Economic Analysis Letters 2022 1(1) 1-7

Economic Analysis Letters

Homepage: https://anser.press/index.php/EAL

Which Component of Deposit Drives Systemic Risk Volatility

Yunying Huang [a], Kenichiro Soyano [b,*]

[a] *College of Economics, Jinan University, Guangzhou, China*

[b] *Department of Law and Public Policy, Takaoka University of Law, Toyama-ken, Japan*

ABSTRACT

Bank deposit is closely related to systemic risks. In addition, considering that resident deposits in China have significant seasonal characteristics, this paper focuses on which component of deposits drives the systemic risk volatility, that is, it can supplement the existing forecast information. We use X-13ARIMA-SEATS to decompose deposit into three subsequences. The research findings show that the forecast effect of subsequence models is better than that of benchmark series. Most importantly, the model with trend component has the best forecast performance.

KEYWORDS

Deposit; Systemic Risk; X-13ARIMA-SEATS

*Corresponding author: Kenichiro Soyano
E-mail address: soyano_kenichiro@alumni.com

ISSN 2972-3272
doi: 10.58567/eal01010001

Received 12 August 2022; Accepted 1 September 2022; Available online 15 September 2022

1. Introduction

Systemic risks are an issue of great concern to policy authorities and investors. Preventing and defusing major risk events is of far-reaching significance for stabilizing social development. There are three main motivations for people to hold money, namely, transaction motivation, prevention motivation and investment motivation. As an important source of funds for banks, deposit has a significant impact on the stability of the banking system. In China, bank deposits have an obvious seasonal effect. For example, during Spring Festival, people tend to convert deposits into cash. The X-13ARIMA-SEATS can well capture different components of deposits and reduce the difficulty of forecasting the systemic risk by the stochastic component.

Existing research explores the impact of deposits on systemic risks from different aspects. Deposit can replace weak institutional environment and reduce systemic risk (Anginer et al., 2018). The endogenous time-varying tightness of liquidity and capital constraints has produced the leverage cycle of intermediaries, affected risk pricing and economic risk level, and the supply of risk-free assets in the intermediate ranges can achieve higher welfare (Adrian & Boyarchenko, 2018). High liquidity creation is related to high systemic risk exposure in calm periods; liquidity creation has a greater impact on bank systemic risk exposure in crisis; and banks with high liquidity creation may lead to overall financial vulnerability (Louhichi et al., 2022). The interbank deposit network enables banks to cope with liquidity risk, and the shape network has the strongest elasticity to systemic risk, which induces banks to hold interbank deposit at the most effective level (Castiglionesi & Eboli, 2018). There is a positive impact between systemic risk and future deposit dividends of banks, indicating that banks can transfer systemic risk to debt holders and deposit insurance companies (Kanas & Zervopoulos, 2020). The characteristics of deposit insurance design will affect systemic risk; deposit insurance will increase idiosyncratic tail risk; and deposit insurance coverage has a U-shaped relationship with fundamental macroeconomic and finance factors and bank interconnectedness, indicating that there is an optimal coverage level to minimize systemic risk (Chen et al., 2021).

However, there is little literature on how systemic risk volatility responds to deposit component. The contribution of this paper may be twofold. First, from the perspective of mixed-frequency, the impact of deposit on the long-term components of systemic volatility is detected. Second, the X-13ARIMA-SEATS is used to decompose the deposit into three different components to discuss whether different characteristics can provide more forecast information.

The rest of this paper is organized as follows. The methodology is described in Section 2. Section 3 shows the data. The empirical results are shown in Section 4. Section 5 presents conclusions.

