“Interaction between decentralized financial services and the traditional banking system: A comparative analysis”

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INTERACTION BETWEEN DECENTRALIZED FINANCIAL SERVICES AND THE TRADITIONAL BANKING SYSTEM: A COMPARATIVE ANALYSIS

Abstract

This paper investigates the interaction between decentralized financial services and the traditional banking system by building VAR models, conducting Granger causality tests, building impulse response functions, and performing variance analysis. To implement the model, banking indicators of the USA, India, and Great Britain were selected: the volume of commercial and industrial loans, interest rate, consumer price index, total liabilities and capital of banks, aggregate deposits, federal funds rate (for the USA), and repo rate (for India). The study examined central bank data of the specified countries from July 2018 to January 2024 with the TVL indicator, which measures the sum of all assets locked in DeFi protocols. The results of the impulse response function (IRF) for countries demonstrate different interactions between TVL and bank indicators. The US response to TVL shocks demonstrates a stimulative monetary policy, with significant Fed rate reductions and increased commercial lending to boost economic activity. In contrast, India's monetary stimulus, marked by declining repo rates and growth in banking sector liabilities and deposits, aims to enhance economic resilience. The UK, however, adopts a conservative monetary approach, with sharp bank rate increases and mixed lending and deposit responses, prioritizing financial stability. Analysis across these nations highlights different impacts of financial indicators on TVL. In the US, the evolving relationship between TVL and bank indicators reflects the financial system's complexity. India's sensitivity to monetary policy, credit conditions, and inflation significantly influences TVL. In the UK, central bank decisions, particularly the bank rate, play a crucial role in financial market dynamics.

Keywords decentralized finance, DeFi, TradFi, VAR, TVL, blockchain, banking system

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INTRODUCTION

Decentralized finance (DeFi) is becoming a driving force in the financial sector, using blockchain technology to facilitate financial transactions and services without the need for traditional intermediaries such as banks or other financial institutions. DeFi has offered new opportunities for financial accessibility and efficiency (Chohan, 2021). The rapid development of DeFi, characterized by transparency and global accessibility, creates both potential synergies and systemic risks for the existing financial ecosystem. Therefore, understanding the interaction between DeFi and the traditional banking system is essential for assessing how new technologies can coexist with, complement, or disrupt established financial systems (Salami, 2021). The integration of DeFi with the traditional banking system can improve the efficiency of financial services such as payments, lending, insurance, asset management, etc. However, achieving the benefits of using decentralized financial services requires a deep understanding of the operational and technical nuances of DeFi platforms, as well as economic incentives and barriers to their adoption by mainstream financial institutions (Werner et al., 2021). The inclusion of DeFi in the traditional financial structure also provides opportunities for increasing financial accessibility and efficiency (Qin et al., 2021).

Interaction and integration processes between decentralized finance (DeFi) and traditional banking systems (TradFi) create a scientific problem, namely, understanding the dynamics and consequences of their interaction. Gudgeon et al. (2020) analyzed DeFi lending markets, highlighting mechanisms and risks inherent in protocols such as Compound and MakerDAO, which may have broader implications for traditional lending markets and banking practices. The scalability of blockchain technology that underpins DeFi raises questions about the future of financial transactions and the role of banks as intermediaries. Schär (2021) provides a comprehensive overview of DeFi, highlighting its potential to create an open financial system that operates without a central authority. Such decentralization may challenge traditional banking models, requiring a review of the legal framework and provision of financial services. Also, the implications of DeFi integration for financial stability and systemic risk are paramount. A report by the Bank for International Settlements (BIS, 2020) examines these risks, suggesting that while DeFi can offer opportunities for diversification and efficiency, it also requires strong regulatory measures to mitigate the risks of liquidity mismatches and leverage cycles that could affect the wider financial system.

