The Macroeconomics of TechFin[*]

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Abstract

Over the past few years, many large technology companies have started lending in the capital markets, i.e., "TechFin". How should we modify our existing macro-finance theories to accommodate the rise of this new financial intermediary? This paper introduces both a banking sector and a TechFin sector into a continuous-time general equilibrium model with heterogeneous entrepreneurs and incomplete markets. These two financial sectors are identical except for the types of borrowing constraints faced by entrepreneurs. Entrepreneurs borrowing from banks are subject to the standard collateral-based borrowing constraints. In contrast, technology advantages allow the big tech companies to resolve agency costs and perform cash flow-based lending. I use a deep learning neural network approach to obtain global solutions, and the main conclusions are twofold. First, this new TechFin credit system leads to a higher capital allocative efficiency in the steady state. Second, the existence of BigTech lending acts as a propagation mechanism and makes the economy sensitive to both first-moment productivity level shocks and second-moment uncertainty shocks.

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1 Introduction

Over the past decade, the financial market has seen the arrival of massive new technologies, raising many debates about their consequences. Two most important ones are *FinTech* and *TechFin*.[1] Using the cross-country dataset provided by Cornelli et al. (2020), in the top graph of Figure 1, I present the world's total lending volume in billion us dollars for both Fintech and TechFin credits. As we can see, both FinTech and TechFin lendings are becoming increasingly important in the modern financial system. The bottom graph shows the relative importance between them in different countries in 2019. Some countries, such as the United States, the United Kingdom, and Singapore, have more development in FinTech lendings; meanwhile, Asian countries, including China, Korea, and Japan, have better TechFin credit access. Generally speaking, these two new types of financial intermediaries have emerged in a fast pace across different credit markets around the world, which leads to a fast-growing empirical literature on them (e.g., Hau et al., 2018; Tang, 2019).

In this paper, I attempt to investigate, **in theory**, the role of BigTech lending in macroeconomy. More specifically, how should we modify the existing theories of financial intermediation and business cycles so as to accommodate the rise of TechFin? In the existing literature, theories of credit are useful for understanding the mechanism of business cycles because the credit system acts as a propagation mechanism of first-moment productivity shocks. However, these theories are centered on banks and the key characteristic on bank lending is this collateral-based borrowing constraint. With this financial friction, people find that the aggregate economy has productivity losses in the steady state because the efficient producers cannot borrow enough money (e.g. Moll, 2014). In addition, a financial accelerator mechanism drives the economic fluctuations: small fundamental shocks can be amplified by financial frictions so that they can generate large and persistent fluctuations in aggregate economic activity (Kiyotaki and Moore, 1997; Bernanke and Gertler, 1989).

In this paper, the fundamental difference between a banking sector and a TechFin sector lies in the specific type of borrowing constraints. When BigTech firms lend to the market, they have less demand for collateral and corporate borrowing is subject to an earnings-based borrowing constraint. The reason why I model is related to how BigTech firms reduce asymmetric information or agency problems

[1] Throughout this paper, FinTech refers to the situation where financial firms adopt new types of technology, while TechFin means that technology companies provide financial services. Typical examples of FinTech are these digital platforms facilitating peer-to-peer (P2P) lending and borrowing, while examples of TechFin include Ant Group, WeBank, and so on. The broad definition of FinTech provided by the Financial Stability Board is "technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions, and the provision of financial services."

in the real world. In the traditional banking sector, banks use covenants to mitigate agency frictions. However, for BigTech companies, their technology advantages such as data, algorithms, platform can help reduce these agency frictions. In Section 2.4.3, I will present a simple model to show if the costs of state verification can be significantly reduced with technology, then these BigTech companies will prefer incomplete-collateralized contracts to fully-collateralized ones. In addition, there is indeed empirical support for the assumption of earnings-based borrowing constraint on BigTech lending. For instance, Gambacorta et al. (2020) find that big-tech credit does not correlate with local business conditions and house prices when controlling for demand factors, but that it does react strongly to changes in firm-specific characteristics, such as the transaction volumes and network scores used to calculate firm credit ratings. They argue that the use of technology can allow firms to borrow without any collateral and this new type of borrowing constraint can generate important impacts on macro-finance researches.

After that, I introduce both a banking sector and a TechFin sector into a continuous-time general equilibrium model with heterogeneous entrepreneurs and incomplete markets. These two financial sectors are identical except for the types of borrowing constraints faced by entrepreneurs. Entrepreneurs borrowing from banks are subject to the standard collateral-based borrowing constraints. In contrast, technology advantages allow the big tech companies to resolve agency costs and perform cash flow-based lending. In equilibrium, aggregate productivity is endogenously determined by the net worth share of highly productive firms. Compared to the standard collateral-based borrowing constraint, earnings-based borrowing constraint will amplify the impacts of micro-level uncertainty on net worth inequality by allowing more productive firms to use more leverage and grow faster. As a result, a transitory micro uncertainty shock can lead to persistent changes in finance allocation efficiency and aggregate productivity. This new financial accelerator mechanism, associated with the new TechFin sector, differs from the classic one in three aspects: micro uncertainty instead of aggregate productivity is the primitive shock; financial friction comes from earnings-based borrowing constraints instead of collateral-based ones; and the feedback loops happen between net worth inequality, instead of net worth level, and asset prices. Therefore, the arrival of this new TechFin credit system leads to a higher capital allocative efficiency in the steady state. Moreover, the existence of BigTech lending acts as a propagation mechanism and makes the economy sensitive to both first-moment productivity level shocks and second-moment uncertainty shocks.

Related literature This paper is related to four different branches of literature. First, this paper builds on an extensive literature on financial frictions and business cycles. Two seminal works in this field are Kiyotaki and Moore (1997) and Bernanke and Gertler (1989). Examples of quantitative explorations include Carlstrom and Fuerst (1997), Bernanke, Gertler and Gilchrist (1999), and so on. Recent studies, especially those done after the 2008-2009 global financial crisis, are mainly focused on analyzing the global dynamics and nonlinear effects of shocks with continuoust-time models. Examples include but are not limited to Brunnermeier and Sannikov (2014), Di Tella (2017), He and Krishnamurthy (2013), and Fernandez-Villaverde, Hurtado and Nuno (2019). Besides, Brunnermeier, Eisenbach and Sannikov (2013) provide an excellent and detailed survey on the discrete-time models of macroeconomics and financial frictions, and Brunnermeier and Sannikov (2017) introduce the fundamental tools used in this field.

Second, this paper is closely related to the literature on the macroeconomics of earnings-based borrowing constraint. In terms of empirical evidence, the key finding in Lian and Ma (2021)'s seminal paper is that 80% of the corporate debt value in the US is closely linked to firm's cash flows from their operations instead of the asset liquidation value. Their work intrigues an increasing number of studies that investigate the role of earnings-based borrowing constraint in aggregate fluctuations. For instance, Drechsel (2019) studies the macroeconomic fluctuations through the interaction between earnings-based borrowing constraint and investment shocks. In contrast, Greenwald (2019) mainly focuses on investigating how the transmission of monetary policy shocks differs across firms with different types of covenants.

Third, the basic model framework used in this paper is from the distributional macroeconomics literature, which refers to macroeconomic theories where the relevant state variable is a distribution and the Kolmogorov Forward equation instead of the Euler equation lies at the heart of the analysis. For instance, Moll (2014) studies the impacts of wealth-based borrowing constraints on misallocation and aggregate productivity. Kaplan, Moll and Violante (2018) investigate monetary policy transmission mechanism in a Heterogeneous Agent New Keynesian (HANK) framework. In addition, Fernandez-Villaverde, Hurtado and Nuno (2019) extend the Krusell and Smith (1998) method and explore the relationship between financial frictions and wealth distributions with aggregate shocks. For a concrete introduction to the tools used in this literature, please refer to Achdou et al. (Forthcoming) for details.

Finally, this paper closely relates to the growing literature on the fundamental difference between

FinTech and traditional banking sector. Some of the key assumptions used in this paper relies on the empirical findings in the growing FinTech literature. For instance, Gambacorta et al. (2020) empirically show that the lending behaviors of big tech and bank credit are different in terms of their link to collateral value, local economic conditions and firm-specific characteristics. By using the US Peer-to-Peer (P2P) lending data, Tang (2019) finds that FinTech lending works as an complements to bank lending for small-scale loans. Similarly, Cornelli et al. (2020) find that BigTech lendings are complements rather than substitutes to other forms of lending with a cross-country panel dataset for 79 countries during 2013-2019. In addition, Hau et al. (2018) show that the existence of FinTech credit in China improves the credit access condition for firms with lower credit scores.

2 Model

2.1 Preference

The model is built upon a standard distributional macro model (e.g., Moll, 2014) but with two different types of financial sectors. Consider a continuous-time infinite horizon economy shown in Figure 2 with three different agents: a continuum of entrepreneurs who borrow from the banking sector $\mathcal{B}$, a continuum of entrepreneurs borrowing from the TechFin sector $\mathcal{F}$, and a fixed number $\bar{L}$ of homogeneous workers. Each worker supplies one efficiency unit of labor inelastically. For simplicity, all workers are hand-to-mouth consumers so that we only need keep track of the wealth distributions of entrepreneurs.

Entrepreneurs in these sectors are identical expect that they face different types of borrowing constraints. Each entrepreneur within sector $j \in \{\mathcal{B}, \mathcal{F}\}$ is indexed by their productivity z and wealth a. All the entrepreneurs in this economy have the same additive utility function shown as follows:

$$\mathbb{E}_0 \int_0^\infty e^{-\rho t} \log c_t dt \tag{1}$$

The choice of this logarithmic utility is purely due to simplification. In this way, the state of the economy can be summarized by the joint distributions of wealth and productivity in two sectors $\left\{\omega_t^{\mathcal{F}}(a,z), \omega_t^{\mathcal{B}}(a,z)\right\}$.

2.2 Technology

At time t, each entrepreneur $i \in [0,1]$ in sector $j \in \{\mathcal{B}, \mathcal{F}\}$ owns a private firm that uses both capital k and labor l to produce the final consumption goods with the same production function shown as follows:

$$y_{i,j,t} = \left(z_{i,j,t} k_{i,j,t}\right)^{\alpha} l_{i,j,t}^{1-\alpha} \tag{2}$$

The equation above shows that the production technology is in the standard Cobb-Douglas form with parameter α, where $\alpha \in (0,1)$. Entrepreneurs accumulate capital k, and hire homogeneous workers in a competitive labor market at a flat wage rate w_t. At the same time, they can trade in a risk-free bond b subject to a certain type of borrowing constraint. More details on borrowing constraints will be discussed in Section 2.4. Capital depreciation rate δ is also the same for both sectors. The reason why I assume that entrepreneurs in both sectors have exactly the same production technology and preference is because the goal of this paper is to investigate the heterogeneous impacts of different types of borrowing constraints. In reality, firms relying on bank financing could have different production technologies from firms using TechFin financing. I denote by $\mathcal{K}_t$ the aggregate units of capital in the economy at time t, and by K_t^j the total capital holdings of entrepreneurs in sector $j \in \{\mathcal{B}, \mathcal{F}\}$.

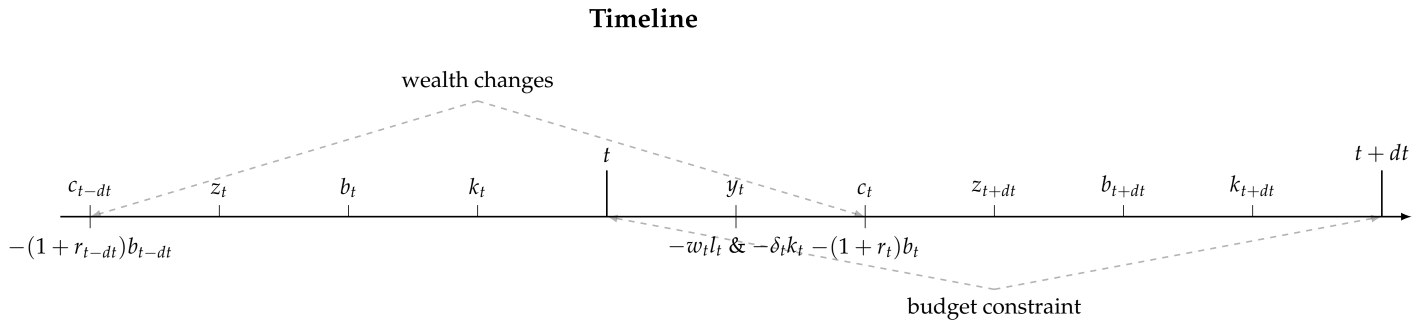
Following the existing literature (e.g. Moll, 2014; Di Tella, 2017), I assume that the idiosyncratic productivity follows a standard Ornstein–Uhlenbeck process

$$dz_{i,j,t} = \frac{1}{\theta}\left(\overline{\mu} - z_{i,j,t}\right) dt + \sigma \sqrt{\frac{1}{\theta}} d\mathcal{W}_{i,j,t} \tag{3}$$

In Equation (3), $\overline{\mu}$ is the long-run mean level of entrepreneur's productivity. $\mathcal{W}_{i,j,t}$ is the standard exogenous Brownian shock, and it is independent and identically distributed (i.i.d.) across different firms. With the incomplete market assumption, entrepreneurs cannot fully hedge their productivity risk, and σ measures the sensitivity of z to the underlying Brownian shock. Throughout this paper, when investigating how the economy reacts to different types of aggregate shocks, I assume that these economy-wide shocks are "M.I.T. shocks". Following the conventional definition, an "M.I.T. shock" is an unexpected shock that hits an economy at its steady-state, which lead the economy transiting into towards a new one. More specifically, I interpret shocks to $\overline{\mu}$ as shocks to the aggregate productivity, while shocks to σ as shocks to the degree of micro-level uncertainty.