2. Methodology

In order to study the impact of deposit on systemic risk volatility, we use the GARCH–MIDAS model of Engle et al., (2013) to better handle the data frequency mismatch between the daily measured systemic risk data and the monthly sampled deposits. The conditional variance of GARCH-MIDAS consists of two parts: short- and long-term components. We allow the long-run variance to be determined by delayed deposits and a MIDAS polynomial that applies to monthly deposits. The GARCH-MIDAS model is specified as follows:

$$r_{i,t} = \mu + \sqrt{m_t g_{i,t}}\xi_{i,t} \tag{1}$$

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{\left(r_{i-1,t}-\mu\right)^2}{m_t} + \beta g_{i-1,t} \tag{2}$$

where $r_{i,t}$ is systemic risk, $g_{i,t}$ and m_t accounts for short- and long-term components, respectively. The long-term component $g_{i,t}$ follows a GARCH (1,1) process with $\alpha > 0$, $\beta \geq 0$, and $\alpha + \beta \leq 1$. Then, in the principle regression and MIDAS filtering, we specify the m_t component by smoothing realized volatility.

$$m_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{t-k} \tag{3}$$

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{4}$$

where K is the period that we smooth the volatility, and we assume $\omega_1 = 1$.

The X-13ARIMA-SEATS can decompose seasonal time series into three additive components of three sub-sequences: trend (T_t), seasonal (S_t), and remainder (R_t) components. We model the long-term volatility as the weighted average of the lagged values of realized volatility and an explanatory variable in order to investigate the effects of these three sub-sequences as exogenous variables on the systemic risk variance. We further extend the long-term component m_t as follows:

$$m_t = m + \theta_{Rv} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{t-k} + \theta_{tv} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, T_{t-k} \tag{5}$$

$$m_t = m + \theta_{Rv} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{t-k} + \theta_{sv} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, S_{t-k} \tag{6}$$

$$m_t = m + \theta_{Rv} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{t-k} + \theta_{rv} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, R_{t-k} \tag{7}$$

where θ_{tv}, θ_{sv} and θ_{rv} reveal the impact of the trend, seasonal, and remainder components on the long-term volatility of the systemic risk, respectively.

3. Data

This paper uses ΔCoVaR as the proxy indicator of systemic risks. In the specific measurement process, we use DCC-GARCH model to measure the difference between the risk value of financial institutions in financial distress and the average state. We use the daily closing price of 23 representative institutions from four industries of China's banking, securities, insurance and trust to measure the overall system risk, which is from April 1, 2003, to August 1, 2022. The monthly deposit is obtained from change rate of RMB deposit balance of financial institutions, and the whole sample period is from April 2003 to August 2022. Figure 1 illustrates the temporal evolution of deposit and its subsequences in the whole sample period. Table 1 reports descriptive statistics for systemic risk and deposit.

Table 1. Descriptive statistics of systemic risk and deposit.

Variable	Obs	Mean	Std. Dev.	Min	Max	ADF
Systemic risk	4,699	0.00001	0.0678	-0.9886	0.5335	-19.566
Deposit	4,699	0.01141	0.0107	-0.0176	0.0724	-14.604

