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FinTech Development, Shadow Banking, and Stock Market Activity in China: Insights from a TVP-SV-VAR Modeling

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Abstract

We adopt a time-varying parameter vector autoregressive model with stochastic volatility (TVP-SV-VAR) to unveil the dynamic nexus between FinTech development, shadow banking, and stock market activity in China. Our analysis highlights the consistent suppressive effect of FinTech on the growth of shadow banking and the diminishing positive effect on stock market activity. The effects show noticeable time-varying characteristics. Besides, the impacts of relevant policy measures regarding FinTech tend to decay over time. We also observe a divergence in the impacts of shadow banking on different types of stocks. This study encapsulates the intricate connections and evolving influences among FinTech, shadow banking, and the stock market.

Keywords

FinTech Development, Shadow Banking, Time-Varying Impulse Response, TVP-SV-VAR

1. Introduction

Past research has predominantly targeted on exploring the effects of FinTech on various aspects of the banking system. This encompasses the examination of banks' risk-taking behaviors (Banna et al., 2021; Guo et al., 2022), profitability (Zhao et al., 2022), liquidity (Fang et al., 2023), risk management (Yao & Song, 2021), and how FinTech companies have disrupted existing banking operations (Jagtiani & Lemieux, 2018). However, there still remains a scarcity of clear perceptions regarding the ramifications of FinTech on non-bank financial intermediaries, especially shadow banks, and there persists an insufficient availability of pertinent empirical evidence. Shadow banks provide alternative channels for credit and funding, influencing overall credit availability in the economy.

From a credit supply perspective, FinTech enables access to alternative data sources and advanced analytics, resulting in transparency and symmetry of information, allowing banks (Sheng, 2021) and FinTech lenders (Hodula, 2022; Cornelli et al., 2023) to profitably serve a wider customer base. Considering the ongoing emergence of partnerships between banks and FinTech firms, we expect the outlook is less rosy for shadow banks undertaking bank-like activities without formal safety nets or oversight.

From a credit demand perspective, as FinTech promotes interest rate liberalization (Li et al., 2023), we posit that this will likely weaken the attractiveness of shadow banking products to investors, as their risk-adjusted returns diminish. The expansion of shadow banks would be restrained. FinTech disruptors are poised to rapidly gain market share in segments where shadow banks previously thrived (Buchak et al., 2018), including consumer and SME lending, and even areas like mortgage origination. We therefore postulate that commercial banks and FinTech lenders will likely crowd out non-FinTech shadow banks.

Meanwhile, as FinTech reshapes financial services, their connection with shadow banking could either amplify or mitigate systemic vulnerabilities, directly affecting market stability. We expect that the possible pullback in shadow banking could significantly affect equity markets. Uncovering the influence of FinTech on shadow banking and its cascading effects on stock market dynamics can help inform regulators about the overall financial landscape and potential regulatory gaps, enabling them to formulate effective policies.

In this article, we provide a timely analysis of how FinTech impacts shadow banking as well as further implications for stock market activity, with an emphasis on time-varying characteristics of these impacts. The significance of this article lies in the fact that it is dedicated to sorting out the impact of shadow banking and FinTech from the development of shadow banking and FinTech in China, helping to understand their operating rules and potential risks, and is of theoretical significance for the prevention and resolution of systemic financial risks and the formulation of corresponding policies for the financial and investment industries in China and the rest of the world.

The rest of the study is structured as follows: Firstly, the composite model TVP-SV-VAR will be selected. Next, FinTech, shadow, and stock will be employed as variables to examine their inherent connections. Finally, based on the study's outcomes, rational suggestions regarding relevant policies will be made.