2.3 Timeline

This economy's timeline is shown below.



This timeline is a little bit different from the conventional one where the borrowing and investment happen before the realization of productivity. In contrast, here I assume that all the people can observe its productivity before they decide their investment and borrowing next period. More specifically, at period t, entrepreneurs can first observe their productivity z_t, then they issue debt b_t to finance their capital investment $x_t = k_t - (1-\delta)\, k_{t-dt}$ to obtain a new capital stock of k_t. After that, the entrepreneurs hire l_t workers and produce y_t. After paying wages to the workers, the entrepreneurs decide how much to consume c_t and how much wealth a_{t+dt} to save to the next period $t+dt$. This way of modelling follows the work of Kiyotaki (1998) and make earnings-based borrowing risk-free so that we can fully investigate the impacts of uncertainty on allocation efficiency and business cycles without taking into consideration corporate default decisions.

According to the timeline of this economy, the budget constraint from time t to time $t+dt$ of any individual entrepreneur can be shown as follows:

$$c_t + k_{t+dt} - (1-\delta)\, k_t + (1+r_t)\, b_t + w_t l_t = y_t + b_{t+dt} \tag{4}$$

Entrepreneurs' wealth is defined as the difference between his capital holdings and debt borrowings, i.e., $a_{i,j,t} \equiv k_{i,j,t} - b_{i,j,t}$. Therefore, the changes in wealth can be computed as follows

$$da_t = a_{t+dt} - a_t = [y_t - w_t l_t - \delta k_t - r_t b_t - c_t]\, dt \tag{5}$$

According to Equation (5), changes in wealth from t to $t+dt$ are from the following items: current output, wage payments, depreciated capital, interest payments of debt, and consumption. More importantly, at time $t+dt$, z_{t+dt} and a_{t+dt} are state variables. Meanwhile b_{t+dt} and k_{t+dt} are endogenously determined by entrepreneurs. In other words, after observing his productivity z_{t+dt}, the entrepreneur will optimally allocate their wealth a_{t+dt} into capital k_{t+dt} and bond b_{t+dt} to maximize the profits at the next period.

From now on, for the simplification of notations, I will suppress the agent and time subscripts unless it is necessary.

2.4 Borrowing constraints

In this section, I explain the difference in borrowing constraint faced by entrepreneurs when they borrow from different financial institutions. Generally speaking, the type of borrowing constraint in the banking sector is simply the standard collateral-based one, while that in the TechFin sector is modeled as the new earnings-based borrowing constraint as documented in some recent empirical works (e.g. Lian and Ma, 2021; Gambacorta et al., 2020). After describing the model setup, I provide its micro-foundation in Section 2.4.3 and discuss the similarity and difference between them in Section 2.4.4.

2.4.1 Banking sector

To begin with, I assume that all the entrepreneurs face the same collateral-based borrowing constraint when they borrowing from the traditional banking sector:

$$(1+r)b \leq \lambda_{\mathcal{B}} k \tag{6}$$

where $0 \leq \lambda_{\mathcal{B}} \leq 1$. Equation (6) shows that due to issues such as limited enforcement or asymmetric information, only a fraction $\lambda_{\mathcal{B}}$ of entrepreneur's capital stock can be externally financed. The level of $\lambda_{\mathcal{B}}$ represents the severeness of these frictions. More specifically, if $\lambda_{\mathcal{B}} = 0$, Equation (6) means the entrepreneurs can only self-financing their capital investment. At the same time, if $\lambda_{\mathcal{B}} = 1$, it means that all the capital stock can be externally financed. Both situations are extreme cases and we will investigate how the magnitudes of $\lambda_{\mathcal{B}}$ affects the role of banking sector in driving the macroeconomic fluctuations.

Rewriting this equation with the definition of wealth a can give us the standard wealth-based borrowing constraint shown as follows:

$$b \leq \frac{\lambda_B}{1+r-\lambda_B} a \tag{7}$$

Similarly, Equation (7) captures the common intuition that the amount of capital available to an entrepreneur is limited by his personal wealth a and again the magnitude of $\lambda_{\mathcal{B}}$ captures the degree of financial development in the banking system. As Equation (7) is more comparable to the borrowing constraint in the TechFin sector, therefore I will use this equation throughout the rest of the paper.

2.4.2 TechFin sector

Of course, the precise modelling of TechFin depends on the interpretation on the fundamental difference between a traditional banking sector and this new financial sector. In this paper, I assume that entrepreneurs can borrow against their future earnings instead of the current collateral values. Therefore, in this paper's perspective, the fundamental difference between banking and the new TechFin sector is that TechFin sector allows the entrepreneurs to borrow against their future earnings.

More specifically, I assume that all the entrepreneurs in the TechFin sector face the same future earnings-based borrowing constraint shown as follows:

$$(1+r)b \leq \lambda_{\mathcal{F}} \pi \tag{8}$$

where π is entrepreneur's earnings and $\lambda_{\mathcal{F}} \leq 1$. Whether the earnings are current or in next period depends on how to interpret the model. On one hand, it could be interpreted as future earnings as firms first borrow and then produce to make money. On the other hand, earnings could also be interpreted as current as financing and production decisions happen after firms can observe their productivity. In this paper, I follow Lian and Ma (2021)'s work and assume that only a fraction $\lambda_{\mathcal{F}}$ of *current* earnings can be externally financed. Again, the existence of $\lambda_{\mathcal{F}}$ also comes from the limited enforcement that entrepreneurs might steal a fraction of their companies' earnings. $\lambda_{\mathcal{F}} = 0$ refers to the situation where entrepreneurs can only self-financing, and $\lambda_{\mathcal{F}} = 1$ means that all earnings can be externally financed. Rewriting this equation can give us the wealth-based borrowing constraint in TechFin sector as follows:

$$b \leq \frac{\lambda_F \xi z}{1+r-\lambda_F \xi z} a \tag{9}$$

where $\xi = \alpha\left(\frac{1-\alpha}{w}\right)^{\frac{1-\alpha}{\alpha}}$. One technical issue with this earnings-based borrowing constraint is that even for a reasonable level of $\lambda_{\mathcal{F}}$, if the firm's productivity is too large, then the maximum amount of borrowing could be infinite. To solve this technical issue, when numerically solving the model, I will impose an *ad-hoc* up boundary $\bar{\phi}$ for this earnings-based borrowing constraint, i.e.,

$$k \leq \begin{cases} \frac{a}{1-\lambda_{\mathcal{F}}\xi z} & z < \left(1 - \frac{1}{\bar{\phi}}\right)\frac{1}{\lambda_{\mathcal{F}}\xi} \\ \bar{\phi}a & z \geq \underline{z} \end{cases} \tag{10}$$

For simplicity, from now on, I will still use equation (9) for characterizing the equilibrium and the optimal decisions. At the same time, when numerically solving the model, I will impose (10) and an ad hoc choice of $\bar{\phi}$.

One caveat is that in the model the only difference between banking sector and FinTech sector lies in the type of borrowing constraints. However, it does not mean that in reality this is the only difference between these two sectors. As pointed out in some recent review papers (e.g. Boot et al., Forthcoming; Thakor, 2020; Huang et al., 2020), what's new about FinTech could be technological innovations in both information processing and communication channels, or some new entrants providing non-intermediated financial services, or some big technology firms provide lending services to small and medium entrepreneurs with no collaterals. For example, with the US loan-level data on mortgage applications and origination, Fuster et al. (2019) show that FinTech lenders originate mortgages faster and screen borrowers more effectively compared to other lenders. Philippon (2016) suggest that FinTech can lower the costs of financial services provided by financial intermediations. Thakor and Merton (2019) have developed a theory of bank and non-bank lending in which banks have an endogenous advantage over non-bank lenders when it comes to being trusted to make good loans because banks possess an advantage in developing investor trust due to their unique access to low-cost deposit funding. However, the reason why I focus on this specific characteristic is because in the existing macro-finance literature, firm's borrowing constraint is essential to the macroeconomic analysis of financial frictions. In addition, there is indeed empirical support for the assumption of earnings-based borrowing constraint on BigTech lending. For instance, Gambacorta et al. (2020) find that big-tech credit does not correlate with local business conditions and house prices when controlling for demand factors, but that it does react strongly to changes in firm-specific characteristics, such as the transaction volumes and network scores used to calculate firm credit ratings. The use of technology can allow firms to borrow without any collateral. The type of borrowing constraints can have important impacts on macro-finance mechanisms.

2.4.3 Microfoundation

There is an extensive number of theoretical papers discussing what determines corporate borrowings. For instance, Stiglitz and Weiss (1981) and Holmstrom and Tirole (1997) point out that corporate debt capacity should be determined by corporate earnings. In contrast, Hart and Moore (1994), Kiyotaki and Moore (1997), and Bernanke and Gertler (1989) argue that corporate borrowing should be tightly linked to the asset liquidation value. Given the fact that there has been a lot of possible explanations in the literature, here I lay out a simple model to explain why we should expect the coexistence of two types of borrowing constraints in reality. Generally speaking, the coexistence could either come from the heterogeneous information technology advantages on the lender's side or the different uses of intangible capital on the borrower's side.

Basic framework Let us consider a revised example in Bernanke and Gertler (1989) or originally from Townsend (1979) to show that some lenders will strictly prefer cash flow-based over asset-based lending while others do the exact opposite.

I assume that entrepreneurs with a capital stock of k need to borrow money from lenders for some investment projects. I denote the amount of money that entrepreneurs can borrow as b. For simplicity, both entrepreneurs and lenders are risk-neutral and entrepreneurs have linear preference in their consumption. The lender's opportunity cost is fixed to be r and the capital's unit liquidation value is assumed to be l. As we will see later, one crucial assumption on intangible capital is that it has a relatively low value of l. For simplicity, here I do not distinguish between the asset's actual resalability and the value damage from agency frictions such as managers' business stealing behaviors. In theory, it is highly possible that firms with more intangibles have lower liquidation values simple because they face severer agency problems. But here I do not distinguish between these two different origins.

There are two possible project outcomes. Entrepreneur's earnings could be $z_G k$ with a probability of p, or they could be $z_B k$ with a probability of $1 - p$. Without loss of generality, we assume that $z_G > z_B > l > 0$.

Investors can choose between two types of lending. The first one is what Bernanke and Gertler (1989) call full-collateralization contract, which means that the entrepreneur's net worth is sufficiently large that he is able to pay lenders their require return even in the worst state, where the lenders seize his capital and resell it in the market:

$$(1+r)\,b \leq lk \tag{11}$$

One advantage of using this type of lending is that lenders do not need to do any earnings verification. Instead, lenders use a contract linked to the liquidation value of capital, which gives us the standard collateral-based borrowing constraint.

The second way of lending is to secure the ownership instead of the collateral. This is the incomplete collateralization case. The focus here is to investigate the characteristics of an optimal contract, which can be stated mathematically as follows:

$$\max_{\{q,c_G,c_B,\tilde{c}_B\}} pc_G + (1-p)\left[qc_B + (1-q)\,\tilde{c}_B\right] \tag{12}$$

subject to the following constraints

$$\begin{aligned}
(1+r)\,b &\leq p\,(z_G k - c_G) + (1-p)\left[z_B k - q\,(c_B + f) - (1-q)\,\tilde{c}_B\right] && (13)\\
c_G &\geq (1-q)\left[(z_G - z_B)\,k + c_B\right] && (14)\\
c_G, c_B, \tilde{c}_B &\geq 0 && (15)\\
0 \leq q &\leq 1 && (16)
\end{aligned}$$

In the equations above, c_G means entrepreneur's consumption when he announces the good state. $\tilde{c}_B$ represents entrepreneur's consumption when he announces the bad state and lenders choose not to verify while c_B represents entrepreneur's consumption when he announces the bad state and lenders choose to verify with a cost of f. As we will discuss later, some lenders such as these big tech companies have a relatively low cost of verification, which is crucial for their preferred choice on cash flow-based lending. Equation (13) represents the participation constraint and (14) is the incentive constraint. The last two equations are feasibility constraints. The optimal contract $\{p, c_G, c_B, \tilde{c}_B\}$ maximizes the entrepreneur's expected consumption in Equation (12) subject to constraints (13) to (16).

Now I provide two different stories on why some lenders prefer cash-flow-based over asset-based lending while others do not. The intuition is the following. From profit-maximization perspective, lenders always prefer earnings-based lending. However, due to the cost of state verification or cash flow pledgeability problems, collateral is useful for resolving these agency costs. At the same time, if lenders can find ways to reduce the cost of state verification or increase cash flow pledgeability, then they will strictly prefer cash flow-based lending.

Information asymmetry story The first result I want to show is that for lenders with low cost of state verification, they strictly prefer using cash flow-based lending. I introduce the following assumption.

ASSUMPTION 1. *Informational technology advantages allow some lenders such as BigTech firms to reduce the cost of state verification.*

The key assumption in this information asymmetry story is that some lenders has Technology advantages in monitoring and predicting firms future earnings while others do not. One great example are BigTech firms and traditional banks. For instance, Thakor (2020) also point out that the use of the Blockchain technology and many other technological advancement in the TechFin sector can lead to the significant reduction in the cost of verification.[2] In reality, *Ant Group* uses *Alipay* system to help their lending because *Alipay* allows it to easily verify the cash flows of companies with a very low cost.

For these lenders with information technology advantage, they will strictly prefer cash flow-based lending. I summarize the main result in the following lemma.

