between TFP and capital; a fall of TFP dampens the growth-enhancing effect through capital accumulation. On the other hand, the impact on physical capital is larger for the SB development than the TB development. This finding is consistent with existing literature in that shadow banks provide a more efficient and cheaper source of finance for physical capital accumulation (Gertler et al. 2016).

5.2 Impulse Response Analysis

In this section, we use impulse response analysis to show the (1) transmission mechanisms of the shadow banking shock and (2) implications of shadow lending on propagation of driving shocks in the business cycles. The analysis provides a foundation for analysing shadow banking booming periods through the lens of our model in the Section 6.

Figure 5 displays impulse response functions to an expansionary SB shock (reduction of shadow intermediation cost). Following the increased efficiency in the shadow intermediation, the shadow business becomes more profitable, encouraging TBs to shift away from traditional lending. Given the positive relationship between amount of traditional loans and services, TBs will be less careful about their asset portfolio and hence screening intensity falls. Such an effect is transmitted to the production sector, resulting in low quality of technology and declined efficiency in the utilization which further pushes down TFP. On the other hand, intermediate producers will use more capital in production due to the negative relationship between technology quality and the knowledge-to-capital ratio A_t/K_t. Consequently, high demand of physical capital will stimulate investment. Overall, output increases slightly since the positive effect through capital accumulation

Figure 5: Shadow Banking (SB) Shock



Note: This figure shows impulse-response functions to a one standard deviation expansionary-SB shock.

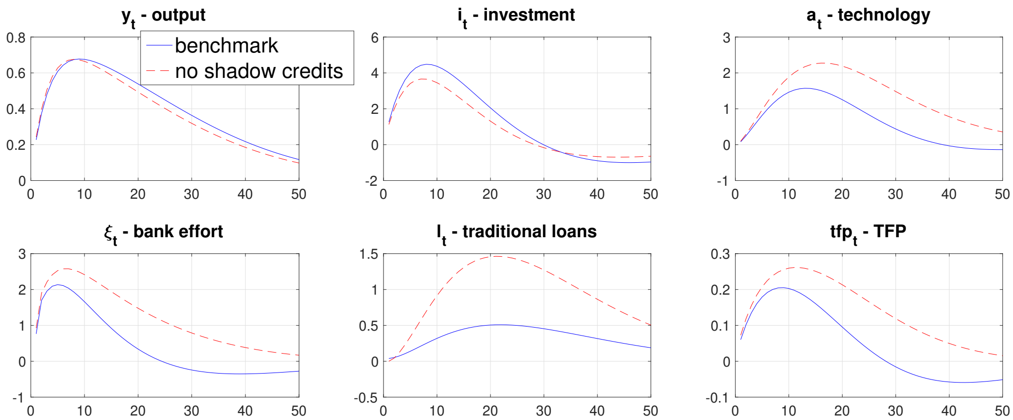
overweights the negative effect through TFP. This is not surprising as capital accounts for larger share than technology in production.

Impulse responses to the SB shock deliver important implications consistent with our empirical evidence and other literature. First, the SB shock stimulates knowledge investment, which is depicted by Figure 1 and 2. Second, the opposite movement between knowledge investment and TFP implies decreased efficiency of innovation, which is found during the shadow banking booming period (Anzoategui et al. 2019).[20] Third, we find that the negative response of TFP is driven by delayed utilization of technology. This finding is consistent with Bianchi et al. (2019) who show that technology utilization is the major channel affecting TFP in the business cycle frequency.

Next, we investigate implications of shadow lending on propagation of other shocks. We focus on investment efficiency shock (Figure 6) and TFP shock (Figure 7) as they are found to be the major drivers of business cycles (Smets & Wouters 2007, Justiniano et al. 2011). We compare the responses of the baseline economy with those of the traditional banking economy where shadow lending is absent. The responses in the benchmark case is consistent with existing literature and we concentrate on differences between the two cases. Following a positive investment shock, both shadow credits and traditional loans increase with the latter leading to improved screening intensity. If the shadow lending is shut down, TBs only originate on-the-balance sheet loans. In this case, incentives to ensure project return will be strengthened. Consequently, the increase of screening intensity will be amplified. This effect can consolidate project quality, leading to amplified movement of technology and TFP. On the contrary, the high financial cost of the traditional loans discourages firms to acquire physical capital, leading to dampened increase of investment. Overall, the ab-