2. The Econometric Model

Based on the methods of Deng and Wu (2023), Hu et al. (2023), and Zhu et al. (2023), we employ a time-varying parameter vector autoregressive model with stochastic volatility (TVP-SV-VAR) to perform estimation. Time series data often gives rise to endogeneity issues, particularly concerning simultaneity problems. Sims (1980) introduced a vector autoregression (VAR) model, endogenizing all variables in a simultaneous equation model. Primiceri (2005) extended this by allowing parameters to vary over time, proposing the TVP-VAR. Nakajima (2011) further refined the framework, resulting in a VAR model characterized by time-varying parameters and stochastic volatility. It allows for the parameters of the model to change over time, which is more realistic as economic relationships and dynamics can evolve. This enables the model to capture structural changes and nonlinearities in the data. Overall, the TVP-SV-VAR model removes the necessity of constructing a model grounded on intricate economic theories. It is well-suited for capturing dynamic effects among multiple variables over time, effectively sidestepping issues related to endogeneity. A basic structural VAR model is specified as equation (1):

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_s y_{t-s} + \mu_t, \;\; t = s+1, \cdots, n \tag{1}$$

In the basic structural VAR model, y_t denotes a $k \times 1$ vector of variables, t represents the time, s represents the lag times. $A, F_1, F_2, \cdots$ and F_s are matrices of coefficients. The term μ_t denotes the structural effect, and it is measured by:

$$\mu_1 \sim N\left(0, \Sigma\Sigma\right) \tag{2}$$

where Σ and A can be expressed as:

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_k \end{pmatrix}, A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ \alpha_{21} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{k1} & \alpha_{k2} & \cdots & 1 \end{pmatrix} \tag{3}$$

Taking $\boldsymbol{B}_i = A^{-1}F_i$, where $i = 1, 2, \cdots, s$, and $\boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{I}_k)$, Equation (1) can then be converted to Equation (4). Converting F_i into $\boldsymbol{\beta}$ (the $k^2 s$Í 1 order vector), setting X_t as $\boldsymbol{I}_k$U ($y'_{t-1}, \cdots, y'_{t-s}$) where U represents Kronecker product, and considering parameters are all time-varying, Equation (1) can be modified as:

$$y_t = X_t \beta_t + A_t^{-1} \Sigma_t \varepsilon_t, \;\; t = s+1, \cdots, n \tag{4}$$

In this model, y_t represents the vector of endogenous variables, model parameters β, A, and Σ are time-varying, X_t represents the matrix containing lag terms of y_t and the term ε_t follows a random walk. The model is suitable for studying time-varying impacts between multiple variables, and it serves as a linear non-Gaussian state space model. By accounting for parameter uncertainty and stochastic volatility, the TVP-SV-VAR model provides a more comprehensive assessment of the uncertainty associated with the estimates and forecasts.

We collected monthly time series data from January 2016 to June 2023. We first build a *"supply-side"* FinTech index representing the overall development level of technological hardware infrastructures behind FinTech solutions (Wu et al., 2023). The composite index is constructed through principal component analysis of data dimensions covering optical cables, stored program control (SPC) switches, mobile communication base stations, optoelectronic devices, and integrated circuits. These technological foundations are the backbones of

FinTech. The extent of shadow banking is measured by the combined level of entrusted loans, trust loans, and undiscounted bankers' acceptances. Data are from the People's Bank of China (PBC). We use the trading volume of the China A-share market to proxy the degree of stock market activities. To mitigate right skewness, we adopt the inverse hyperbolic sine (IHS) function transformed values. Meanwhile, as financial time series data are usually subject to seasonality, we conduct seasonal adjustments with the Census X-12 method and apply standardization prior to model estimation. To avoid pseudo-regression, we further check stationarity of the adjusted time series data. Results are presented in **Table 1** and **Table 2**.

Table 1. Unit root test for stationarity.

Variable	ADF(0) t-statistic	5% critical level	*P*-value	Decision
FinTech	−8.545857	−3.461686	0.0000	stable
Shadow	−3.189354	−3.462912	0.0935	unstable
Stock	−5.246308	−3.461094	0.0055	stable

Notes: We perform Augmented Dickey-Fuller (ADF) unit root test for stationarity. The ADF test results indicate that the Shadow time series is not stationary at the 5% level.