1. LITERATURE REVIEW

Traditional banking institutions provide services that try to meet customer expectations in the digital age. Customers require more convenient, efficient, and personalized banking services, often finding traditional banking systems lacking compared to digital alternatives. This has put traditional banks at a disadvantage compared to fintech and digital banking platforms (Ahmadpour et al., 2014; Pakhnenko et al., 2021; Khasawneh & AlBahsh, 2024; Islam et al., 2024; Alhanatleh et al., 2024; Wahyuni et al., 2024). Banks are required to navigate regulatory changes, technological advances, and changing market dynamics while maintaining profitability and stability (Prasad et al., 2002; Kozmenko et al., 2014; Kozmenko & Korneev, 2014). The traditional banking model faces challenges in effectively screening and lending to small borrowers. The emergence of peer-to-peer lending platforms demonstrates alternative lending models that use technology for verification, offering insight into how traditional banks can adapt to improve their lending practices and reduce risk (Iyer et al., 2009; Diep & Canh, 2022). Morris (2011) and Kozmenko and Savchenko (2013) determine that a more focused approach to the main banking functions can help in better risk management and ensuring financial stability. Technological innovations in the form of digital and mobile banking are creating opportunities for greater financial inclusion, but also require banks to adapt and innovate to stay relevant (Lumsden, 2017).

Decentralized finance and traditional finance are based on different principles and infrastructures, but they also share common financial mechanisms and objectives (Strilets et al., 2022; Shkolnyk et al., 2021). DeFi operates in a decentralized network that is built on blockchain technology, eliminating the need for central authorities or intermediaries such as banks or clearing houses. In contrast, traditional finance operates through centralized institutions that control and regulate financial transactions and services (Kravitz & Halverson, 2022). DeFi offers greater transparency and accessibility. Transactions and smart contract codes are visible in the blockchain to everyone, making the system transparent. In addition, DeFi services are available to anyone with internet access without the need to have a bank account or be physically present, which contrasts with the nature of traditional finance (Qin et al., 2021). Traditional finance is strictly regulated by established frameworks for operation, consumer protection, and financial stability. However, DeFi is still in a relatively early stage in terms of regulation, leading to uncertainty and potential risks related to regulatory compliance, consumer protection, and anti-money laundering (AML) practices (Makarov & Schoar, 2022).

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Both DeFi and traditional financial systems aim to provide similar services such as lending, borrowing, trading, and investment opportunities. DeFi reproduces these services in the blockchain network, while traditional finance provides them through institutional structures (Schär, 2020). Both systems face risks, including credit risk, market risk, and operational risk. In DeFi, these risks are managed through smart contracts, while traditional finance uses regulatory capital, risk assessment models, and intermediaries to manage and mitigate risks (Carter & Jeng, 2021). Both sectors are constantly evolving due to technological progress. Traditional finance has seen innovations such as online banking, digital payments, and financial services. Similarly, DeFi is rapidly evolving with new protocols, services, and integration with traditional financial assets (Umarov et al., 2022).

DeFi offers a new approach to risk assessment, as opposed to traditional methods such as credit scores, stress testing, and historical analysis. While preserving privacy and pseudonymity by integrating offline identity verification with online activity, online chain methods for risk assessment are being explored (Kravitz & Halverson, 2022). DeFi relies on oracles (algorithms that are the transmission channel between the smart contract and the offline source in which it is deployed to receive external data), but this creates risks if oracles are poorly managed. Solutions to the oracle problem are critical to the security and integrity of DeFi (Caldarelli & Ellul, 2021). As DeFi grows, it faces new challenges in the fight against financial crime. The research expects innovative solutions adapted accordingly to the unique DeFi ecosystem (Wronka, 2021). Meanwhile, traditional financial institutions are exploring blockchain to improve services such as payments, lending, and asset management. Blockchain has been identified as having the potential to improve transparency, efficiency, and access to financial services, although implementation and regulatory challenges remain (Harvey et al., 2021). The potential of DeFi to complement traditional finance by removing its limitations, such as affordability and efficiency, is substantiated. However, the need for a regulatory framework to manage the risks associated with the decentralized nature of DeFi has been emphasized (Zetzsche et al., 2020).

DeFi platforms are deployed in a transparent, open output code, permissionless, and no central-authority financial system, relying on smart contracts in blockchain networks to execute transactions (Salami, 2021). This setup ensures that DeFi services are available to anyone with internet access, promoting financial inclusion and democratization. The execution of DeFi programs is managed by smart contracts that automate and enforce the terms of financial agreements. Such automation reduces the need for traditional financial intermediaries, allowing for more direct and efficient transactions (Carapella et al., 2022). At the heart of DeFi is blockchain technology, specifically Ethereum, which supports the development and execution of complex smart contracts required for DeFi applications. The technology ensures the immutability, security, and transparency of financial transactions (Schär, 2021). DeFi platforms have been identified as facilitating decentralized lending and borrowing by allowing users to lend their crypto assets in exchange for interest or borrow by providing collateral. The system works without the need for traditional credit checks, instead relying on collateral provided and terms set by smart contracts (Kaplan et al., 2023). Users can make payments in their cryptocurrencies to participate in the security and management of the network, receiving payment rewards in return. The process not only secures the network but also provides a passive income flow for stakeholders, increasing the utility of DeFi ecosystems (Jensen et al., 2021).