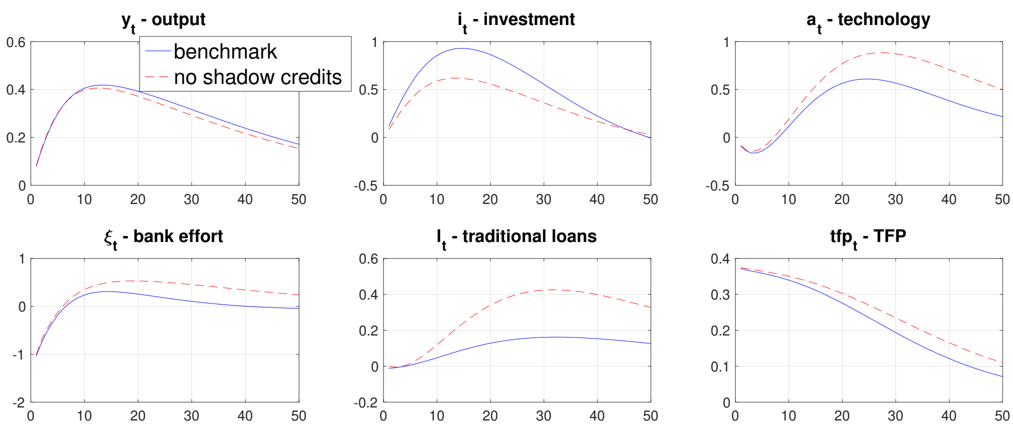
[20]Anzoategui et al. (2019) finds that a negative shock on R&D efficiency was the major cause of TFP slowdown in the mid of 2000s. This period coincides with the peak of the shadow banking boom in the US.

Figure 6: Inv. efficiency Shock



Note: This figure shows impulse-response functions to a one standard deviation expansionary-investment shock.

Figure 7: Exo.TFP Shock



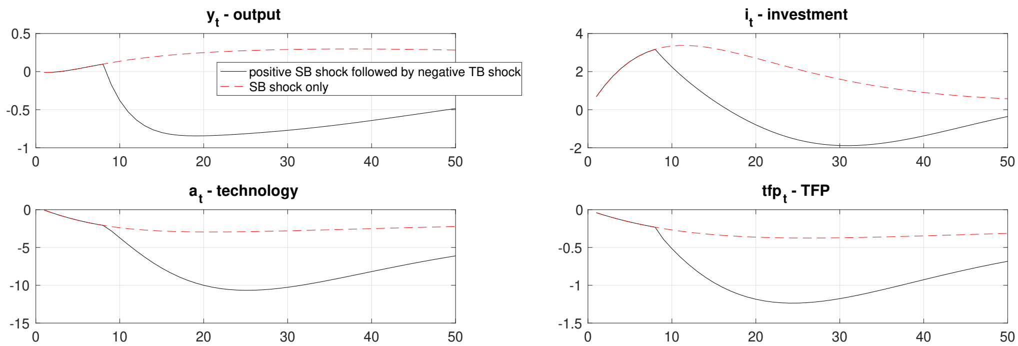
Note: This figure shows impulse-response functions to a one standard deviation expansionary-TFP shock.

sence of shadow banks curbs the increase of output. A similar pattern is found from a positive TFP shock, suggested by Figure 7. Our analysis suggests that shadow lending provides an extra propagation which results in a trade-off between output and TFP, similar as the case for SB shock.

Before analysing shadow banking boom periods, we conduct one experiment to shed light on the financial crisis experiences. That is, a collapse in the TB sector followed by a SB boom. We capture this in our framework by a tightened TB shock hitting the economy eight quarters after the initial expansionary SB shock.[21] One may think the initial point as the beginning of 2006 in the US, around the peak of shadow banking development, and the TB shock captures the financial crisis which happened two years later. Figure

[21] We consider a four standard deviation of the SB shock which generates about 14% increase in shadow credits within four quarters. The TB shock is 5% decrease in γ_3 which generate about 2.5% decrease of tradition credits. Both magnitudes are in line with annual growth of the two credit variables. The AR(1) parameter of the TB shock is assumed to be the same as the SB shock.

Figure 8: SB shock followed by negative TB shock



Note: The magnitude of the SB shock is 4 standard deviation.