Table 2. Johansen cointegration test results.

Hypothesized No. of CE (s)	Eigenvalue	Trace statistic	5% Critical value	*P*-value
None*	0.32066	54.6478	29.79707	0.0000
At most 1*	0.20102	21.7836	15.49471	0.0049
At most 2*	0.03136	2.70852	3.841465	0.0998

Notes: We conduct Johansen cointegration test for time series data. Trace test results indicate two co-integrating equations at the 5% level. The symbol * denotes rejection of the null hypothesis at the 5% level.

Furthermore, the analysis regarding model lag order selection suggests a value of 2, based on multiple selection criteria. **Table 3** shows the selection test results.

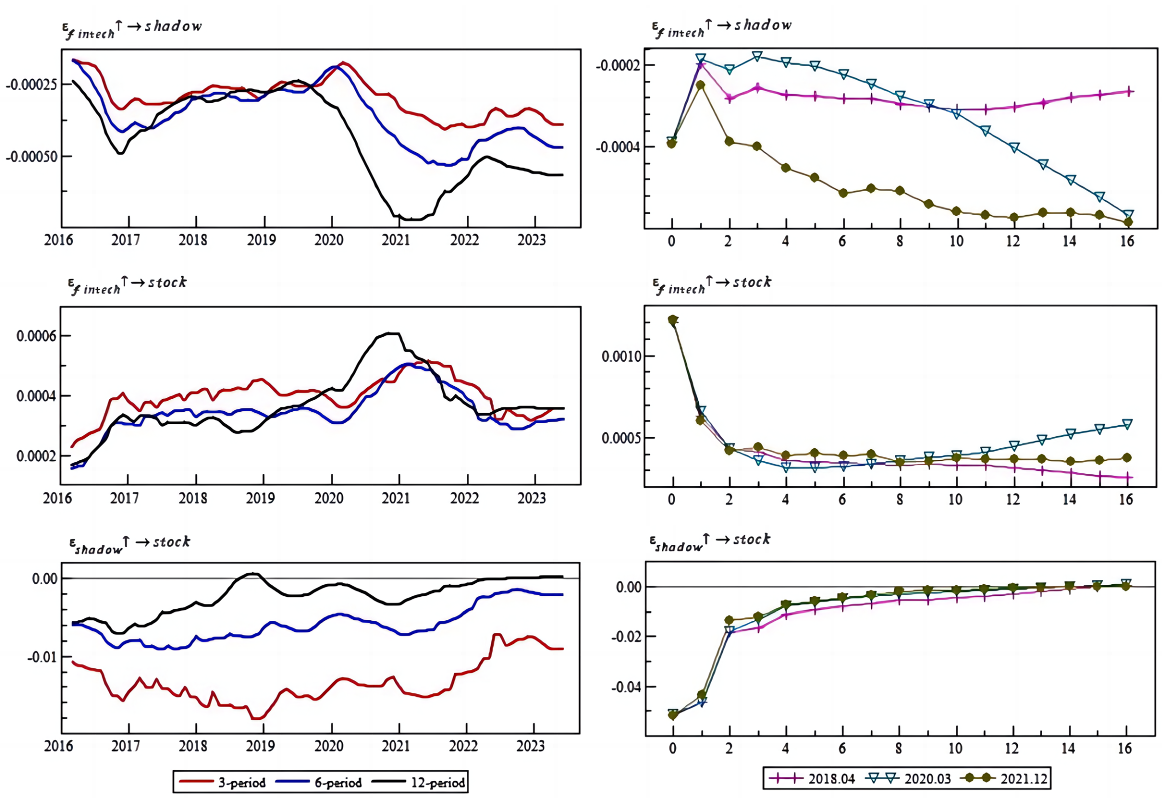
Table 3. Lag order selection test.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−189.2567	NA	0.027765	4.929660	5.020302	4.965946
1	256.9897	846.724	3.75E−07	−6.281787	−5.919217*	−6.136643*
2	267.4728	19.08454*	3.62E−07*	−6.319814*	−5.685316	−6.065813
3	270.7049	5.635575	4.21E−07	−6.171921	−5.265495	−5.809062
4	276.3689	9.439987	4.61E−07	−6.086382	−4.908028	−5.614666