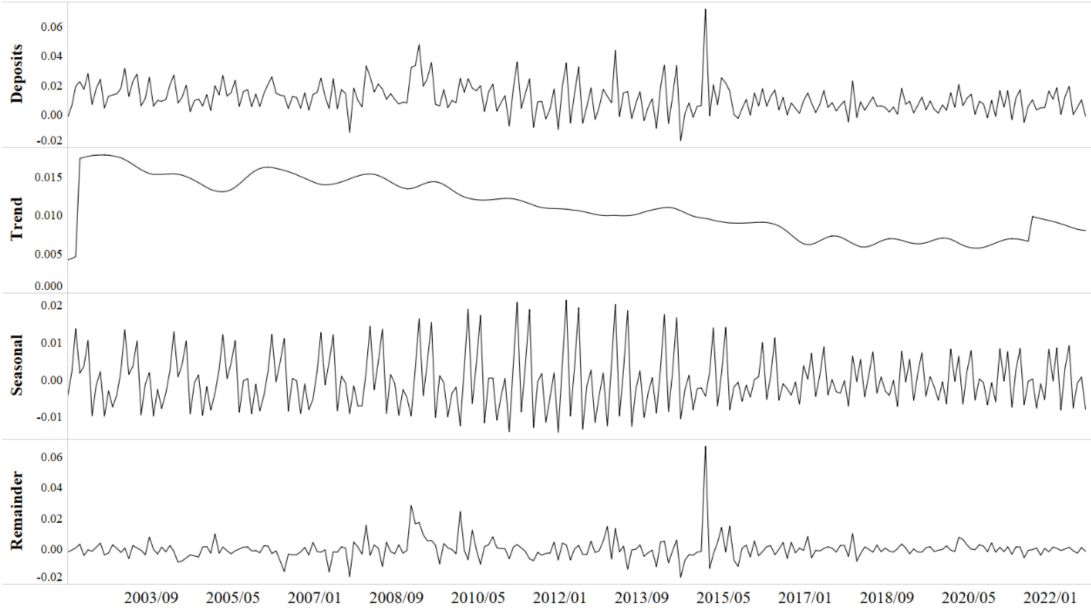

Figure 1. Deposit and its X-13ARIMA-SEATS-based subsequences.

4. Empirical results

4.1. Estimation of GARCH-MIDAS models

How much does the component of deposit have to do with the volatility of systemic risk, especially how much does the volatility have to do with future forecast? In order to explore the results of this problem, we add the decomposed indicators to the basic model as exogenous variables. The sign of θ implies the response of long-term volatility to systemic risk. Table 2 reports the estimates of the GARCH-MIDAS coefficients for systemic risk. Variables μ, α, β are statistically significant, indicating the volatility persistence and aggregation of China's systemic risk.

Table 2. GARCH-MIDAS model parameter estimates and evaluation results.

Panel A: GARCH-MIDAS model with RV					
μ	α	β	θ_v	ω_v	m_v
-0.002**	0.042***	0.954***	-2.999***	10.315***	-4.589***
(0.001)	(0.001)	(0.001)	(0.247)	(0.991)	(0.124)
Panel B: GARCH-MIDAS model with trend component					
μ	α	β	θ_v	ω_v	m_v
-0.0034***	0.2290***	0.5921***	146.2200***	1.0012***	-6.8801***
(0.001)	(0.007)	(0.011)	(3.151)	(0.162)	(0.043)
Panel C: GARCH-MIDAS model with seasonal component					
μ	α	β	θ_v	ω_v	m_v
-0.003***	0.063***	0.924***	83.375***	12.630***	-5.000***
(0.001)	(0.002)	(0.002)	(4.871)	(0.917)	(0.070)
Panel D: GARCH-MIDAS model with remainder component					
μ	α	β	θ_v	ω_v	m_v
-0.003**	0.052***	0.935***	86.440***	4.551***	-5.159***
(0.001)	(0.001)	(0.001)	(5.189)	(0.644)	(0.059)

Panel E: GARCH-MIDAS model with RV and trend component							
μ	α	β	θ_{Rv}	θ_{tv}	ω_{Rv}	ω_{tv}	m_v
-0.003***	0.218***	0.445***	2.572***	96.339***	6.837***	1.004***	-6.944***

(0.001)	(0.009)	(0.016)	(0.095)	(3.171)	(0.551)	(0.204)	(0.035)
Panel F: GARCH-MIDAS model with RV and seasonal component							
μ	α	β	θ_{Rv}	θ_{sv}	ω_{Rv}	ω_{sv}	m_v
-0.002**	0.044***	0.953***	-3.979***	121.80***	15.177***	12.753***	-4.376***
(0.001)	(0.001)	(0.001)	(0.2067)	(5.202)	(1.108)	(0.706)	(0.146)
Panel G: GARCH-MIDAS model with RV and remainder component							
μ	α	β	θ_{Rv}	θ_{rv}	ω_{Rv}	ω_{rv}	m_v
-0.003**	0.044***	0.951***	-2.338***	147.91***	19.040***	2.411***	-4.683***
(0.001)	(0.001)	(0.001)	(0.185)	(8.130)	(2.340)	(0.211)	(0.119)

*Note: The sample covers from April 2003 to August 2022. The numbers in parentheses are the standard deviations. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The same below.*