8 illustrates how the economy behaves. The SB shock drives the economy up yet with weakened technology and TFP. Around the corner of the crisis, the output is only slightly above the trend.[22] When the crisis happens, the economy turns suddenly into recession with the expansionary effects being erased. On the other hand, the weakened productivity performance is significantly exacerbated. Overall, the economy stuck into a slow recovery and persistent TFP slowdown.

6 Shadow Banking Development and Macroeconomic Implications

The last two decades witnessed sharp development of shadow banking in the major economies over the world. In this section, we examine macroeconomic implications of shadow banking development in the light of our model mechanisms. Particularly, we interpret shadow banking boom for three cases: the US in 1990s-2000s, China in 2010s and Euro area (EA) in 2000s. To this end, we also evaluate our model based on Chinese and EA data. Our strategy is similar to Wang et al. (2018). That is, standard parameters are calibrated based on the US case (unless data for calibration is readily available) and the remaining ones are estimated using Bayesian method. The Chinese sample period is from 2002Q1, when shadow banking business roughly emerged, until 2018Q4. The EA sample period is from 1999Q1, the earliest available time of shadow credits data, to 2019Q4. We define Euro area in terms of the fixed composition concept (EA-19). Note that R&D data for China and the EA are only available at annual frequency.[23] The mixed-frequency of data for the two economies is accounted for by adapting a version of Kalman filter in estimations (see Anzoategui et al. (2019) and Spitzer & Schmöller (2020) among others). Following the estimation results, we conduct counter-factual analyses for each economies to analyse their shadow banking boom period. For the reason of brevity, we report estimation results in the Online Appendix.

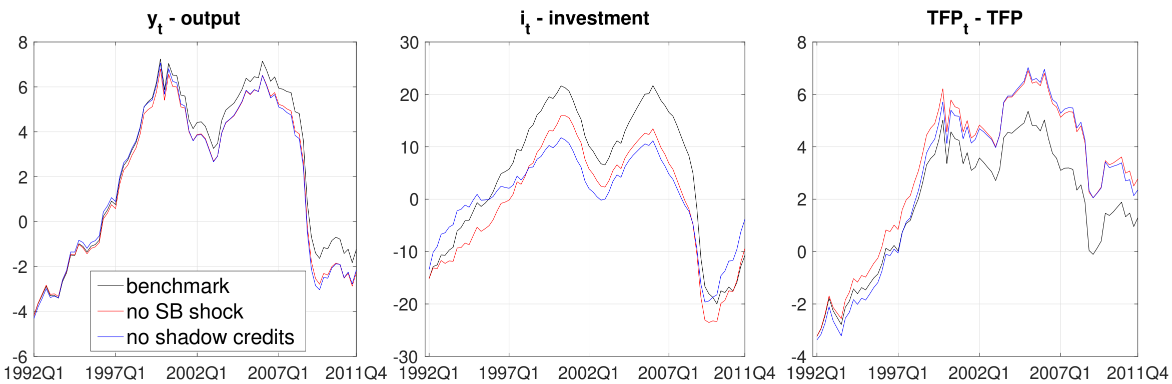
[22]Data suggest that US growth became low in the run-up to the financial crisis.

[23]We also try estimation based on interpolated R&D data. Results do not change fundamentally. Please see the Online Appendix for more details.

6.1 The US

Figure 9 analyzes the shadow banking boom for the US through the lens of our model, with particular focus on output, investment and TFP. In each panel, we compare the benchmark economy (the black line) with two counter-factual cases, including one removing contributions of the SB shock (the red line) and the other one further switching off the shadow banking sector (the blue line).

Figure 9: Counterfactual comparisons: effects of shadow banking



Note: This figure shows percentage deviation of output, investment and TFP from their trends.

Figure 9 suggests that the shadow banking had persistent and significant impacts on the economy. When removing the SB shock, both investment and output would be dampened particular for the former. On the contrary, TFP would be lifted up in this case. These patterns would be more significant if we further switched off the shadow banking sector. These results suggest opposite contributions of shadow banking to output or investment and TFP, consistent with our theoretical analysis. Moreover, Figure 9 shows quantitative importance of both the SB shock and the extra propagation (differences between the blue and the red lines) provided by the shadow lending. Comparatively, both of them were important for affecting investment while TFP was mainly affected by the SB shock. Over the 2001-2007 period, the averaged contribution of the SB shock and that of the extra propagation on investment were 5.71% and 3.03% respectively. At the same time, TFP was damped by 1.53% on average due to the SB shock, far more significant than that owing to the extra propagation (0.22%). Furthermore, the overall impacts from shadow credits gradually became significant, which peaked in the run-up to the financial crisis. For example, in 2008Q1 TFP would be about 2.5% above the actual level if shadow lending was absent. Therefore, the shadow banking development in the 1990s and 2000s persistently undermined TFP.