Notes: The symbol * indicates lag order selected by the specific criterion. LR: sequential modified LR test statistic (each test at 5% level). FPE: Final prediction error. AIC: Akaike information criterion. SC: Schwarz information criterion. HQ: Hannan-Quinn information criterion.

3. Estimation Results

We estimate parameters using the Markov Chain Monte Carlo (MCMC) approach for Bayesian inference, with 1000 burn-in samples and 10000 simulated samples. Figure 1 shows the final results regarding the impulse responses to a unit standard deviation shock of FinTech.

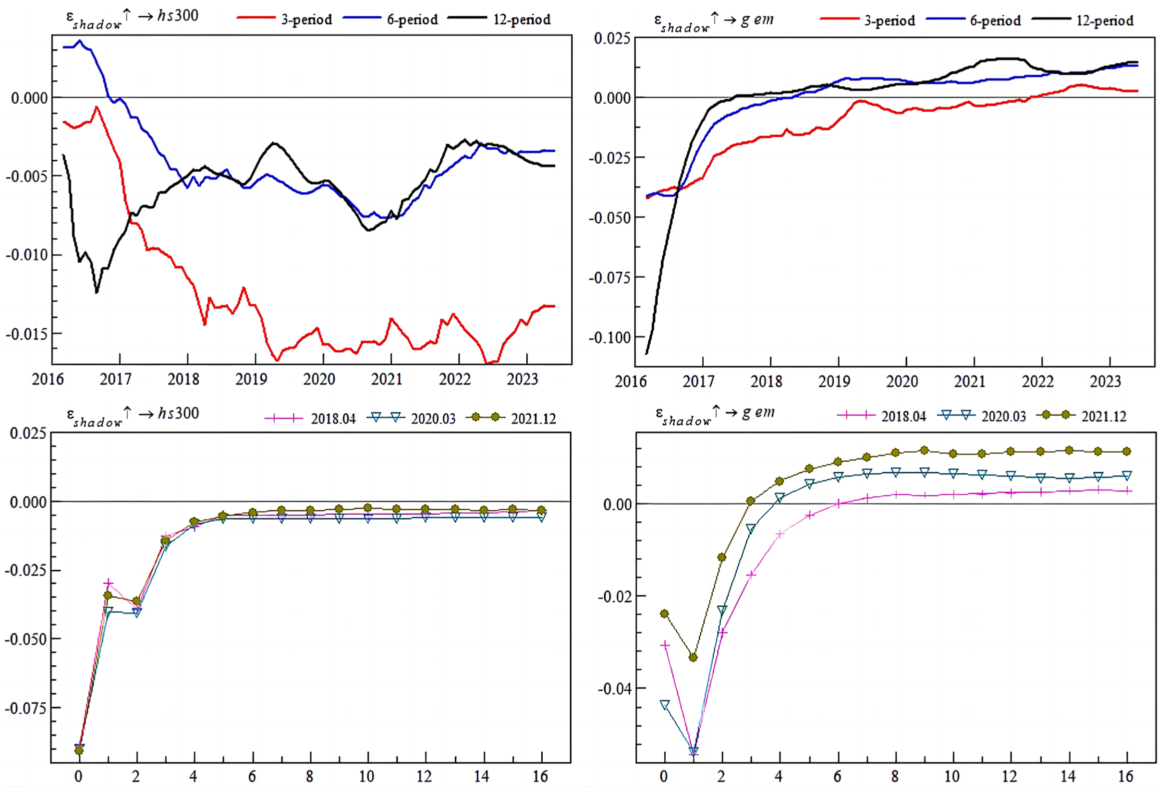


Notes: FinTech, Shadow and Stock are endogenous variables in the TVP-SV-VAR model. The Geweke convergence test returns p-values less than 1.96 for all parameters and inefficiency factors are satisfactory. The equal-interval impulse response (left side) analysis sets the lag of 3 periods, 6 periods, and 12 periods respectively. The time-point based impulse response (right side) sets April 2018, March 2020, and December 2021 as time points.

Figure 1. Impulse responses at different lag periods and at different time points.

We select 3 months, 6 months, and 12 months as lag periods to reveal various time-varying impacts of FinTech. We find that FinTech dampens the growth of shadow banking, and the negative effect continues to amplify even after 2020. FinTech has an overall enduring positive nexus with stock market activity and the time-varying patterns are generally similar at different lag periods. The impulse response of stock market activity to shadow banking shock is mostly negative during the observation period. In China, shadow banking activities have been closely tied to the growth of China's real estate investments, which are perceived to be more stable and could divert funds away from the volatile stock market, especially during periods of economic uncertainty. Furthermore, to reveal the impacts of relevant policy shocks, we select April 2018 (China announced the sweeping asset management rules and started fostering a systematic FinTech regulatory framework), March 2020 (China issued a government work report and emphasized the supervision of FinTech companies by China's central bank), and December 2021 (China's central bank officially released the Fintech Development Plan for 2022-2025), as three key time points. It is clear that the time-varying response plots support our previous findings. We also note that the impacts of FinTech and shadow banking on stock market activity diminish away after around 4 months, suggesting the decay of policy impact.