Harvey et al. (2021) indicated that DeFi could fundamentally change aspects such as deposits, lending, lending rates, and other traditional banking services. DeFi loan protocols such as Compound demonstrate that loan durations are generally short, with volatile loan rates. This volatility reflects the emerging market dynamics of DeFi, which is significantly different from the more stable conditions in traditional banking. Additionally, the presence of leveraged investment strategies among DeFi users may create new forms of systemic risk (Saengchote, 2021). Traditional banks are increasingly facing competition not only from DeFi platforms but also from fintech companies. Competition encourages banks to innovate and diversify their service offerings. However, the rapid growth of DeFi and the regulatory arbitrage opportunities they represent may further accelerate the shift away from traditional banking products (Buchak et al., 2018). The regulatory environment for DeFi is evolving, with significant implications for traditional banking. Due to its decentralized nature, DeFi can create problems with regulatory compliance, consumer protection, and financial stability. Regulatory efforts can focus on finding a balance that ensures the safety and soundness of financial markets without stifling innovation (Zetzsche et al., 2020). The integration of DeFi tools into traditional banking systems opens up an opportunity to improve financial products and services.

Integration can potentially lead to greater efficiency, inclusiveness, and innovation in financial services. However, it also comes with challenges and risks. Smart contracts can automate many banking processes, such as transaction processing and regulatory compliance, thereby reducing operational costs and increasing efficiency (Zetzsche et al., 2020). DeFi allows the creation of innovative financial products, such as algorithmic stablecoins, yield farming (a highly profitable way of earning on cryptocurrency (tokens), by placing them in liquidity pools (earning on trading commissions in the pool) or on deposits in cryptocurrency (earning interest for issuing deposited tokens to borrowers)), and liquidity, which can offer new ways of saving, investing and managing capital for traditional banking customers (Majumdar & Gochhait, 2022). Regulatory approaches to DeFi face unique challenges due to its decentralized nature, reliance on smart contracts, and global accessibility. Despite these challenges, regulators and academics are exploring different approaches to ensure that DeFi operates within a framework that protects consumers, ensures financial stability, and promotes innovation. Some jurisdictions have created regulatory prototypes to allow DeFi projects to test their innovations in a controlled environment. This approach makes it possible for regulators to better understand DeFi technologies and business models while providing legal certainty for innovators (Wronka, 2021). Regulators explore how the existing financial regulations can be adapted to the DeFi space. This includes applying anti-money laundering (AML) and know-your-customer (KYC) regulations to DeFi platforms, even though implementing these measures in a decentralized environment poses significant challenges (Zetzsche et al., 2020; Gaspareniene et al., 2022). An innovative approach involves building regulatory compliance into the DeFi protocols themselves using smart contracts. This could automate compliance with certain regulatory requirements, such as transaction reporting and fraud detection (Makarov & Schoar, 2022). DeFi's reliance on blockchain technology complicates regulatory efforts due to the inherent anonymity and pseudonymity of transactions. This characteristic challenges traditional anti-money laundering and know-your-customer enforcement mechanisms (Zetzsche et al., 2020). The pace of innovation in the DeFi environment often outpaces the development of the regulatory framework, creating a gap between technological progress and regulatory standards. This dynamic environment poses challenges for regulators to keep up with new developments and risks (Carter & Jeng, 2021). Addressing the global nature of DeFi requires international cooperation between regulatory authorities to establish common standards and frameworks. This can facilitate more effective cross-border enforcement and compliance, contributing to a more stable and secure DeFi ecosystem (Maia & Santos, 2021). Exploring technology-neutral regulatory approaches that focus on activities and associated risks rather than the underlying technology can help create an adaptive and sustainable regulatory framework. Such approaches enable flexibility and innovation in the DeFi environment while meeting regulatory goals related to consumer protection and financial stability (Werner et al., 2021). Developing a regulatory framework that emphasizes desired outcomes, such as consumer protection, market integrity, and financial crime prevention, can provide the necessary flexibility for innovative DeFi projects. This approach encourages the development of DeFi solutions that meet regulatory objectives, contributing to a more secure and inclusive financial ecosystem (Salami, 2021).