Lemma 1. *If the cost of state verification f is lower than some threshold f^*, then it is more attractive for lenders to implement cash flows-based lending instead of asset-based lending.*

Detailed proof can be found in the appendix. The basic idea here is that, if lenders manage to overcome such problems with big data or platform advantages, they will use cash flow-based lending. As pointed out in some recent review papers (e.g. Boot et al., Forthcoming; Thakor, 2020; Huang et al., 2020), one of the most important new characteristics about FinTech is that some big technology firms provide lending services to small and medium entrepreneurs with no collateral.

The theoretical result in Lemma 1 is also consistent with some empirical findings in the existing literature. For instance, Gambacorta et al. (2020) find that big-tech credit does not correlate with local business conditions and house prices when controlling for demand factors, but that it does react strongly to changes in firm-specific characteristics, such as the transaction volumes and network scores used to calculate firm credit ratings. The use of technology can allow firms to borrow without any collateral. They also argue this new type of borrowing constraints can have important impacts on macro-finance mechanisms.

[2]The other possible changes mentioned in Thakor (2020) are the reduced search costs of matching transacting parties, increasing economics of scale in gathering and using large data, and cheaper and more secure information transmission.

Intangible capital story An alternative way of understanding the different uses of lending is based on the difference between intangible capital and tangible capital. I assume that intangible capital has a low liquidation value.

ASSUMPTION 2. *Intangible capital has low liquidation value l.*

A business is typically liquidated as part of a bankruptcy process. During this process, tangible assets such as machines and plants are sold quickly and their value can be easily evaluated. In practice, when investors evaluate the liquidation value of companies, they often exclude the intangible assets as the value of intangible investments is difficult to assess by outsiders. Our assumption here is consistent with the existing literature that assumes liquidation cost is decreasing in investment tangibility (e.g., Beck et al., 2020).

With Assumption 2, we can easily show that if the asset tangibility is lower than some threshold, it is optimal for lenders to impose a cash flow-based lending.

Lemma 2. *If the liquidation value l is lower than some threshold l^*, then it is more attractive for lenders to implement cash flow-based lending instead of asset-based lending.*

The detailed proof can be shown in the appendix. The intuition behind Lemma 2 is that if the nature of assets is not collaterizable, then it is better for lenders to use cash flow-based lending as it is more profitable to do that. Our result on the relationship between intangible capital and cash flow-based lending is also consistent with the existing literature. For example, Haskel and Westlake (2018) find that the financing of intangibles is less related to traditional forms of credit constraints. Our result in Lemma 2 rationalizes this empirical finding in the data.

2.4.4 Similarity and difference between two types of borrowing constraints

debt capacity and net worth In the existing literature, some papers argue that these two types of borrowing constraints are fundamentally different because earning is a concept of flows while collateral is a stock variable. However, here I argue that if we investigate the relationship between debt capacity and net worth, then there is some similarity between these two borrowing constraints. More specifically, based on the previous model setup, by the time entrepreneurs need to repay their debt at $t + dt$, earnings at t have already become part of the net worth at $t + dt$. Therefore, both borrowing constraints link debt capacity to verifiable net worth as follows:

$$\textbf{debt capacity} = \phi \times \textbf{verifiable net worth}$$

Therefore, if entrepreneurs' net worth can be observed, then these two types of borrowing constraints are similar in the sense that they impose a requirement that the maximum amount of debt entrepreneurs can borrow is a fraction of their net worth.

cross-sectional difference Comparing equations (7) and (9), we can clearly see that the fundamental difference between these two types of borrowing constraints lies in their cross-sectional difference. For the entrepreneurs faced with collateral-based borrowing constraint, given their wealth, productive firms do not face any additional advantages because the tightness of borrowing constraint is the same for all entrepreneurs. However, as for entrepreneurs with earnings-based borrowing constraint, given their wealth, productive firms have additional advantages because the tightness of constraints is decreasing in productivity. As we will see in the following sections, such a difference is crucial for our understanding in the different macroeconomic implications of these two borrowing constraints.

2.5 Equilibrium definition

The equilibrium definition here can be summarized as in Definition 1.

DEFINITION 1. *A stationary recursive competitive equilibrium consists of prices* $\{r_t, w_t\}_{t=0}^{\infty}$ *and allocations* $\left\{ \left(l_{t,i,j}, k_{t,i,j}, b_{t,i,j}, c_{t,i,j}\right)_{i\in[0,1], j\in\{\mathcal{B},\mathcal{F}\}} \right\}_{t=0}^{\infty}$ *that satisfy the following conditions:*

1. ***Optimization**: given market prices* $\{r_t, w_t\}_{t=0}^{\infty}$*, resource allocations*

$$\left\{ \left(l_{t,i,j}, k_{t,i,j}, b_{t,i,j}, c_{t,i,j}\right)_{i\in[0,1], j\in\{\mathcal{B},\mathcal{F}\}} \right\}_{t=0}^{\infty}$$

   maximize each entrepreneur's life-time utility (1) subject to constraints (2), (4), (7), (9), and initial endowment $\left(k_{0,i,j}, a_{0,i,j}\right)$.

2. ***Market clearance**: market prices* $\{r_t, w_t\}_{t=0}^{\infty}$ *satisfy the following conditions*

   - *labor market at any time t*

$$\iint l_t^{\mathcal{B}}(a,z)\,\omega_t^{\mathcal{B}}(a,z)dadz + \iint l_t^{\mathcal{F}}(a,z)\,\omega_t^{\mathcal{F}}(a,z)dadz = \bar{L} \tag{17}$$

- *bond market at any time t*

$$\iint b_t^{\mathcal{B}}(a,z)\,\omega_t^{\mathcal{B}}(a,z)dadz + \iint b_t^{\mathcal{F}}(a,z)\,\omega_t^{\mathcal{F}}(a,z)dadz = 0 \tag{18}$$

- *final goods market at any time t*

$$\mathcal{C}_t^{\mathcal{F}} + \mathcal{C}_t^{\mathcal{B}} + \mathcal{C}_t^{\mathcal{L}} + \mathcal{X}_t^{\mathcal{F}} + \mathcal{X}_t^{\mathcal{B}} = \mathcal{Y}_t^{\mathcal{F}} + \mathcal{Y}_t^{\mathcal{F}} \tag{19}$$

where

$$\begin{aligned}
\mathcal{C}_t^{j} &= \iint c_t^{j}(a,z)\,\omega_t^{j}(a,z)dadz,\ j\in\{\mathcal{B},\mathcal{F}\}\\
\mathcal{C}_t^{\mathcal{L}} &= w_t\bar{L}\\
\mathcal{X}_t^{j} &= \iint x_t^{j}(a,z)\,\omega_t^{j}(a,z)\,dadz,\ x = k' - (1-\delta)\,k \text{ and } j\in\{\mathcal{B},\mathcal{F}\}\\
\mathcal{Y}_t^{j} &= \iint y_t^{j}(a,z)\,\omega_t^{j}(a,z)\,dadz,\ j\in\{\mathcal{B},\mathcal{F}\}
\end{aligned}$$

3. ***Stationary distribution****: the wealth distributions in two sectors $\left\{\omega_t^{\mathcal{F}}(a,z),\omega_t^{\mathcal{B}}(a,z)\right\}$ obey entrepreneur's optimal decision and the exogenous productivity process (3), and they are stationary, i.e., $\frac{\partial\omega_t^{\mathcal{B}}(a,z)}{\partial t}=0$ and $\frac{\partial\omega_t^{\mathcal{F}}(a,z)}{\partial t}=0$.*

2.6 Preliminary Analysis

2.6.1 Individual optimal decisions

To begin with, I first characterize the optimal policy functions for each individual entrepreneur. The optimal decisions of bond holdings and capital investment can be summarized as in Lemma 3.

Lemma 3. *Given the market prices r and w, there is a same productivity cutoff for being active $\underline{z}$ for entrepreneurs in both sectors. The optimal capital and debt holdings for entrepreneurs in the banking sector are*

$$\begin{aligned}
b_{\mathcal{B}}(a,z) &= \begin{cases}\frac{\lambda_{\mathcal{B}}a}{1+r-\lambda_{\mathcal{B}}} & z\geq\underline{z}\\ -a & z<\underline{z}\end{cases}\\
k_{\mathcal{B}}(a,z) &= \begin{cases}\frac{(1+r)a}{1+r-\lambda_{\mathcal{B}}} & z\geq\underline{z}\\ 0 & z<\underline{z}\end{cases}
\end{aligned}$$

Meanwhile, the optimal capital and debt holdings for entrepreneurs in the TechFin sector are

$$
\begin{aligned}
b_{\mathcal{F}}(a,z) &= \begin{cases} \frac{\lambda_{\mathcal{F}}\xi z a}{1+r-\lambda_{\mathcal{F}}\xi z} & z \geq \underline{z} \\ -a & z < \underline{z} \end{cases} \\
k_{\mathcal{F}}(a,z) &= \begin{cases} \frac{(1+r)a}{1+r-\lambda_{\mathcal{F}}\xi z} & z \geq \underline{z} \\ 0 & z < \underline{z} \end{cases}
\end{aligned}
$$

where $\underline{z} = \frac{r+\delta}{\xi}$ *and* $\xi = \alpha\left(\frac{1-\alpha}{w}\right)^{\frac{1-\alpha}{\alpha}}$.

Given our assumption on the constant return-to-scale technology and frictionless labor market, the marginal product of capital for any individual entrepreneur with productivity z is always proportional to $z-\delta$. If the current interest rate on the market is r, then the optimal capital choice is a corner solution: it is zero for entrepreneurs with productivity lower than some threshold $\underline{z}$, and the maximal amount of borrowing for entrepreneurs with productivity higher than $\underline{z}$. At the same time, these inactive entrepreneurs will lend all their wealth to the market so that they can get a constant return r. The cutoff $\underline{z}$ is the same for two sectors simply because we assume the production technology in these two sectors is the same.

Again, one important observation from Lemma 3 is that compared to entrepreneurs in the traditional banking sector, productive firms borrowing from BigTech companies have additional advantages in lending and capital accumulation. As shown in the following lemma, these advantages eventually reflect on the wealth evolution dynamics.

Lemma 4. *With preference assumption (1), entrepreneur's wealth a in both sectors evolves according to the following equations:*

$$
\begin{aligned}
da_{\mathcal{B}} &= \left\{\mathbb{1}_{z\geq\underline{z}} \times \left[\frac{(1+r)(\xi z - r - \delta)}{1+r-\lambda_{\mathcal{B}}} + r - \rho\right] + \mathbb{1}_{z<\underline{z}} \times (r-\rho)\right\} a_{\mathcal{B}} dt \equiv \Gamma^{\mathcal{B}}(z)\, a_{\mathcal{B}} dt \\
da_{\mathcal{F}} &= \left\{\mathbb{1}_{z\geq\underline{z}} \times \left[\frac{(1+r)(\xi z - r - \delta)}{1+r-\lambda_{\mathcal{F}}\xi z} + r - \rho\right] + \mathbb{1}_{z<\underline{z}} \times (r-\rho)\right\} a_{\mathcal{F}} dt \equiv \Gamma^{\mathcal{F}}(z)\, a_{\mathcal{F}} dt
\end{aligned}
$$

For simplicity, we will write them as

$$
da_j = \Gamma_t^j(z)\, a_j dt \tag{20}
$$

where Γ *is the wealth growth rate function, and it depends on entrepreneur's idiosyncratic productivity* z *and the sector* $j \in \{\mathcal{B}, \mathcal{F}\}$ *he belongs to.*

As we can see from the proof in the appendix, with the assumption of log-utility, the optimal consumption choice will always be a constant ρ fraction of wealth, where ρ is the time value. Therefore, wealth growth rate of firms with lower productivity in two sectors is always $r - \rho$ because these firms are not producing anything on the market. Instead they will lend all their wealth to these productive entrepreneurs, as a result, they will get a constant rate of return r before determining their consumption.

What is interesting here is that the wealth growth rate is different for productive firms in different sectors. For any active producer borrowing from the banking sector, his wealth growth rate is $(\xi z - r - \delta)\,\lambda_{\mathcal{B}} + r - \rho$, which is a linear function in z. In contrast, wealth growth rate of any active firm with productivity z borrowing from the TechFin sector is $\frac{\lambda_{\mathcal{F}}(\xi z - r - \delta)}{\lambda_{\mathcal{F}} - (\lambda_{\mathcal{F}} - 1)\xi z} + r - \rho$, which is a convex function of z. Such difference can be better illustrated in Figure 3. As we will see it later, the convexity of wealth growth rate in the TechFin sector is the underlying reason why uncertainty, i.e., the second-moment shocks, matters for the aggregate quantities over the business cycles. The degree of $\lambda_{\mathcal{F}}$ determines the convexity of this relationship, which as a result affects the impacts of uncertainty.

Besides, the different types of borrowing constraints will also lead to difference in distributions of capital holdings and outputs in these two sectors. In the top two graphs in Figure 4, I present the capital holdings for firms with different productivity and wealth. If the entrepreneur's productivity is lower than the threshold, then firms will not produce anything therefore the capital holdings are zeros for these low-productivity firms. Once firms become productive, then the equilibrium capital holdings are different in these two sectors. In the banking sector, entrepreneurs face wealth-based borrowing constraint, therefore the capital holdings only depend on wealth and do not depend on productivity at all. In contrast, in the TechFin sector, capital holdings are increasing in both wealth and productivity, which makes the sectoral capital is concentrated on firms with highest wealth and productivity. Since optimal output is linear in capital, as we can see from the bottom two graphs in Figure 4, we can achieve the same conclusion for firms output.