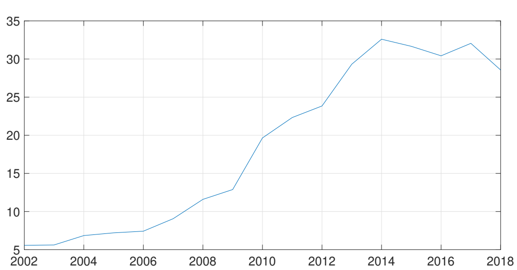
The counter-factual analyses deliver important macroeconomic implications of shadow banking. Our results suggest that sizeable effects of shadow banking impede contributions of TFP on output. As a result, the relationship between output and TFP could be weakened. This finding is consistent with our empirical evidence (see the last column of Table 3) which suggests a weakened relationship between TFP growth and economic growth due to the presence of shadow banking. Focusing on the US, we also find the correlation between TFP growth and GDP growth over 1992 to 2007 (0.56) is relatively low compared with the last four decades since 1980 (0.75). The latter includes periods when shadow banking was either less developed (1980s) or shrank (2010s). On the other hand, we find that capital deepening gradually played more important role in steering output between 1992 to 2007 for the US, consistent with Anzoategui et al. (2019). Overall, during the shadow banking boom period the US economy became less productivity-driven which cast shadow on the sustainability of growth. This also shed light on the issue why the recovery in the aftermath of the great recession is slow (Smets & Villa 2016).

6.2 China

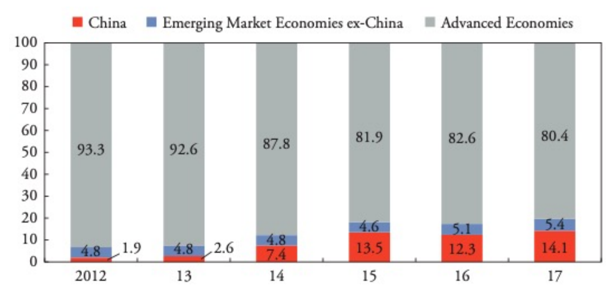
In this subsection, we assess the macroeconomic consequences of a shadow banking boom in China. Since the early 2000s, shadow banking business emerged in China and became flourished after the global financial crisis. Figure 10a shows that the depth of shadow credits increased rapidly, accounting for about 30% of GDP in 2018. Moreover, the world share of Chinese shadow banking rose significantly. Figure 10b shows that the Chinese share of money market funds, a key component of shadow banking, increased from 1.9% in 2012 to 14.1% in 2017. Given the quantitative significance of shadow banking in China, it is potential to have important impacts on the Chinese economy.

Figure 10: Chinese Shadow Banking

(a) Shadow credits/GDP



(b) Chinese money market funds (MMF) share



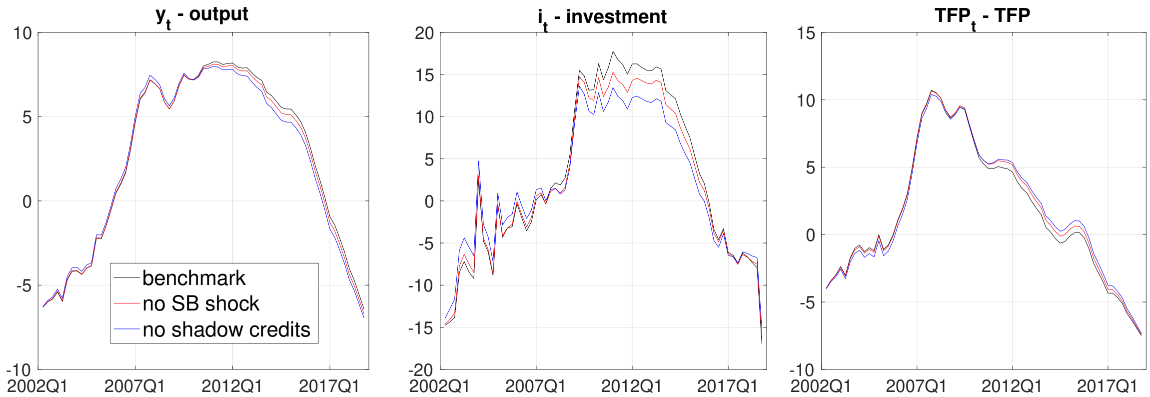
Source: Figure 10a is Compiled by the authors. Data is from National Bureau of Statistics, China. Figure 10b is from Adrian & Jones (2018).