The development of decentralized finance requires a comprehensive analysis of how DeFi integrates with and affects TradFi.

The purpose of the study is to examine the dynamic interaction between decentralized finance and the traditional banking sector in order to understand the implications of the growth of DeFi for financial stability, monetary policy, and the overall health of the financial environment.

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2. DATA DESCRIPTION AND METHODOLOGY

The study analyzes the interaction between decentralized finance (DeFi) and the traditional banking system using the example of three countries that are leaders in the implementation and development of DeFi (Chainalysis, 2023): the United States of America, India, and Great Britain. The proposed analysis will not only reveal general trends and patterns of interaction between DeFi and traditional finance but also take into account unique national features and differences in regulatory policy, economic development, and the structure of the banking system.

For each of the selected countries data were collected and analyzed on key banking indicators (Table 1), including commercial lending volumes, bank rates, federal funds rates (for the US), the consumer price index as a measure of inflation, total liabilities and bank capital, and volumes of deposits. The indicators will help to assess the state and dynamics of the banking system, the level of credit activity, the cost of borrowing and trends in the purchasing power of the currency.

The data were obtained from the Federal Reserve Economic Data (FRED, 2024) database for the USA, the Reserve Bank of India (RBI, 2024) for India, and the Bank of England (Bank of England, 2024) for the UK. They are presented in monthly terms from July 2018 up to and including January 2024, providing more than 68 observations for each time series.

In decentralized financial services, TVL is a key indicator that reflects the total amount of funds (in cryptocurrencies or stablecoins) locked in smart contracts of various DeFi projects (Zhou et al., 2022). This indicator is used as a measure of popularity and trust in the DeFi sector, as well as an indicator of the total amount of capital invested in decentralized financial products and services. The growth of TVL indicates an increase in user activity and the influx of new investments into the DeFi sector, which may indicate the expansion of the influence of decentralized finance on traditional financial systems. The data on the total value locked in decentralized finance were obtained from the DeFiLlama platform, which is one of the leading aggregators of statistical information on the decentralized finance sector. DeFiLlama provides up-to-date TVL data across various DeFi projects, including credit platforms, decentralized exchanges (DEX), staking pools, and other blockchain-based financial instruments and services (DefiLlama, 2024).

Using a vector autoregression (VAR) model, a comprehensive time series analysis was conducted for each of the countries under study to identify causal relationships between DeFi growth and key banking indicators. Granger causality tests, impulse response analysis, and forecast error variance decomposition will allow for assessing the impact of changes in one segment on the dynamics of another and predicting the potential consequences of DeFi integration into traditional financial systems.

Table 1. Indicators of the traditional banking system used in the study

Country	Indicator
USA	• Volume of commercial and industrial loans (BUSLOANS), billions of U.S. dollars • Basic bank lending rate (MPRIME), percent • Rate of federal funds (FEDFUNDS), percent • Consumer price index (CPIAUCSL), index 1982–1984 = 100 • Total liabilities and capital of banks (TLAACBW027SBOG), billions of U.S. dollars • Volume of deposits in commercial banks (DPSACBW027SBOG), billions of U.S. dollars
India	• Loans, cash loans and overdrafts, rupees crores • Repo rate, percent • CPI (consumer price index), index 2012 = 100 • Total liabilities and capital of banks, rupees crores • Aggregate deposits, rupees crores
United Kingdom	• Volume of commercial and industrial loans (LPMBF36), millions of pounds sterling • The interest rate set by the Bank of England, percent • CPI (consumer price inflation), index 2015 = 100 • Total liabilities and capital of banks (RPMB3KN), millions of pounds sterling • Total deposits (LPMB2US), millions of pounds sterling

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This study will consider the building of a VAR model using the US data. Similarly, models were built for India and Great Britain. It is assumed that Y_t is a vector containing n time series (in our case $n = 7$), including *TVL, BUSLOANS, MPRIME, FEDFUNDS, CPIAUCSL, TLAACBW027SBOG, DPSACBW027SBOG* in time t. Following Johansen (1988), Johansen and Juselius (1990), and Frolov et al. (2023), a vector autoregressive model with Gaussian errors can be expressed by:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t, \quad (1)$$

where Y_t – $n \times 1$ is a vector of observed variables in time t; $A_1, A_2, ..., A_p$ – matrices of coefficients of size $n \times n$, which describe the influence of previous values of time series on current values; ε_t is a vector of $n \times 1$ shocks (errors) in time t, it is assumed that $\varepsilon_t N(0, \Sigma)$, where Σ is the matrix of covariance error.