2.6.2 Dynamics of wealth distributions

After discussing the optimal policy function for any individual entrepreneur, now I turn to characterize how the wealth distributions in both sectors evolve over time. With the exogenous productivity process (3) and the endogenous wealth process (20), the wealth distribution evolves according to the following equations:

$$\frac{\partial \omega_t^j(a,z)}{\partial t} = -\frac{\partial \left[\Gamma_t^j(z)\, a\omega_t^j(a,z)\right]}{\partial a} - \frac{\partial \left[\frac{1}{\theta}(\overline{\mu}-z)\,\omega_t^j(a,z)\right]}{\partial z} + \frac{1}{2}\frac{\partial^2\left[\frac{1}{\theta}\sigma^2\omega_t^j(a,z)\right]}{\partial z^2} \text{ where } j \in \{\mathcal{B},\mathcal{F}\} \tag{21}$$

Generally speaking, what determines the evolution of wealth distribution in this economy is a system of high-dimensional partial differential equations (PDEs). Previous works, including Kiyotaki (1998), Caselli and Gennaioli (2013), and Moll (2014), use wealth shares to characterize aggregates so that we can save one state variable. However, this method is not applicable here as we have two different sectors in this economy. Scaling the wealth by using aggregate capital and getting wealth share cannot reduce the number of state variables. Therefore, I follow Raissi, Perdikaris and Karniadakis (2019) and use Physics-informed neural network (PINN) approach to numerically solve the dynamics of ω_j. This deep learning method utilizes the advantages of deep neural networks to solve high-dimensional PDEs and it has a significantly reduced time and memory costs compared to those classical methods such as finite difference and finite element. The advantage of deep learning approach lies in the fact that the algorithm does not require interpolation and coordinate transformation because it is universal nonlinear approximators (Bach, 2017) and thus avoids the curse of dimensionality. In addition, it can overcome the local optimization problem by introducing some penalty factors or stochasticity into the loss function. Other possible solving methods include adaptive sparse grids approach by Brumm and Scheidegger (2017) and some different neural network approaches proposed by Fernandez-Villaverde et al. (2020) and Chen, Didisheim and Scheidegger (2021).

3 Two Types of Financial Accelerators

In this section, I turn to investigating model implications with numerical exercises. The focus is to investigate the impacts of different types of borrowing constraints on both steady-state allocative efficiency and business cycles.

3.1 Parameterization

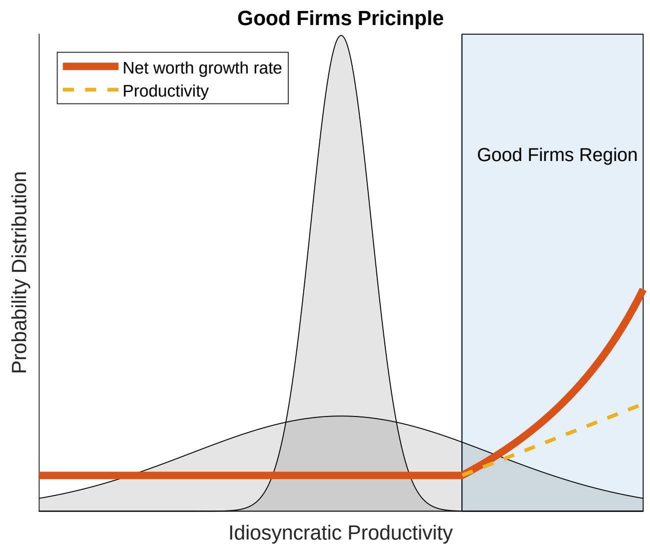
The choice on values of different parameters is shown in Table 1. Following the existing literature, I set the rate of time preference to be 0.05, capital share to be 0.33, and the labor market size normalized to be 1.0. Using the U.S. Bureau of Economic Analysis (BEA) Fixed Assets Tables dataset, I compute the average capital depreciation rate to be 6%. Based on Moll (2012), the random death rate of entrepreneurs is picked to be 0.05. Following Asker, Collard-Wexler and Loecker (2014), in the baseline model, I set $\overline{\mu}$ to be zero, the persistence of productivity to be 0.85, and the idiosyncratic productivity to be 0.56. The choices of these parameters related to the underlying productivity are consistent with the actual firm-level TFP measure in the data. In addition, the ad hoc choice on the upper boundary for corporate leverage is assigned to be 10. However, the precise choice on this parameter does not matter significantly for the model outcomes.

Throughout this section, I will discuss how various choices on the tightness of constraints in banking $\lambda_{\mathcal{B}}$, the tightness of constraints in TechFin $\lambda_{\mathcal{F}}$, degrees of first-moment shocks $\Delta\bar{\mu}$, and degrees of second-moment shocks $\Delta\sigma$, affect our final conclusions.

3.2 Earnings-based borrowing constraint as the financial accelerator of micro-uncertainty

Before investigating the macroeconomic implications of the co-existence of two types of financial sectors, I start with discussing the interesting amplification mechanism between micro-uncertainty and earnings-based borrowing constraint. As mentioned before, one important characteristic of this earnings-based borrowing constraint is that it will generate an asymmetric net worth growth rate: for unproductive firms, their wealth growth rate is always the market interest rate; meanwhile, for productive firms, their wealth rate is increasing in their productivity. As a result, compared to the standard collateral-based borrowing constraint, earnings-based borrowing constraint can help productive firms quickly build up their net worth, and this interesting feature will make the TechFin sector sensitive to the underlying second-moment shocks.

There are three key implications from our numerical exercises in this part. First, within the TechFin sector, aggregate allocative efficiency is increasing in the dispersion of underlying firm-level productivity. As shown in Graph (A) in Figure 5, the aggregate allocative efficiency is higher when the micro-level uncertainty is larger. This conclusion seems counter-intuitive at first, but the underlying mechanism can be easily summarized as "good-firms principle" shown as in the following figure:



In an economy with a higher degree of micro-level uncertainty, it means that there exists more firms that are highly unproductive and productive, i.e., the productivity dispersion is significantly wider. However, unproductive entrepreneurs do not matter for the aggregate economy because they choose to not operate and lend their wealth to the productive entrepreneurs. With the help of earnings-based borrowing constraint, the highly productive entrepreneurs can increase their wealth faster because they get to use more leverage. As a result, there will be more active and highly productive entrepreneurs in this economy when dispersion is higher. Therefore, an increase in micro uncertainty leads to higher total outputs and allocative efficiency because the good firms become more important. I name this mechanism "good firms principle" to echo "good news principle" proposed by Bernanke (1983). Good news principle in Bernanke (1983) means that only good news matters in growth options because bad news will not be proceeded further. With earnings-based borrowing constraint, what is essential for an economy is the number of superstar firms and their relative importance. Therefore, an increased uncertainty will generate positive outcomes on the aggregate productivity.

Second, there is a feedback loop between micro-uncertainty and earnings-based borrowing constraint. As shown in Graph (B) in Figure 5, when there is a positive or negative shock to micro-level uncertainty, it generates amplified and persistent fluctuations to the aggregate productivity. This outcome is similar to the classical financial accelerator mechanism as shown in Bernanke and Gertler (1989) and Kiyotaki and Moore (1997). The underlying mechanism for this new financial accelerator mechanism comes from the fact that the shocks to micro-level uncertainty also changes the wealth share of firms with different productivity in this economy. For example, a positive shock to micro-level uncertainty, combined with the asymmetric wealth growth rate characteristic of earnings-based borrowing constraint, leads to the increasing importance of large firms in this economy. In this way, earnings-based borrowing constraint amplifies the impacts of uncertainty on net worth inequality by allowing more productive firms to use more leverage and grow faster. This effect is persistent as these changes on net worth inequality are persistent over time. As a result, a transitory micro-level uncertainty shock can lead to persistent changes in finance allocation efficiency and aggregate productivity. This new financial accelerator mechanism differs from the classic one in three aspects: micro uncertainty instead of aggregate productivity is the primitive shock; financial friction comes from earnings-based borrowing constraint instead of collateral-based borrowing constraints; and the feedback loops happen between net worth inequality, instead of net worth level, and asset prices.

Third, the strength of this new financial accelerator mechanism crucially depends on the tightness of the borrowing constraint and also the persistence of underlying productivity process. As shown in Figure 6 and 7, the importance of this new type of financial accelerator mechanism in driving the economic fluctuations is larger when the borrowing constraint is more slack and the underlying productivity process is more persistent. This result shows up again because their impacts on the wealth share of the highly productive firms in this economy.

3.3 A Macroeconomic Model with Two Financial Sectors

Now I turn to investigate the model implications with two types of financial sectors. For better comparison and discussion, I include one benchmark economy with a banking sector only, i.e., $\lambda_{\mathcal{F}} = 0$. In all the following exercises, I report the behavior of all variables relative to their steady-state values.

3.3.1 Impacts on aggregate allocative efficiency

The impacts of the development of TechFin sector on aggregate allocative efficiency can be summarized in Figure 8. As the TechFin sector develops, the aggregate allocative efficiency is increasing in the economy. More importantly, compared to the development of traditional banking sector, the availability of this new type of financial intermediaries is more essential to reducing the wedges between marginal products of capital. The underlying mechanism is the following. In an idea world with a perfectly well-functioning credit market, only the entrepreneur with the highest productivity should be operating in equilibrium. With financial frictions, we can no longer achieve this first-best outcome as some productive firms are financially constrained so their marginal products of capital are higher than the market average. However, there is a fundamental difference between the collateral-based borrowing constraint in banking sector and the earnings-based borrowing constraint in TechFin sector. In banking sector, the maximum amount of debt can be borrowed is linked to capital stock. Meanwhile, in TechFin sector, the upper limit of debt financing is directly related to productivity. Therefore, compared to the traditional banking sector, the *de facto* tightness of borrowing constraints for highly productive firms are looser for BigTech lendings. Thus, the equilibrium wealth is more concentrated towards productive firms, and the degree of capital misallocation is lower in TechFin sector.

The result here has some important policy implications. It is widely common that underdeveloped countries have underdeveloped financial markets. The existence of financial frictions will affect the accumulation of capital and wealth, which eventually slows the economic growth rate in these emerging countries. However, if the superstar firms in these countries, especially those Tech Giants, can provide financial services to other firms, then it has the potential to narrow down the differences in per capita income. Based on our numerical exercises here, the technology advantage of these superstar firms can work better to improve the aggregate capital allocative efficiency, compared to the traditional banking sector.

3.3.2 Impacts on economic fluctuations

For investigating the implications on business cycles, I conduct two different experiments. For both experiments, I compute the impulse responses from three different models: a standard real business cycle model with no financial frictions, a model with banking sector only, and a model with both banking and TechFin sectors. As the steady-state values are also different across these models, I report the behaviors of all variables relative to their steady-state values.

The first experiment I consider is a one-time shock to the level of (aggregate) productivity. This shock is the standard one in the traditional real business cycle models. Although this is one-time shock, because technology is autocorrelated, productivity will stay above/below trend for several periods. Graph (A) in Figure 9 presents the economy's response to a one-time 1% increase in the productivity level. As we can see from this graph, in the frictionless real business cycle model, capital structure is indeterminate and irrelevant to real economic outcomes. Therefore, the decline in the need for external finance has no negligible amplified impacts on the aggregate economy. In contrast, in a model with collateral-based borrowing constraint, increases in aggregate productivity level. It is consistent with the classical financial accelerator literature: when credit markets have asymmetric information and agency problems, the role of credit-market frictions are important drivers of cyclical economic fluctuations. What's interesting here is that the magnitude of these effects is about the same for an economy with two different types of financial sectors. A different type of borrowing constraint will not weaken this mechanism as the link between external financing cost and the net worth of borrowers still exists for earnings-based borrowing constraint. A higher borrower net worth reduces the agency costs of financing, and this mechanism holds for both types of borrowing constraints. Therefore, if the underlying fundamental shock is from the productivity level, then the earnings-based borrowing constraint magnifies and propagates the technology shocks in a similar way as the collateral-based one. Compared to the frictionless benchmark economy, Graph (A) in Figure 9 shows that the dynamics in the early periods are quite different because of the role of net worth (inequality). In addition, the hump shape in investment and the reverse hump shape in consumption indicate the unique role of borrowing constraints in driving business cycles.

The real difference between these two types of borrowing constraints shows up when the fundamental shock is from the second-moment uncertainty. The second experiment I consider is a one-time shock to micro-level uncertainty. This experiment is useful for considering the impacts of various shocks to the economy that only affect the degree of uncertainty. As we can see from Graph (B) in Figure 9, a positive shock to micro-level uncertainty has essentially no effect in the frictionless benchmark and the economy with a banking sector only, but has both significant impact and propagation effects when there exists a TechFin sector with earnings-based borrowing constraint. The transfer of wealth inequality drives up the demand for investment, initiating a positive feedback loop. The substantial persistence comes from the slow decay of entrepreneurial net worth inequality. The introduction of a TechFin sector raises the possibility that relatively small changes in micro-level uncertainty could generate significant economic fluctuations. In contrast, such characteristic is negligible in the frictionless benchmark economy, as well as the economy with only a banking sector, as this feature of asymmetric wealth growth rate is a special characteristic of TechFin.

The results here are closely related to several papers documenting the real effects of second-moment shocks (e.g. Bloom, 2009; Bloom et al., 2018; Alfaro, Bloom and Lin, 2019). However, there exists a fundamental difference. Indeed, as the TechFin sector develops, the whole economy is becoming more sensitive to uncertainty shocks, but in a positive relationship. In contrast, the standard uncertainty literature documents the negative impacts of uncertainty on the real economy. The reason why such a difference exists comes from the different underlying mechanisms. In this paper, the mechanism is feedback loop between earnings-based borrowing constraint and micro-level uncertainty. In contrast, in their works, the mechanism comes from the fact that is higher uncertainty causes firms to temporarily pause their investment and hiring, which leads to a decline in productivity growth.