Figure 11 suggests that the impact of shadow credits on the Chinese economy shows a similar pattern as in the US. Particularly, the spur of shadow credits led to a pickup in investment between 2009 and 2014, positively contributing to output and hence helping the Chinese economy weather the global financial crisis. Moreover, the cushion effect peaked in 2015, the timing of which coincided with the end of the fast expansion of shadow credits in China (see Figure 10a). Despite this positive contribution, the expansion persistently exacerbated the TFP slowdown[24] which already emerged during the global financial crisis period.

Overall, our estimation results suggest that shadow credits play less important role in China than in the

[24]We find the TFP slowdown in China is mainly driven by negative contributions form investment and TFP shocks.

Figure 11: Counterfactual comparisons: effects of shadow banking

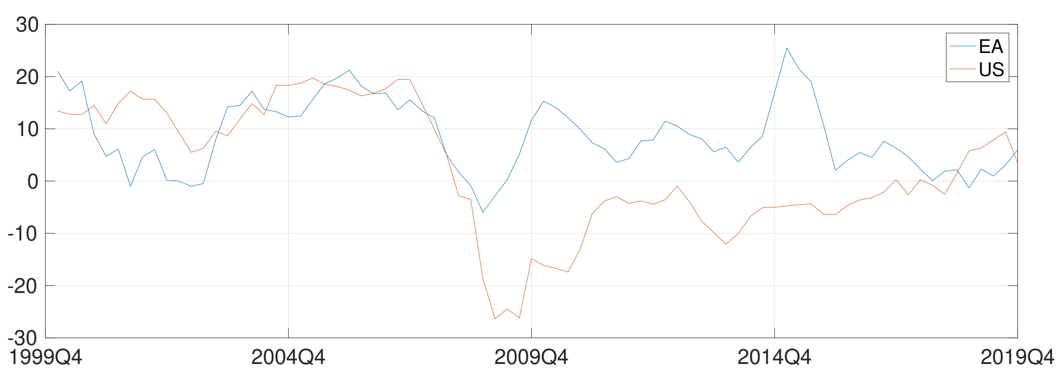


Note: This figure shows percentage deviation of output, investment and TFP from their trends.

US until the end of the 2010s. This finding by no means suggests unimportance of shadow banking in China. In 2020, China started a new round of financial reform to allow commercial banks to engage in brokerage business.[25] Some aspects of this reform is similar to the US Gramm–Leach–Bliley Act in terms of removing the divide between commercial and investment banking, and could further opened space of shadow banking development in China. With this background, it is potential for shadow banking to further play significant roles in the future of Chinese economy. Given the historical experiences of the US and the fact that China is transitioning to a innovation-driven economy, our results signal alerts for the Chinese financial reform. The policy maker need to be cautious as to develop the shadow credit market.

6.3 The EA

Figure 12: Shadow banking expansion: comparing EA and US



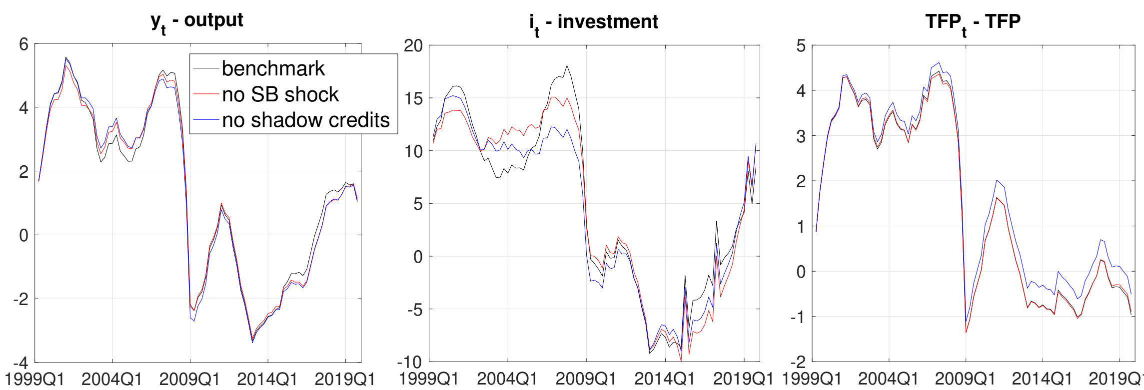
Note: This figure shows four-quarter growth rate of shadow banking assets in the EA and US.