The Granger causality test examines whether the past dynamics of one time series is a significant predictor of future values of another time series in the context of a multivariate VAR model. For two variables X and Y included in the VAR model, the test can be formulated as follows (Engle & Granger, 1987):

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_i X_{t-i} + \varepsilon_{Y,t}, \quad (2)$$

where Y_t is the current value of time series Y in time t; α_0 is a constant reflecting the base level of the time series Y, which does not depend on its past values or the values of the time series X; α_i – coefficients at lag values Y_{t-i}, which reflect the influence of past values of Y on its current value; Y_{t-i} – the value of time series Y for i periods up to time t; β_i – coefficients at lag values X_{t-i}, which reflect the influence of past values X on the current value Y. These coefficients are the subject of the Granger causality test; X_{t-i} – the value of the time series X for i periods up to time t; $\varepsilon_{Y,t}$ is the error of the model for the time series Y in time t, which is the unpredictable component of Y.

The Granger causality test consists in testing the null hypothesis $H_0 : \beta_i = 0$ for all i, which means that there is no statistically significant influence of past values X on current values Y. If the null hypothesis is rejected, one can conclude that past values of X impact Y within this model.

Impulse response analysis in the context of a VAR model makes it possible to estimate how a time series responds to a standard shock (usually one standard deviation) in one of the model variables over a certain number of time periods. For a pth-order VAR model, the impulse response formula is: *IRF* for a shock in variable j on variable i at horizon h is defined as the change in the expected value of i, assuming that variable j received a shock of one standard deviation and all other variables did not receive shocks.

$$IRF_{i,j}(h) = \sum_{k=0}^{h} \Phi_k, \quad (3)$$

where Φ_k – coefficients of the impulse response matrix obtained from the VAR model; h – time horizon.

3. RESULTS & DISCUSSION

3.1. Descriptive statistics

The analysis of descriptive statistics for the financial indicators of the US, India and the UK provides insight into economic and banking conditions in these countries.

The analysis of the US input data (Table 2) shows considerable variability in TVL with a high standard deviation and positive skew, indicating a concentration of lower values but with the potential for very high values. The base rate and the reserve funds rate show moderate volatility and a slight trend toward higher rates, indicating periods of tighter monetary policy. The constant increase in the CPI reflects inflationary pressure. The banking sector, represented by commercial loans, liabilities, and capital, as well as deposits, shows growth and stability, but with marked volatility, indicating a dynamic banking environment that responds to economic conditions.

An analysis of the input data for India (Appendix A, Table A1) shows that TVLs and loans exhibit a wide range, indicating a diverse investment landscape and credit market. The repo rate, which is an instrument of monetary policy, shows less volatility, indicating the relatively stable monetary policy of the Reserve Bank of India. CPI data indicate inflationary trends, albeit with moderate volatil-

Table 2. Descriptive statistics of incoming (raw) data for the US

Metrics	TVL	Commercial Loans	Prime Rate	Fed Funds Rate	CPI	Bank Liabilities & Capital	Bank Deposits
Mean	45,114,032,864.11	2,568.35	5.09	1.93	274.87	20,522.39	15,742.94
Median	39,698,867,463.60	2,563.51	4.99	1.83	266.75	21,295.67	16,890.21
Maximum	189,345,628,417.74	3,034.06	8.50	5.33	309.69	23,248.35	18,148.98
Minimum	20,500.41	2,201.55	3.25	0.05	251.21	16,703.49	12,202.79
Std. Dev.	52,784,786,118.00	211.52	1.86	1.86	20.36	2,416.37	2,193.39
Skewness	1.16	0.03	0.66	0.63	0.43	−0.44	−0.52
Kurtosis	3.37	1.82	2.13	2.10	1.56	1.55	1.59
Jarque-Bera	15.53	3.90	6.91	6.67	7.87	8.00	8.64
Probability	0.00	0.14	0.03	0.04	0.02	0.02	0.01
Observations	67	67	67	67	67	67	67

ity. Total liabilities and aggregate deposits indicate a stable banking sector with significant growth potential, but the standard deviation of deposits indicates fluctuating savings behavior among the population.