4 Conclusion

This paper investigates the role of a TechFin sector in driving macroeconomic fluctuations. I introduce both a traditional financial sector and a TechFin sector into a general equilibrium model with heterogeneous entrepreneurs and incomplete markets. These two financial sectors are identical expect for the types of borrowing constraints faced by entrepreneurs: entrepreneurs borrowing from the banking sector are subject to the standard collateral-based borrowing constraints, while those borrowing from the TechFin sector are subject to the earnings-based borrowing constraints. I use a deep learning neural network approach to obtain global solutions, and the main conclusions are twofold. First, this new TechFin credit system leads to a higher capital allocative efficiency in the steady state. Second, the existence of BigTech lending acts as a propagation mechanism and makes the economy sensitive to both first-moment productivity level shocks and second-moment uncertainty shocks.

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Figures and Tables

Figure 1: The Rise of FinTech and BigTech Lending

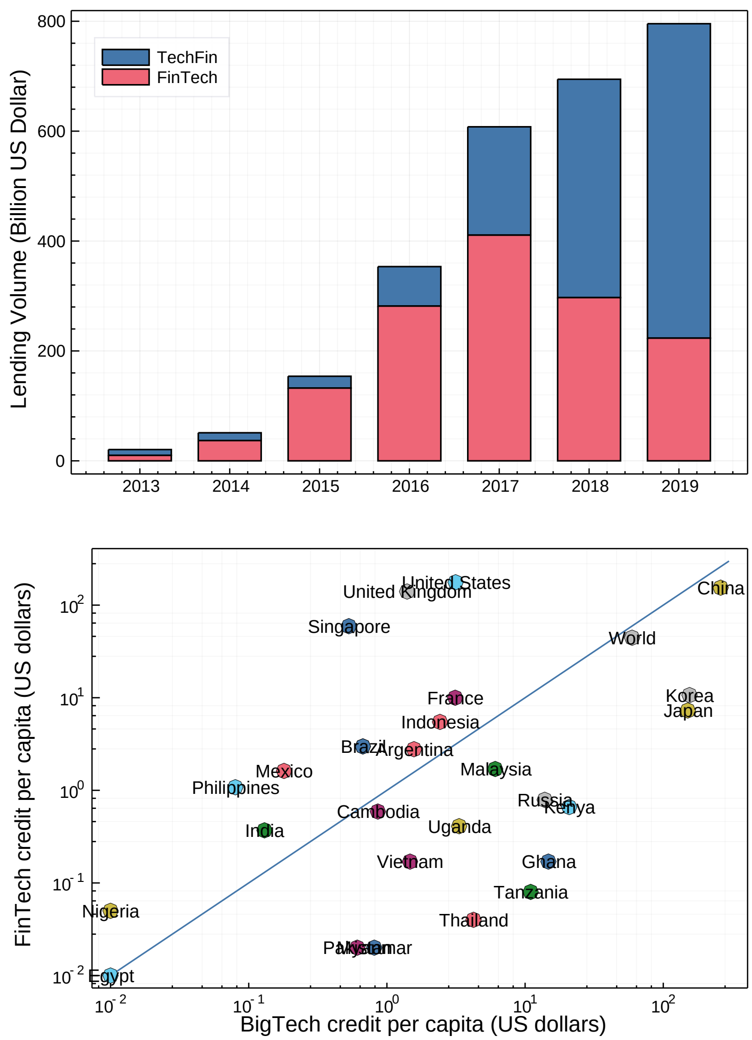


Figure 2: Summary of Economic Environment

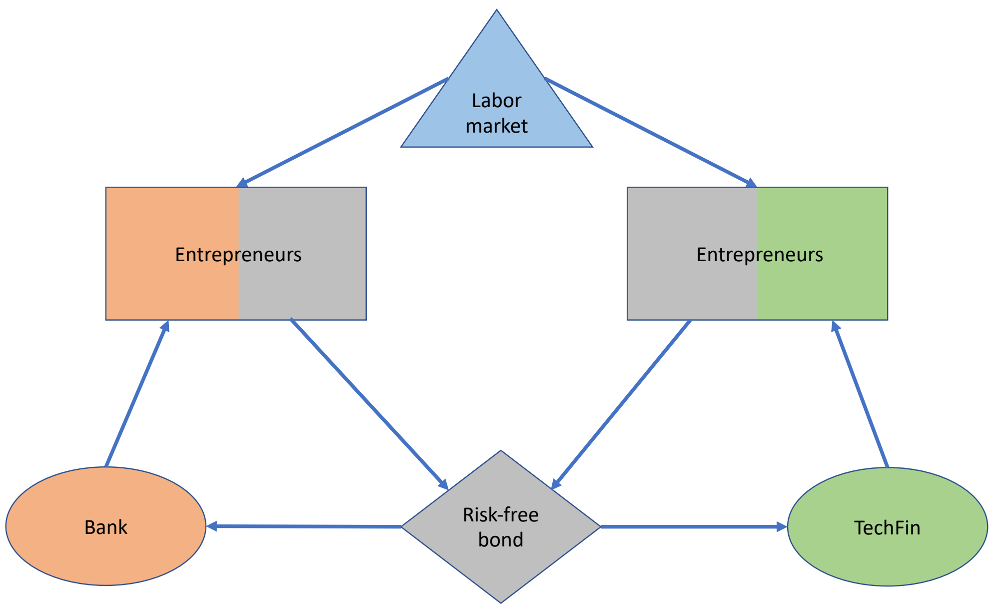


Figure 3: Wealth growth rate in Banking and TechFin sector: an example

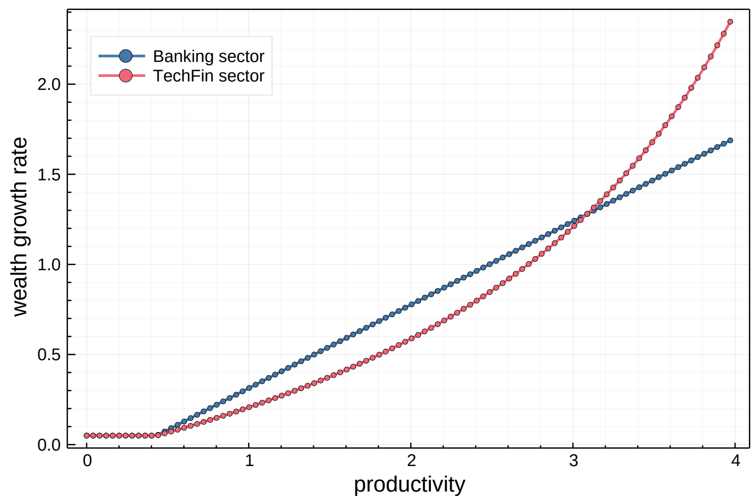


Figure 4: Capital and output in Banking and TechFin sector: an example

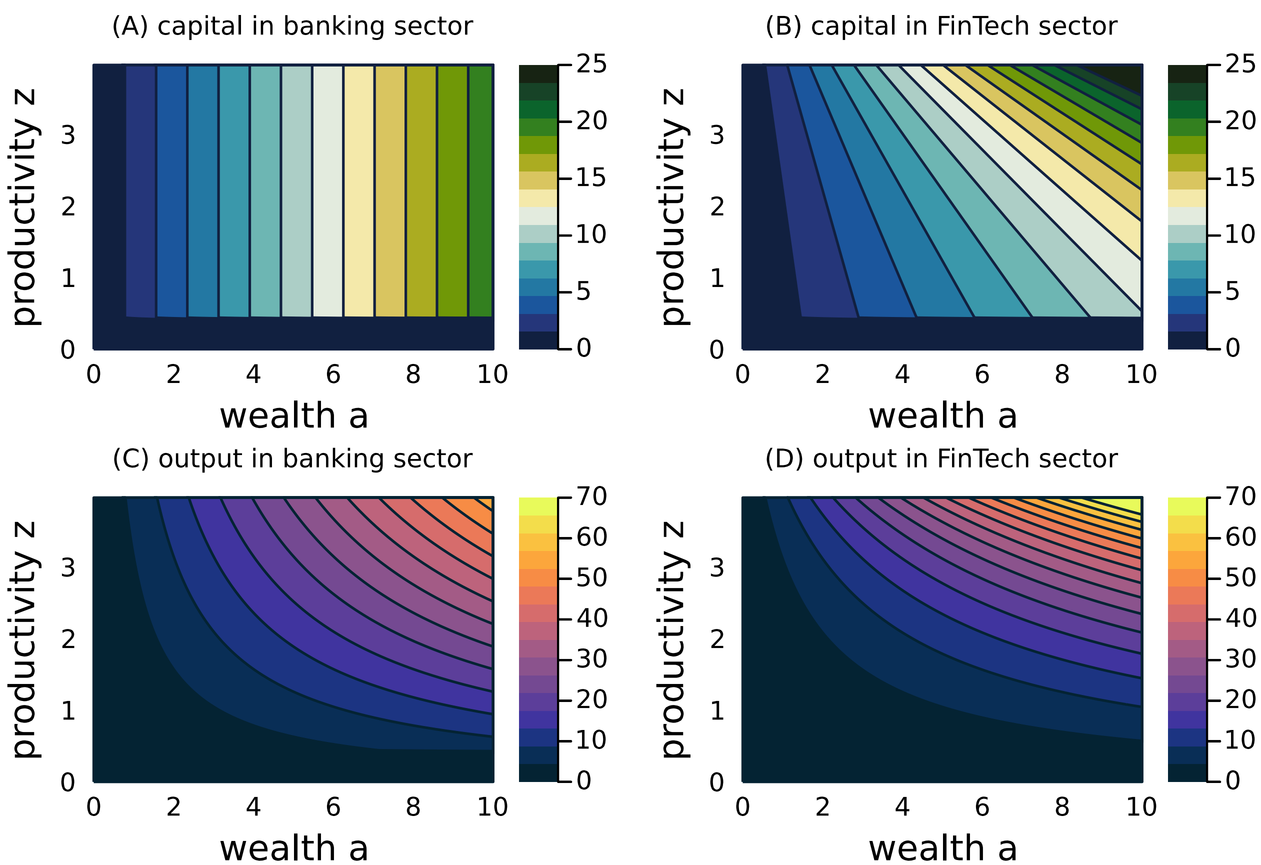
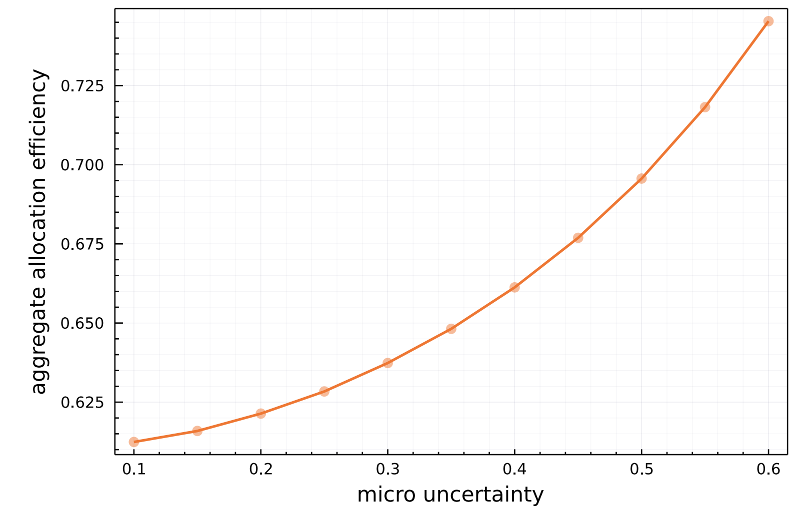


Figure 5: Micro-uncertainty and earnings-based borrowing constraint: a new type of financial accelerator