Panel A in Table 2, as the basic model, shows the results of GARCH-MIDAS model used to estimate systemic risk during the whole sample period. From the regression results of Panel B-D, it can be seen that the trend, seasonal and remainder components of deposit based on X-13ARIMA-SEATS have significant positive effects on the volatility of systemic risk. That is to say, the trend, seasonal and remainder components of deposits will lead to an increase in the future systemic risk volatility, thus increasing systemic risks. At the same time, we add the trend, seasonal and remainder components as the long-term components on the basis of realized volatility, and give the $RV_t + T_t$ model estimation results in Panel E, which reflects that the response of the systemic risk volatility to the realized volatility and trend component is significantly positive. The estimation results of $RV_t + S_t$ and $RV_t + R_t$ models are given in Panels F and G, respectively, reflecting that the systemic risk volatility is significantly negative to the realized volatility, while the response to seasonal and residual components is significantly positive. It shows that the trend, seasonal and remainder components based on X-13ARIMA-SEATS have strong forecast ability for systemic risk.

4.2. Evaluation of the forecast performance

In this section, we divide the whole sample into two parts, namely, in-sample estimation which covers 2003.04-2018.8 and out-of-sample estimation which covers 2018.09-2022.08. Table 3 reports in-sample estimates of the GARCH-MIDAS coefficients for systemic risk. The in-sample estimation of GARCH-MIDAS model is similar to that of the whole sample. The AIC of the RV+X-13ARIMA-SEATS-based component model is smaller than the RV model, implying that component of deposit contains supplementary information and drives the systemic risk volatility. Besides, the trend component has the best forecast ability.

Table 3. In-sample estimation.

Panel A: GARCH-MIDAS model with RV					
μ	α	β	θ_v	ω_v	m_v
-0.003*	0.032***	0.963***	-2.297***	10.703***	-4.855***
(0.001)	(0.001)	(0.001)	(0.229)	(1.309)	(0.109)

Panel B: GARCH-MIDAS model with RV and trend component							
μ	α	β	θ_{Rv}	θ_{tv}	ω_{Rv}	ω_{tv}	m_v
-0.002*	0.031***	0.966***	-9.321***	56.851***	1.001***	49.999	-4.370***
(0.001)	(0.001)	(0.001)	(0.350)	(9.236)	(0.020)	(182.20)	(0.167)
Panel C: GARCH-MIDAS model with RV and seasonal component							
μ	α	β	θ_{Rv}	θ_{sv}	ω_{Rv}	ω_{sv}	m_v
-0.002*	0.027***	0.970***	-6.874***	57.887***	1.001***	12.071***	-4.137***
(0.001)	(0.001)	(0.001)	(0.381)	(4.632)	(0.028)	(1.453)	(0.143)
Panel D: GARCH-MIDAS model with RV and remainder component							
μ	α	β	θ_{Rv}	θ_{rv}	ω_{Rv}	ω_{rv}	m_v
-0.002*	0.028***	0.969***	-8.458***	136.63***	1.001***	2.037***	-3.852***

(0.001)	(0.001)	(0.001)	(0.358)	(12.444)	(0.024)	(0.239)	(0.141)

Panel E: Evaluation results of GARCH-MIDAS models				
	RV	RV + trend	RV + seasonal	RV + remainder
AIC	9057.18	8795.85	8816.33	8808.13
BIC	9019.81	8746.02	8766.49	8758.3
LLF	-4534.59	-4405.93	-4416.16	-4412.07

Note: The sample covers from April 2003 to August 2018. AIC represents Akaike information criterion, BIC represents Bayesian information criterion and LLF is the log-likelihood function.

The above model is estimated using the estimation window, and the out-of-sample variance is forecasted using the estimated parameters. Similar to Fang et al., (2017), we use four loss functions, specifically, the root mean squared error (RMSE), root mean absolute error for conditional variance (RMAE), mean squared prediction error (MSPE) and root mean absolute error for conditional variance (MAPE).