In this subsection we carry the counter-factual analysis as in Section 6.1 and 6.2 but focus on the EA.

[25]https://www.reuters.com/article/us-china-bank-securities/china-plans-to-grant-investment-banking-licenses-to-lenders-caixin-idUSKBN23Z04W

Figure 12 compares growth rate of shadow banking assets in the EA and the US. From visual inspection, only the EA shadow banking maintained expansion in the last decade though both economies experienced fast expansion in shadow banking before the global financial crisis. This difference suggests that the shadow credit market in the EA is relatively stable and less likely subject to strong disturbance as in the US. Not surprisingly, Figure 13 shows quantitatively small effects of shadow credits on the EA economy. Interestingly, in the EA the effects are mainly determined by the extra propagation of shadow lending. This contrasts to the US finding that effects of shadow credits are mainly driven by the the SB shock. Particularly, the EA TFP would be 0.4% higher in the 2010s if removing the shadow credit market while setting the SB shock as zero would narrowly influence TFP.[26]

Figure 13: Counterfactual comparisons: effects of shadow banking



Note: This figure shows percentage deviation of output, investment and TFP from their trends.

Table 7: Counterfactual comparisons: effects of shadow banking

	on output	on investment	on TFP	TFP/output	TFP/investment	output/investment
US	0.76	11.59	-2.48	-3.26	-0.21	0.07
CN	1.02	6.69	-0.87	-0.85	-0.13	0.15
EA	0.45	6.04	-0.20	-0.43	-0.03	0.07

Note: column *TFP/output* and *TFP/investment* show relative cost of shadow credits. Coefficients in column *output/investment* show efficiency of the boosting effect of shadow credits on output.

Finally, we summarize the impacts of shadow banking for the three economies in Table 7. For each economy, we report respectively the impacts in the peak of shadow banking boom, namely 2014 for China[27] and 2007 for the EA and the US.

Comparing the three economies, Table 7 suggests that the US is the most affected by shadow lending. During the peak of the shadow banking development, shadow credits boosted 0.76% of output and 11.59% of

[26]Figure 13 shows a slowdown pattern of TFP in the EA in the aftermath of the crisis. Our estimation results suggest this is mainly due to negative contributions of knowledge efficiency shock, consistent with Spitzer & Schmöller (2020).
[27]The shadow banking boom for China may continue but our data is only available until 2018.

investment but costed 2.48% of TFP. China receives the largest impact on output (1.02%) while investment and TFP were moderately affected (6.69% and -0.87% respectively). The largest stimulating effect is due to the fact captured in the calibration that capital share in production is larger for China than the US and the EA (Hsieh & Klenow 2009, Chang et al. 2019). The boosting effect fuelled by capital deepening generates larger impact on output. Particularly, output increased 0.15% for 1% of investment boosted in China, as doubled as the coefficient for the US and the EA. In terms of the EA, the most striking finding is its lowest relative cost on TFP over the boosting effects. The magnitude of the relative cost was about 12% of the US one. Our estimation suggests that shadow credits in the EA was largely determined by real-sided shocks rather than the SB shock. Consequently, the effect of shadow credits was mainly channelled through the extra propagation which marginally affected TFP. On the country, the impact of shadow credits in the US was mainly from the SB shock which causing significant loss in TFP. This result implies that shadow banking development originated from financial sector is more detrimental than that driven by credit demand motive. In other words, if growth of shadow banking is to meet funding demand of firms rather than driven by regulation arbitrage or banking profits, the trade-off induced by shadow banking development could be milder.

7 Conclusion

The uprising of shadow banking system and historical lessons from the global financial crisis prompt investigations of both “bright” and “dark” sides of shadow banking. Motivated by a negative SB-productivity relationship, this paper adds to the literature another set of macroeconomic consequences of shadow banking and shed light on a productivity slowdown pattern observed in many economies. A fundamental finding is that shadow banking development undermines innovation outcome and total factor productivity. This contrasts to traditional financial development which promotes them to sustain long-run growth.