(A) steady states



(B) business cycles

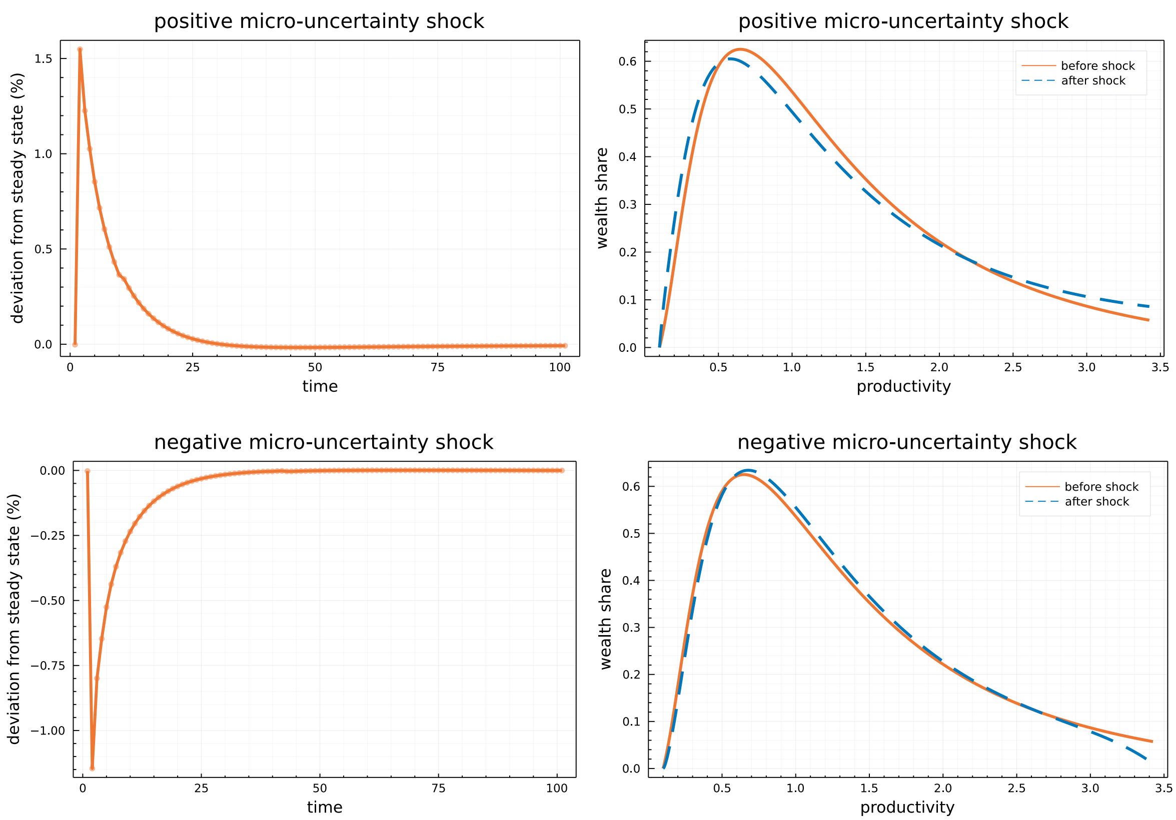
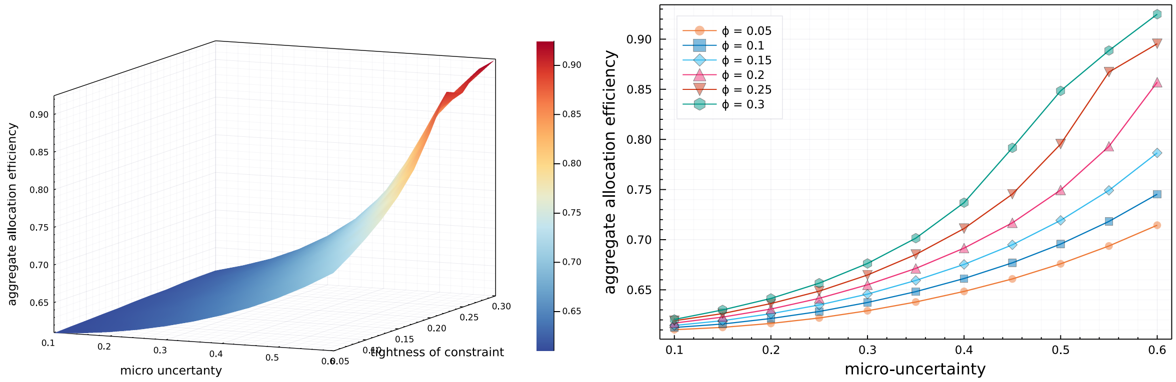


Figure 6: Determinants of aggregate allocation efficiency

(A) micro-uncertainty and cash flow-based borrowing constraints



(B) micro-uncertainty and autocorrelation

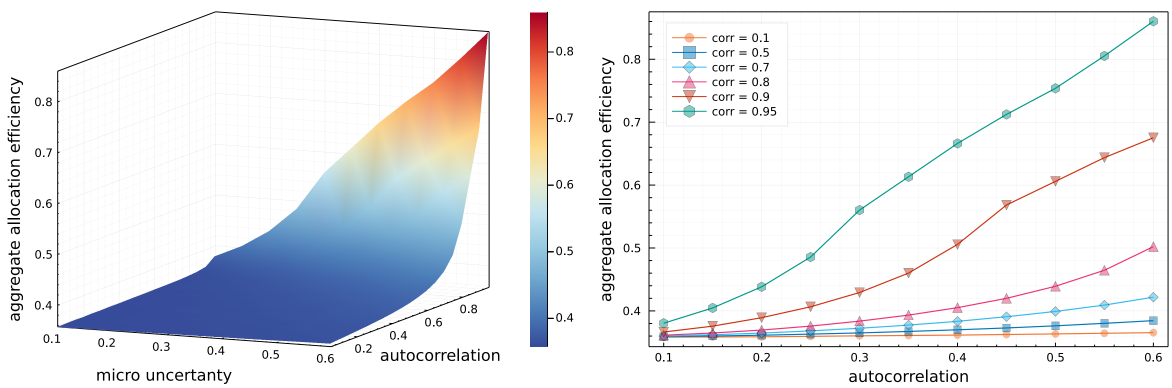


Figure 7: Determinants of business cycle fluctuations

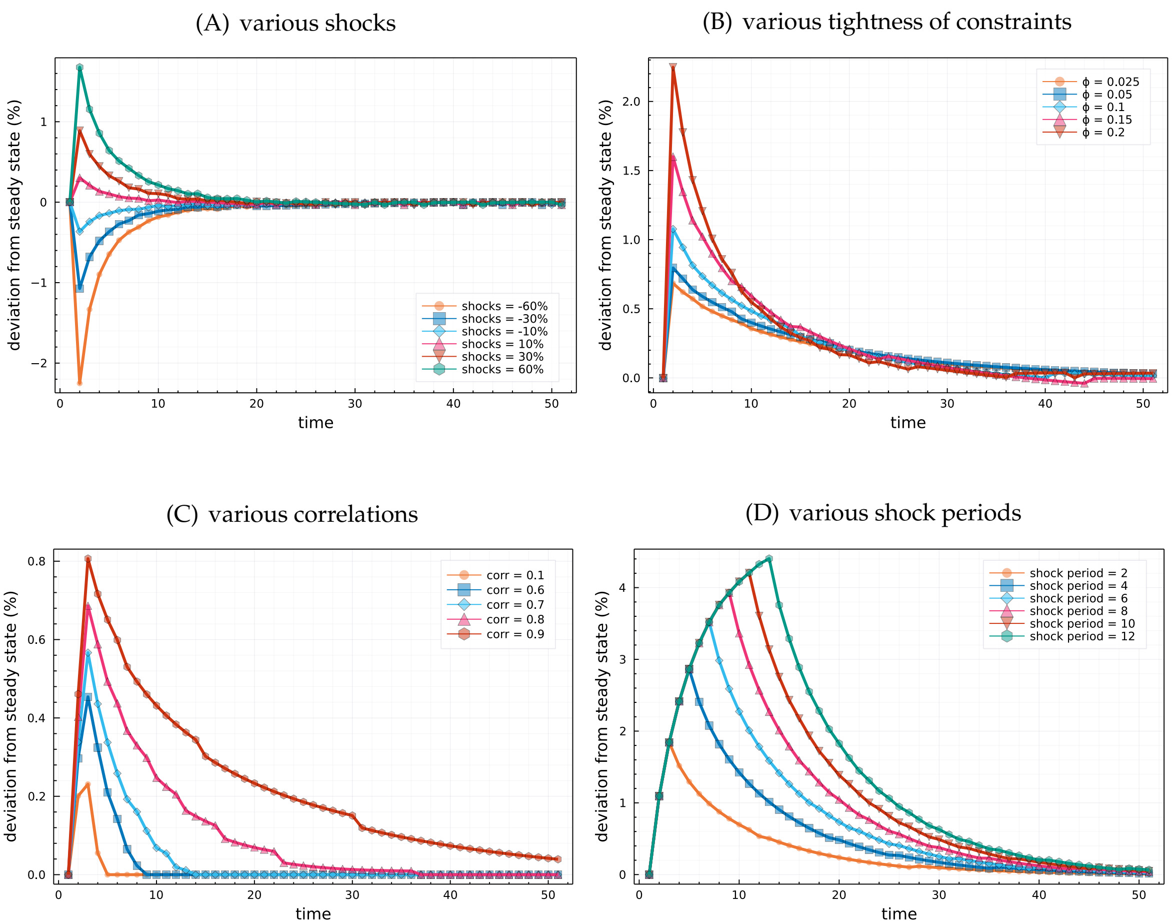


Figure 8: A Macroeconomic Model with Two Financial Sectors: aggregate allicative efficiency

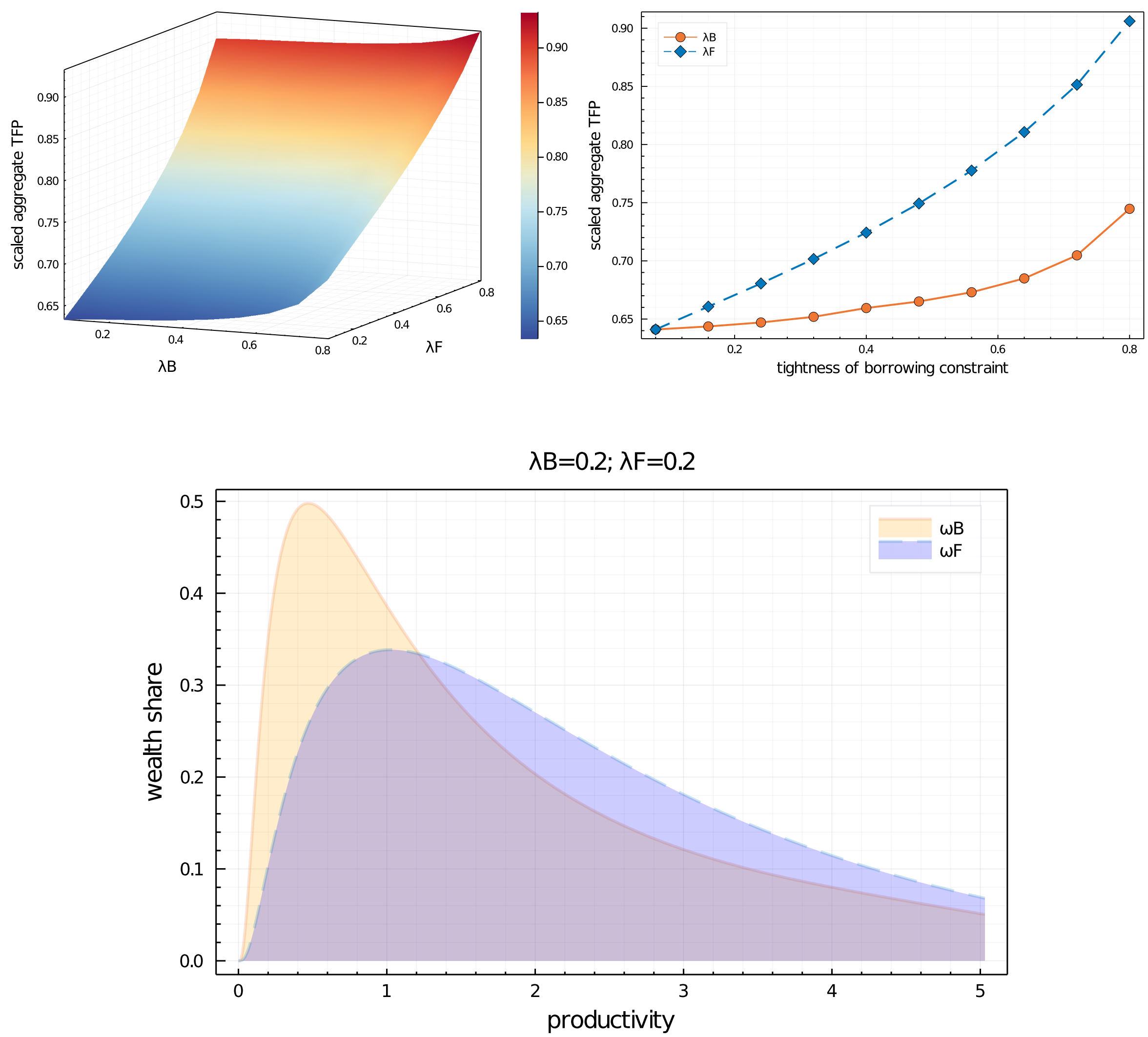
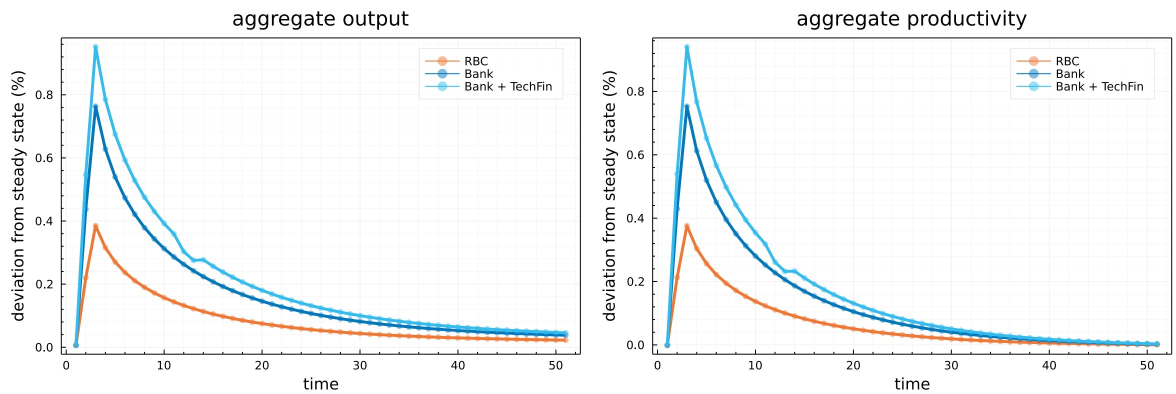