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\sigma_{t+1}^2 + E_t(\sigma_{t+1}^2)\right)^2} \tag{8}$$

$$RMAE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}|\sigma_{t+1}^2 + E_t(\sigma_{t+1}^2)|} \tag{9}$$

$$MSPE = \frac{1}{T}\sum_{t=1}^{T}\left(\sigma_{t+1} + E_t(\sigma_{t+1})\right)^2 \tag{10}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}|\sigma_{t+1} + E_t(\sigma_{t+1})| \tag{11}$$

Then, we use the DM test to verify the forecast ability of the comparative model by the loss function.

$$E(d_t) = E\left(g(e_{i,t}) - g(e_{j,t})\right) \tag{12}$$

$$\bar{d} \sim N\left(0, \hat{V}(\bar{d})\right), \quad DM = \frac{\bar{d}}{\sqrt{\hat{V}(\bar{d})}} \sim N(0,1) \tag{13}$$

where $e_{i,t}$ and $e_{j,t}$ denote the forecast errors of models i and j, respectively and $g(\cdot)$ denotes the loss function. Table 4 shows the results of four loss functions and DM test for out-of-sample performance of the different models in forecasting systemic risk.

Table 4. Out-of-sample estimation.

	RMSE	RMAE	MSPE	MAPE	AIC	RV
RV	0.0155	0.0466	0.0022	0.0338	9057.18	-
RV + trend	0.0135	0.0451	0.0012	0.0321	8795.85	Y
RV + seasonal	0.0136	0.0455	0.0013	0.0327	8816.33	Y
RV + remainder	0.0135	0.0458	0.0013	0.0334	8808.13	Y

Note: The out-of-sample forecasts cover the period from September 2018 to August 2022. Y in last column indicates that the model given in the row performs better than the benchmark model.

From Table 4, we can get that the loss functions and AIC of the RV+X-13ARIMA-SEATS-based component model is smaller than the RV model. According to DM test, it shows that adding component of deposit to GARCH-MIDAS model can improve the forecast performance of the model. It is also consistent with the above conclusion that the model with trend component has the best forecast ability.

5. Conclusion

This paper conducts a X-13ARIMA-SEATS of deposits to explore the performance of trend, seasonal, and remainder components in the systemic risk. First of all, these three components of deposit have a significantly positive impact on the volatility of systemic risk. This phenomenon is easier to observe when RV is added to the GARCH-MIDAS model. Secondly, all components of the deposit can provide additional effective forecast information for the systemic risk, and all subsequence models are superior to the benchmark model in forecast performance. Most importantly, among these three components of deposit, the model with trend component has the best forecast performance.

Funding Statement

This research received no external funding.

Declaration of Competing Interest

All authors claim that the manuscript is completely original. The authors also declare no conflict of interests.

References

Adrian, T., & Boyarchenko, N. (2018). Liquidity policies and systemic risk. *Journal of Financial Intermediation*, *35*, 45-60. https://doi.org/10.1016/j.jfi.2017.08.005

Anginer, D., Demirguc-Kunt, A., & Mare, D. S. (2018). Bank capital, institutional environment and systemic stability. *Journal of Financial Stability*, *37*, 97-106. https://doi.org/10.1016/j.jfs.2018.06.001

Castiglionesi, F., & Eboli, M. (2018). Liquidity Flows in Interbank Networks. *Review of Finance*, *22*(4), 1291-1334. https://doi.org/10.1093/rof/rfy013

Chen, W., Zhang, Z. W., Hamori, S., & Kinkyo, T. (2021). Not all bank systemic risks are alike: Deposit insurance and bank risk revisited. *International Review of Financial Analysis*, *77*, Article 101855. https://doi.org/10.1016/j.irfa.2021.101855

Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock Market Volatility And Macroeconomic Fundamentals. *The Review of Economics and Statistics*, *95*(3), 776-797. http://www.jstor.org/stable/43554794

Fang, L., Chen, B., Yu, H., & Qian, Y. (2017). The importance of global economic policy uncertainty in predicting gold futures market volatility: A GARCH-MIDAS approach. *Journal of Futures Markets*, *38*. https://doi.org/10.1002/fut.21897

Kanas, A., & Zervopoulos, P. D. (2020). Systemic risk-shifting in US commercial banking. *Review of Quantitative Finance and Accounting*, *54*(2), 517-539. https://doi.org/10.1007/s11156-019-00797-5

Louhichi, W., Saghi, N., Srour, Z., & Viviani, J. L. (2022). The effect of liquidity creation on systemic risk: evidence from European banking sector. *Annals of Operations Research*. https://doi.org/10.1007/s10479-022-04836-8