We further explore the dynamics between shadow banking and market turnover rate. As shown in **Figure 2**, the impacts on turnover rates of hs300 (a composite of value stocks) and gem (stocks listed in China's growth enterprise market) are divergent.



Notes: We estimate the impacts of shadow banking (shadow) on the monthly turnover rates of China's growth enterprise market (gem) and the top 300 stocks (hs300) on the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The equal-interval impulse response (upside) analysis sets a lag of 3 periods, 6 periods, and 12 periods respectively. The time-point based impulse response (downside) sets April 2018, March 2020, and December 2021 as time points.

Figure 2. Impulse responses of gem and hs300 to shadow banking activities.

We think that funds from shadow banks may indeed flow preferentially into gem stocks (as most are small capitalized and usually associated with speculative trading activities). The time-point based analysis further implies that shadow banking could revert to produce a persistent positive effect on speculative trending, amid the diminishing impact of regulatory policy.

4. Concluding Remarks

Our results supplement a growing body of knowledge on the far-reaching effects of FinTech on the broader financial market. Based on the TVP-SV-VAR analysis, we revealed that FinTech, shadow banking, and stock market activity could be intricately intertwined. We particularly showed that FinTech persistently dampens shadow banking, and shadow banking could provoke divergent shocks on different types of stocks. The impacts exhibit temporal variations, and the impact of relevant policies also diminishes over time.

Based on the analysis and findings, we recommend that policymakers should closely monitor the development of FinTech and its impact on the financial market. Given that FinTech persistently dampens shadow banking, regulations should be in place to ensure that this dampening effect is managed in a way that does not lead to unintended consequences. Additionally, since shadow banking can have divergent shocks on different types of stocks, policymakers should consider implementing differentiated regulatory measures to mitigate these effects. It is crucial to continuously assess and update these regulations to adapt to the temporal variations in impacts. Moreover, to address the diminishing effectiveness of relevant policies over time, there should be a mechanism for regular review and adjustment of policies to ensure their continued relevance and effectiveness in the ever-changing financial landscape.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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