Figure 9: A Macroeconomic Model with Two Financial Sectors: business cycles

(A) productivity level shocks



(B) micro-uncertainty shocks

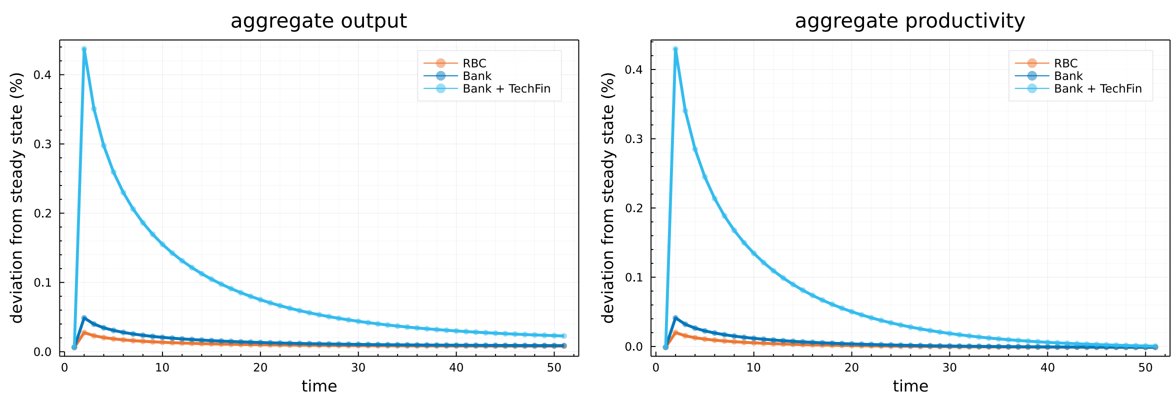


Table 1: Parameterization

Parameter	Description	Value	Source/Reference
ρ	rate of time preference	0.05	
α	capital share	0.33	Moll (2014)
$\overline{L}$	labor market size	1.0	
δ	capital depreciation rate	0.06	BEA-FAT
χ	death rate	0.05	Moll (2012)
$\overline{\mu}$	log idiosyncratic productivity mean	0.0	
θ	autocorrelation $e^{-\theta}$	0.16 (corr = 0.85)	Asker, Collard-Wexler and Loecker (2014)
σ	log idiosyncratic productivity s.d.	0.56	
$\bar{\phi}$	upper boundary for corporate leverage	10.0	

APPENDIX

A Proof

Proof of Lemma 1 and 2

Proof. To begin with, it can be easily shown that lenders will not verify if entrepreneur announces the good state as entrepreneurs have no incentives to announce the good state when the actual is a bad one.

There are several conditions on this optimal contract. First, the lenders must be break-even. As shown in Equation (13), the funding cost for investors is $(1+r)\,b$, and the expected return should be a weighted average of his payoff in the good state and his payoff in the bad state. Since there is no verification in the good state, investor's payoff is $z_G k - c_G$. However, in the bad state, there is a probability of q that investors will verify entrepreneurs' earnings and the cost of verification is assumed to be f. Therefore, his expected payoff in the bad state is $z_B k - q\left(c_B^v + f\right) - (1-q)\,c_B^{nv}$.

The second condition that an optimal contract needs to satisfy is that the entrepreneurs have no incentives to lie about the realized outcomes. Of course, entrepreneurs do not have any incentives to lie when it is a bad state. Entrepreneurs consumption in good state is always c_G. If he lies about the state and say it is a bad state. Then his expected consumption should be $(1-q)\left[(z_G - z_B)\,k + c_B\right]$.

The third condition that an optimal contract needs to meet is that the executions of contracts are feasible, which means all of c_G, c_B^v, and c_B^{nv} should be at least higher than or equal to zero. More importantly, p is a probability so it must lie between 0 and 1.

In this incomplete-collateralization case, the optimal verification probability is

$$q = \frac{(1+r)\,b - z_B k}{p\,(z_G - z_B)\,k - (1-p)\,f} \tag{A1}$$

when f is too large, q will be higher than 1 or even negative, which makes this earnings-based borrowing constraint infeasible. Therefore, in this paper, the micro-foundation for these two types of borrowing constraints is from the different earnings verification costs for banks and TechFin firms. As a result, they choose different ways of lending contracts, TechFin leads to the specialization-induced fragmentation in the financial services industry. In the following part of the paper, we will take these two types of borrowings as given, and investigate their macroeconomic implications.

Therefore, the expected profits of using these two types of lending can be shown as follows:

$$
\pi = \begin{cases} (1+r)\left[pz_G k + (1-p) z_B k - (1-p) f\right] & \text{if} \quad \text{cash flow-based lending} \\ (1+r) lk & \text{if} \quad \text{asset-based lending} \end{cases} \tag{A2}
$$

Therefore, if $f < f^* = \frac{pz_G + (1-p)z_B - l}{1-p} k$ or $l < l^* = pz_G + (1-p) z_B - (1-p) \frac{f}{k}$, then the lenders will strictly prefer cash flow-based lending over asset-based lending. □

Proof of Lemma 3

Proof. The entrepreneur's wealth in banking sector evolves according to

$$
da = (y - wl - \delta k - rb - c - \chi) dt = \left[(zk)^{\alpha} l^{1-\alpha} - wl - (r+\delta) k + ra - c - \chi\right] dt \tag{A3}
$$

subject to the collateral-based borrowing constraint

$$
k \leq \frac{a}{1-\lambda_{\mathcal{B}}}
$$

The first order conditions show that the optimal capital to labor ratio for firm with productivity z satisfies the following condition

$$
\frac{l}{k} = \left(\frac{1-\alpha}{w}\right)^{\frac{1}{\alpha}} z \tag{A4}
$$

Therefore, the firm's equilibrium profits can be written as

$$
\pi = \alpha \left(\frac{1-\alpha}{w}\right)^{\frac{1-\alpha}{\alpha}} zk \tag{A5}
$$

As the profit is a linear function of z, the firm's optimal choice on capital stock is a corner solution and meets the following condition

$$
k_{\mathcal{B}}(a,z) = \begin{cases} \frac{a}{1-\lambda_{\mathcal{B}}} & z \geq \underline{z} \\ 0 & z < \underline{z} \end{cases} \tag{A6}
$$

where $\underline{z} = \frac{r+\delta}{\xi}$ and $\xi = \alpha \left(\frac{1-\alpha}{w}\right)^{\frac{1-\alpha}{\alpha}}$.

Meanwhile, the firm's optimal debt holdings are

$$b_{\mathcal{B}}(a,z)=\begin{cases}\frac{\lambda_{\mathcal{B}}a}{1-\lambda_{\mathcal{B}}} & z\geq \underline{z}\\ -a & z<\underline{z}\end{cases} \tag{A7}$$

Equations (A6) and (A7) lead to the wealth growth for entrepreneurs in the banking sector as

$$da_{\mathcal{B}}(a,z)=\begin{cases}\left[\frac{(\xi z-r-\delta)a}{1-\lambda_{\mathcal{B}}}+ra-c-\chi\right]dt & z\geq \underline{z}\\ (ra-c-\chi)\,dt & z<\underline{z}\end{cases} \tag{A8}$$

Similarly, for TechFin entrepreneurs, we can derive the entrepreneur's optimal choice on capital stock, debt holdings, and the wealth growth rate. □

Proof of Lemma 4

Proof. As shown in the previous lemma, the wealth follows a process of $da_j=\left[\Gamma_j(z)\,a_j-c_j\right]dt$ for the entrepreneurs in sector j. Therefore, the Bellman equation $\mathcal{V}_j$ should satisfy the following equation

$$\rho\mathcal{V}_j(t,a,z)=\max_{c_j}\left\{\log c_j+\frac{1}{dt}\mathbb{E}\left[d\mathcal{V}_j(t,a,z)\right]\right\} \tag{A9}$$

subject to the condition that $da_j=\left[\Gamma_j(t,z)\,a_j-c_j\right]dt$.

With the guess and verify approach, we can show that the optimal consumption choice is $c_j=\rho a_j$ for all entrepreneurs in the economy. Assume that the value function takes the form of $\mathcal{V}_j(t,a,z)=\mathcal{B}_j v_j(t,z)+\mathcal{B}_j\log a_j$. Then we have

$$\mathbb{E}\left[d\mathcal{V}_j(t,a,z)\right]=\frac{\mathcal{B}_j}{a_j}da+\mathcal{B}_j\mathbb{E}\left[dv_j(t,z)\right] \tag{A10}$$

Combining Equations (A9) and (A10) gives us the following equation:

$$\rho\mathcal{B}_j v_j(t,z)+\rho\mathcal{B}_j\log a_j=\max_{c_j}\left\{\log c_j+\frac{\mathcal{B}_j}{a_j}\left[\Gamma_j(t,z)\,a_j-c_j\right]+\mathcal{B}_j\frac{1}{dt}\mathbb{E}\left[dv(t,z)\right]\right\} \tag{A11}$$

The first-order condition gives us $c_j=\frac{a_j}{\mathcal{B}_j}$. Substituting back in, we have

$$\rho\mathcal{B}_j v_j(t,z)+\rho\mathcal{B}_j loga_j=\log a_j-\log\mathcal{B}_j+\mathcal{B}_j\Gamma_j(t,z)-1+\mathcal{B}_j\frac{1}{dt}E\left[dv_j(t,z)\right]$$

which is

$$\left(\rho\mathcal{B}_j - 1\right)\log a_j = -\rho\mathcal{B}_j v_j\left(t,z\right) - \log\mathcal{B}_j + \mathcal{B}_j\Gamma_j\left(t,z\right) - 1 + \mathcal{B}_j\frac{1}{dt}E\left[dv_j\left(t,z\right)\right] \tag{A12}$$

Therefore, we can conclude that $\mathcal{B}_j = \frac{1}{\rho}$ for both sectors, and we have

$$\begin{aligned} c_j &= \rho a_j && \text{(A13)} \\ da_j &= \left[\Gamma_j\left(z\right)a_j - \rho\right]dt && \text{(A14)} \end{aligned}$$

Finally, the value function is

$$\mathcal{V}_j\left(t,a,z\right) = \frac{1}{\rho}\left[v_j\left(t,z\right) + \log a_j\right] \tag{A15}$$

and $v_j\left(t,z\right)$ satisfies the following condition:

$$\rho v_j\left(t,z\right) = \rho\log\rho + \Gamma_j\left(t,z\right) - \rho + \mathcal{B}_j\frac{1}{dt}E\left[dv_j\left(t,z\right)\right] \tag{A16}$$

In addition, we also need to prove that $\Gamma_{\mathcal{F}}\left(z\right)$ is a convex function of z. This step is relatively easy as we only need to check the signs of first and second derivatives:

$$\begin{aligned} \frac{\partial\Gamma_{\mathcal{F}}\left(z\right)}{\partial z} &= \frac{\xi\left[1-\left(r+\delta\right)\lambda_{\mathcal{F}}\right]}{\left[1-\lambda_{\mathcal{F}}\xi z\right]^2} > 0 && \text{(A17)} \\ \frac{\partial^2\Gamma_{\mathcal{F}}\left(z\right)}{\partial z^2} &= \frac{2\lambda_{\mathcal{F}}\xi^2\left[1-\left(r+\delta\right)\lambda_{\mathcal{F}}\right]}{\left(1-\lambda_{\mathcal{F}}\xi z\right)^3} > 0 && \text{(A18)} \end{aligned}$$

The above two equations are both positive because $1-\lambda_{\mathcal{F}}\zeta z > 0$ and $z > \underline{z} = \frac{r+\delta}{\xi}$.

Therefore, the wealth growth rate in the TechFin sector $\Gamma_{\mathcal{F}}\left(z\right)$ is a strictly convex function of productivity z. $\square$

B A Note on Lian and Ma (2021)

Lian and Ma (2021) document the prevalence of cash flow-based lending. They argue that 20% of debt by value is based on tangible assets, whereas 80% is based predominantly on cash flows from corporate operations. Here I want to argue that their main conclusion, especially the dominating use of cash flow-based lending, is not robust. A better and less controversial way of interpreting the empirical result is the co-existence of earnings-based and collateral-based borrowing constraints.

Graph (A) in Figure A1 replicates one of their main results in the paper. To be clear, all the raw data used in this section are directly obtained from Quarterly Journal of Economics Dataverse.[1] In their paper, Lian and Ma (2021) argue that "Figure I, Panel A, shows that the median share of asset-based and cash flow–based lending among large nonfinancial firms is generally less than 20% and slightly over 80%, respectively, in recent years." The key words in their original statement are **large** and **median**. More specifically, when they prepare the data for this graph, first they classify all the firms in Compustat dataset into five different groups according to their total asset levels. Then they drop the bottom 20% firms out of the sample. Finally, they compute the *median* share of asset-based and cash flow–based lending. As we can see from the replicated result in Graph (A), the median share of asset-based lending on average is 17.8%, while that of cash flow–based lending is 77.2%.

To begin with, I want to point out that these numbers are sensitive to the choice of sub-samples and the use of median. In Graph (B) of Figure A1, I plot the same results but without dropping the smallest firms out of the sample. In Graph (C) of Figure A1, I drop all the firms in the lowest quintile but use mean instead of median. In Graph (D), I include all the firms and use mean to calculate the average value. As we can see from these graphs, whether cash flow-based lending is really prevalent depends on the specific choice of our empirical measure. For example, in Graph (D), the average use of cash flow-based lending is 51.7% while the average use of asset-based lending is 41.6%. In this way, both types of lending are important financial frictions in the real economy.

The subsample selection is not the most problematic issue in their work. In fact, Lian and Ma (2021) do mention this point. They find that for small firms, asset-based lending is more common and the median value of asset-based lending among these small firms is roughly 54%.