To study macroeconomic consequences of shadow banking, we develop and estimate a DSGE model with risky technology utilization and extended financial markets. Essentially, this model presents an agency problem in which shadow intermediation reduces banks’ incentives to screen loans, leading to deteriorated utilization efficiency which persistently damage productivity. A SB-based financial development may weakly stimulate growth in short-run but could cast shadow on long-run economic performance to the contrary.

We use our estimated model to interpret shadow banking booms for the US, China and the EA. In this exercise, we highlight two factors facilitating growth of shadow credits, including a financial innovation or regulation arbitrage motive and a credit demand motive. For the US, there was the most long-lasting expansion of shadow banking development and the most significant loss on TFP which is mainly driven by the financial innovation or regulation arbitrage motive. Whereas, in the EA and China, the credit demand motive played more important role and productivity loss was relatively modest. Our findings imply a less-harmful role of shadow credits driven by real-sided factors. The last finding has important implications on banking regulations and financial liberalization.

Finally, our framework could be further developed. In the model, we view our shadow banks as a consolidate entities of major forms of shadow banks with focus on their common features. In practice, it would be interesting to distinguish different types of shadow banking. It is also interesting to consider some small but rapidly expanded form of shadow banking, particularly appeared in emerging economies. Moreover, our framework can be extended to introduce regulations, such as capital requirement, and unconventional monetary policies. By doing so one can study interaction between government policies and productivity performance through shadow banking. All these are interesting topics for future research.

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Appendix A Background and Data

Shadow banking broadly refers to non-bank financial intermediation outside the regular banking system (FSB 2019). The composition of shadow banking is complicated, varying across countries, and changes over time. In this paper, we focus on the components of shadow banking which could pose threats to the financial stability. Some common features of these shadow banking components are credit enhancement, transformation of liquidity and maturity, regulatory arbitrage, et cetera (Adrian & Jones 2018, FSB 2019). After the global financial crisis, regulations were strengthened. However, the major types of shadow banking in developed countries are still market-based finance. For example, collective investment vehicles continued to rise despite that asset-backed securities were largely shrunk. Another important scope of the shadow banking development is that in the emerging market in the recent decade, especially in China. Contrary to the market-based system in developed countries, the Chinese shadow banking is characterised as a bank-like system (Ehlers et al. 2018). Commercial banks play the major role in shadow credits intermediation while market-based instruments play only a limited role. For instance, commercial banks issue wealth management products to raise funds and provides liquidity to trust companies which further originate loans to firms. Despite the different structures compared with the developed countries, the Chinese shadow banking also heavily involves credit enhancement and liquidity transformation (Adrian & Jones 2018).

Appendix A1 Cross-country Data

Table 8: List of Economies included in Data

Economies
Argentina, Australia, Belgium, Brazil, Canada, Chile, China, France, Germany, Hong Kong, India, Indonesia, Ireland, Italy, Japan, Republic of Korea, Luxembourg, Mexico, Netherlands, Russian Federation, Saudi Arabia, Singapore, South Africa, Spain, Switzerland, Turkey, United Kingdom, United States

Appendix A2 Time-series Data

All nominal variables are adjusted by GDP deflator. GDP, consumption, investment, R&D spending and shadow credits are expressed as per capita term. The US sample period is from 1992Q1 to 2019Q4; the Chinese sample period is from 2002Q1 to 2018Q4; the EA sample period is from 1999Q1 to 2019Q4. The US and EA variables are form Federal Reserve and Eurostat respectively. The Chinese GDP, enterprise R&D spending and averaged hour worked per week are from National Bureau of Statistics of China. Chinese consumption, investment, GDP deflator, employment level, officially defined shadow credits (including entrusted loan, trusted loan and bank acceptance bills) and population data are from Chang et al. (2016). Details about construction of data can be referred to Higgins & Zha (2015).