The real problem comes from the use of median because the actual distribution of the borrowing constraints is a **bimodal** one. It is true that both median and mean can be interpreted as the "representative" value for the data sample, and sometimes the median is used as an alternative to the mean.

[1] Replication data and codes for Lian and Ma (2021) can be downloaded from here.

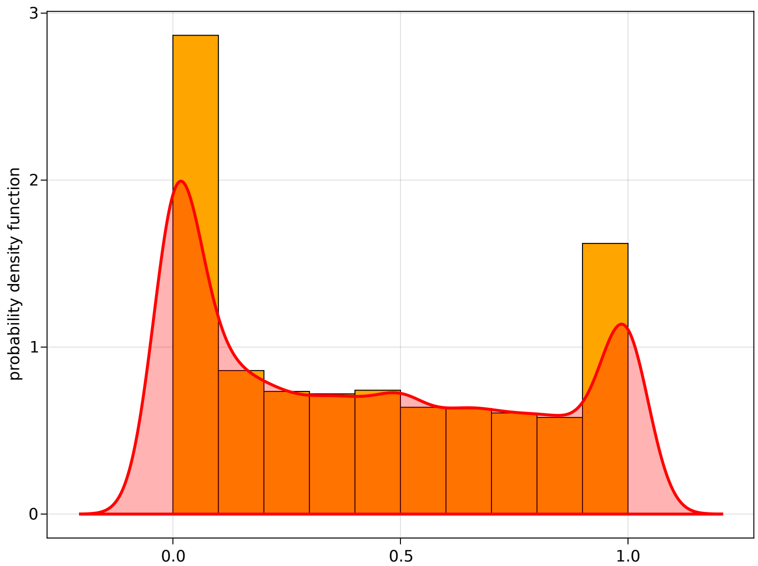
However, if the underlying distribution is a bimodal one, both indicators can be misleading, as there is no such a representative borrower in the data. Graph (A) and (B) in Figure A2 present the distribution of individual firm's use of asset-based and cash flow-based lending, respectively. As we can see from these two graphs, when we attempt to describe the use of borrowing constraint by individual firm, there is no such a representative firm in this economy because some firms rely heavily on cash-flow based lending while the other firms use more collateral-based lending. The detailed breakdown for each year throughout the data sample period can be shown in Figure A3 and A4. Generally speaking, the less controversial way of describing the reality is the co-existence of two types of borrowing constraints.

Figure A1: Anatomy of Corporate Borrowing Constraints

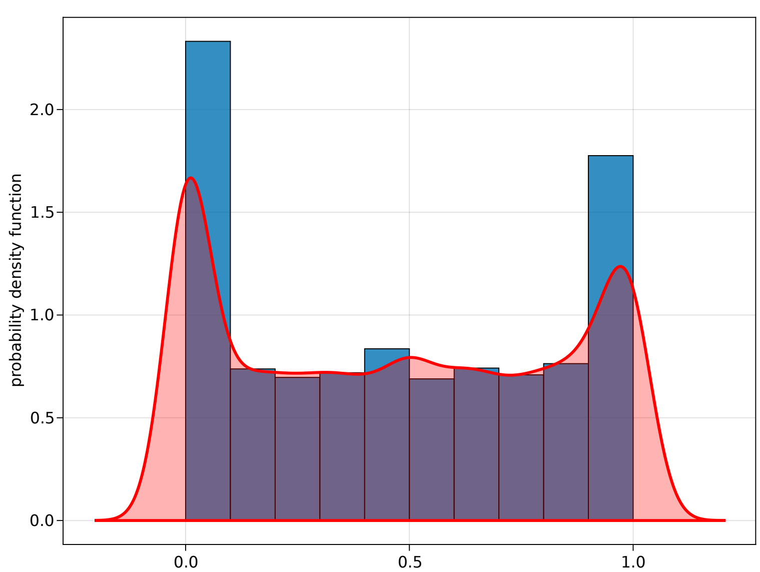
Notes: This figure presents anatomy of corporate borrowing constraints with different choices of summarizing the data. Main data source for this figure is obtained directly from the replication package for Lian and Ma (2021).

Figure A2: Distributions on the types of borrowing constraints

(A) distribution of the share of asset-based lending



(B) distribution of the share of cash-flow-based lending



Notes: This figure presents the distributions of inividual firm's use of two types of lending. Main data source for this figure is obtained directly from the replication package for Lian and Ma (2021). Orange and blue rectangles represent histogram distributions with normalized probability density. Red lines are the Kernel smoothing function fits.

Figure A3: Asset-Based Lending Distribution in each year

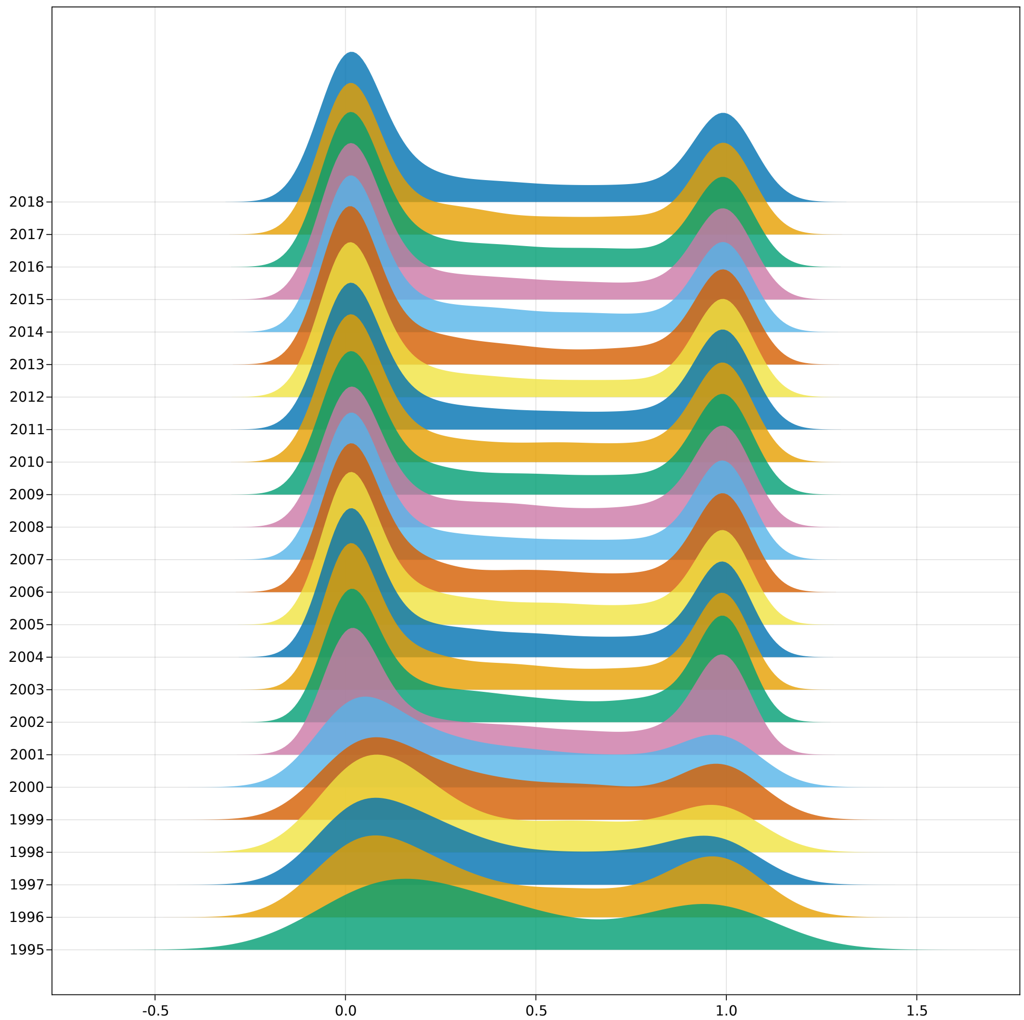
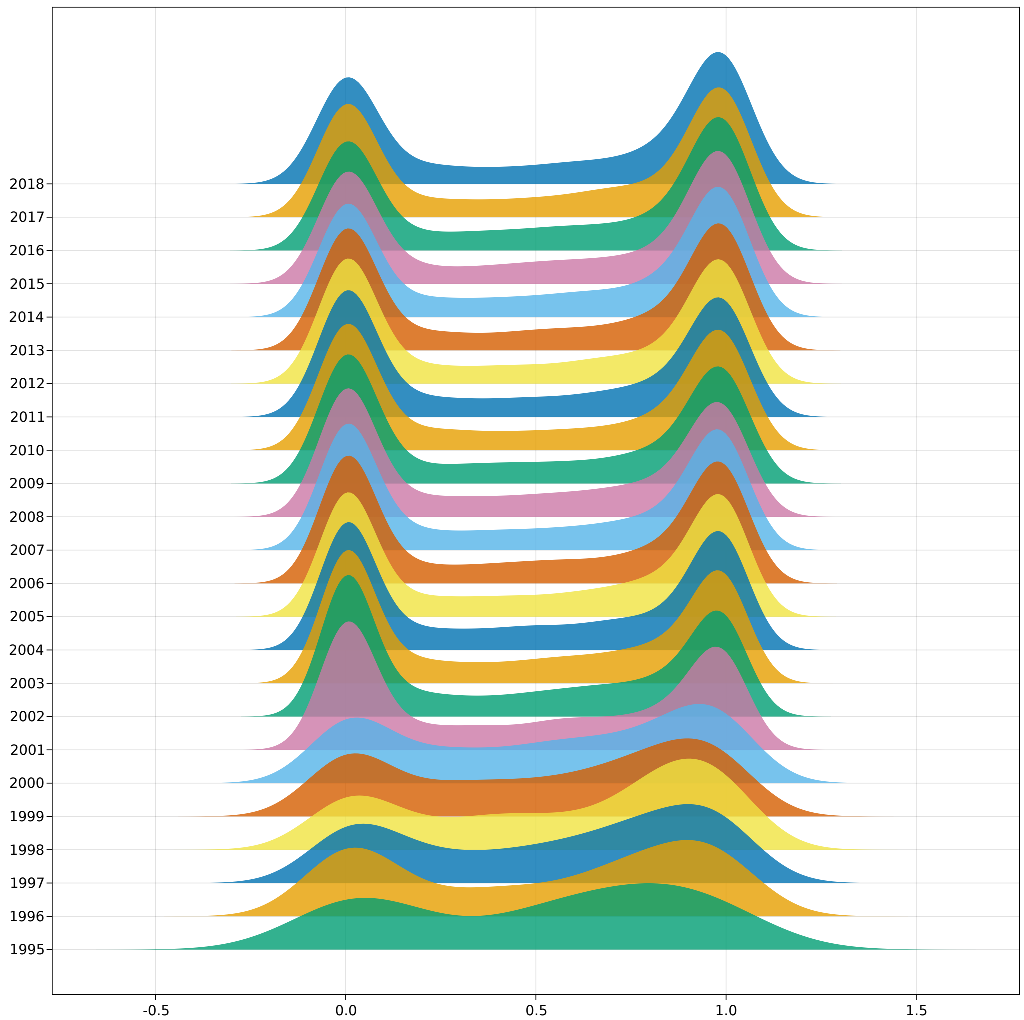
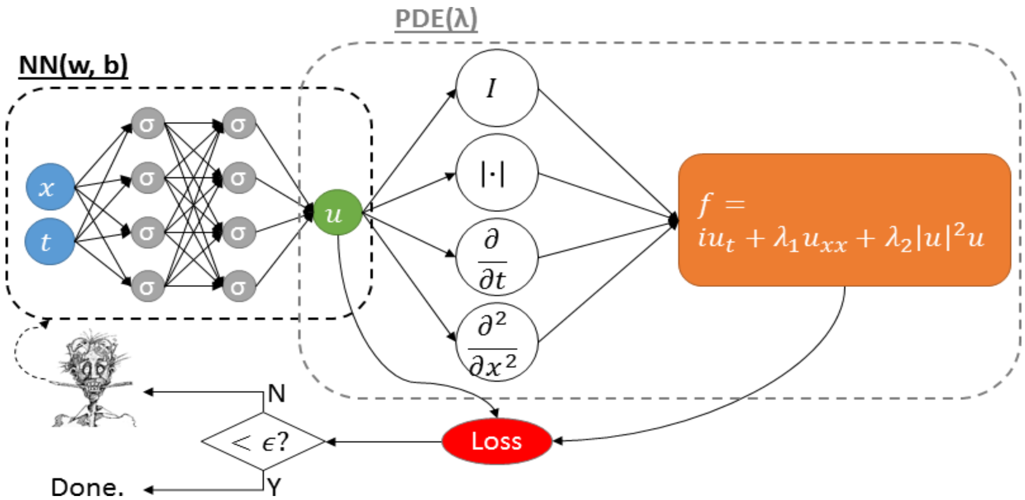


Figure A4: Cash Flow-Based Lending Distribution in each year



C Physics-Informed Neural Networks Algorithm

Physics-Informed Neural Networks (PINN) algorithm is proposed by Raissi, Perdikaris and Karniadakis (2019) and represents a new deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. The basic idea of this algorithm can be summarized as in the following graph:



Generally speaking, the idea of PINN is to employ two or more neural networks that share the same parameters. In addition, the objection function is to minimize the sum of mean squared errors of original neural network and those of partial derivatives. In this way, we can make full use of the synergy between machine learning and classical computational physics to solve some high dimensional partial differential equations without encountering the curse of dimensionality. More importantly, this approach is feasible because the PINN approximation theorem guarantees that feed-forward neural nets with a sufficiently large enough number of neural nodes can simultaneously and uniquely approximate any partial differential equations and their partial derivatives.