The R&D data in China and EA are only available at annual frequency. In order to conduct empirical

Table 9: Definition of Variables

Variables	Description	Sources
Shadow Banking	Assets of other financial intermediaries. OFIs includes all financial institutions that are not central banks, banks, insurance corporations, pension funds, public financial institutions or financial auxiliaries.	FSB (2019)
Patent Application	Patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office.	World Bank Data
Journal Article	Scientific and technical journal articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences.	World Bank Data
Population	Total population.	World Bank Data
GDP Per Capita	Logarithm of GDP at purchaser's prices divided by total population.	World Bank Data
FDI	Foreign direct investment, net inflows as a share of GDP.	World Bank Data
Schooling	Average total years of schooling for adult population (years).	Our World in Data
Regulatory Quality	A composite measure of transparency around proposed regulations, consultation on their content, the use of regulatory impact assessments, and the access to enacted laws.	World Bank Data
Investment	Gross fixed capital formation as a share of GDP.	World Bank Data
Openness	Openness is the sum of exports and imports of goods and services measured as a share of GDP.	World Bank Data
Government Spending	General government final consumption expenditure as a share of GDP.	World Bank Data
Inflation	GDP deflator.	World Bank Data

analysis (in Section 2.2), we make frequency transformation using Denton method in the Eviews. When evaluating the model for China (in Section 6.2) and EA (in Section 6.3), we used either transformed quarterly data or annual data with a Kalman filter as in Anzoategui et al. (2019) and Spitzer & Schmöller (2020). TFP data for China is not available and hence we estimate it by ourselves. Following the standard TFP estimation approach in the business cycle literature (e.g., Fernald (2014)), we use the following formula

$$tfp_t = ln(real\ per\ capita\ GDP_t) - \alpha * ln(capital_t) - (1-\alpha) * ln(employed\ labour_t * hour\ worked_t)$$

where α=0.5 (Hsieh & Klenow 2009). Capital is estimated based on perpetual inventory method with quarterly depreciation rate δ equal to 0.025 (Wu 2008). Initial capital is calculated as initial investment (investment in 2002Q1) over depreciation rate plus growth rate $Inv_{2002Q1}/(\delta + g^y)$.

Considering diversity of shadow credit instruments in the US, China and the EA, we follows a narrow measure in the benchmark estimations while a broad measure is used for robustness check. Specifically speaking, the US narrow shadow banking measure includes two components, security brokers and dealers and issuers of asset-backed securities, following Fève et al. (2019). For robustness check, we also add extra five components, including money market funds, government-sponsored enterprises, agency- and GSE-backed mortgage pools, finance companies, real estate investment trusts and other financial business.

In terms of China, we consider the officially defined shadow banking as the narrow measure which includes entrusted lending, trusted lending and bank acceptance bills. For robustness check, we also use the broad measure which further includes wealth management products. The information about wealth management products is from Wind Database (the data information system created by the Shanghai-based company called WIND Co. Ltd., the Chinese version of Bloomberg (Chen et al. 2018)).

The Euro area includes Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Greece, Slovenia, Cyprus, Malta, Slovakia, Estonia, Latvia, and Lithuania. The narrow and broad shadow banking measures for EA follows Doyle et al. (2016). The narrow measure comprises monetary-market funds (MMF), non-money market investment funds and financial vehicle corporations. The broad measure which is used in robustness check comprises MMF and other non-monetary financial institutions excluding insurance corporations and pension funds.

Table 10: Descriptions and sources for variables used in VAR and estimation

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
$r\&d$ R&D	enterprise R&D spending	FRED
s Shadow credits	security brokers and dealers	
	and issuers of asset-backed securities	FRED
Population	civilian noninstitutional population	FRED
TFP	total factor productivity	Fernald (2014)

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	
	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 NBS, China
$r\&d$ R&D	enterprise R&D spending	NBS, China
s Shadow credits	entrusted loan, trusted loan	
	and bank acceptance bills	Chang et al. (2016)
Population	total population	Chang et al. (2016)
TFP	total factor productivity	Estimated by the authors

Variables	Description-EA	Source
gdp GDP	gross domestic product	Eurostat Database
c Consumption	household and NPISH final consumption expenditure	Eurostat Database
i Investment	gross fixed capital formation	Eurostat Database
π Inflation	GDP Deflator	Eurostat Database
r Interest rate	Euribor	Eurostat Database
h Labour	hour worked times employed labour	Eurostat Database
$r\&d$ R&D	enterprise R&D spending	Eurostat Database
s Shadow credits	monetary market funds,	Eurostat Database
	financial vehicle corporations assets	
	and non-money market investment funds	
Population	population over 16	Eurostat Database

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.