An analysis of the UK inputs (Appendix A, Table A2) shows that the UK TVL and loan data show a wide range similar to that of the US, indicating considerable variation in the value of investment and lending. The higher Bank Rate maximum and positive asymmetry reflect periods of higher interest rates, perhaps to contain inflation, as evidenced by the CPI maximum showing spikes in inflation. Total liabilities and aggregate deposits point to a robust banking sector, but with less volatility than in the US, suggesting a more stable deposit base and liability structure.

3.2. VAR stability conditions and residual diagnostics

All roots for the characteristic polynomials of the VAR models are inside the unit circle, which confirms the model's stability (Figure 1; Appendix B: Figure B1, Figure B2). This means that the models are suitable for further analysis and forecasting of time series. Confirming that none of the roots exceed unity in modulus ensures that there are no "explosive" processes in the system and that the time series returns to long-run equilibrium after shocks. Satisfying the stability conditions also indicates that the chosen model specification (number of lags and included variables) is correct for the analyzed data.

The analysis of the residual cross-correlations for the VAR model shows how the variables are in-

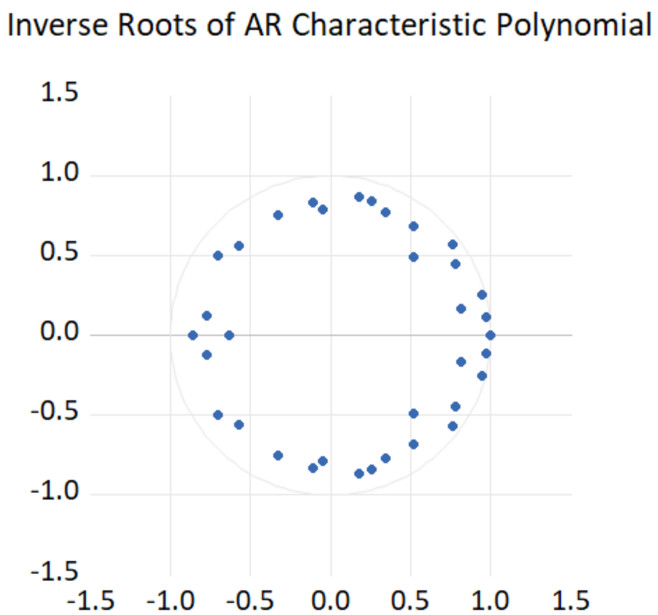

Figure 1. Inverse roots of AR characteristic polynomial (USA)

terrelated with each other through different lags. Notably, the observed residual cross-correlation between the variables and their lags falls within the standard error range from –2 to 2. This indicates the absence of significant autocorrelation, suggesting that the VAR model has effectively captured the dynamic relationships between the variables without leaving significant unexplained shocks or trends in residuals. According to the data from the US (Figure 2), India (Appendix C, Figure C1), and the UK (Appendix C, Figure C2), the ability of the VAR model to capture the complex relationships between commercial loans, the prime rate and other financial indicators without significant residual autocorrelation underlines the robustness of the model.

According to the obtained results, it is confirmed that the model successfully captures the relationships between the variables without leaving significant unexplained shocks or trends in the residuals.

The LM (Lagrange Multiplier) serial correlation test for VAR model residuals is a test for autocorrelation in the model residuals at different lags. The null hypothesis of the test is the absence of serial correlation for the given lag.

The US data (Table 3) revealed relatively high probabilities (Prob.) for all lags, with the lowest p-value at lag 1 (0.0811 for LRE* and 0.1041 for Rao F), indicating no significant serial correlation at conventional levels of statistical significance. This indicates that the VAR model for the US correctly captures the underlying financial dynamics without leaving unexplained autocorrelation in the residuals. The model is specified for time series data, making it suitable for forecasting and analysis.

The VAR model for India shows a significant residual serial correlation at lag 1 (p-values 0.0001 and 0.0002), indicating potential model misspecification or omitted variable problems at this starting point (Appendix D, Table D1). However, from lag

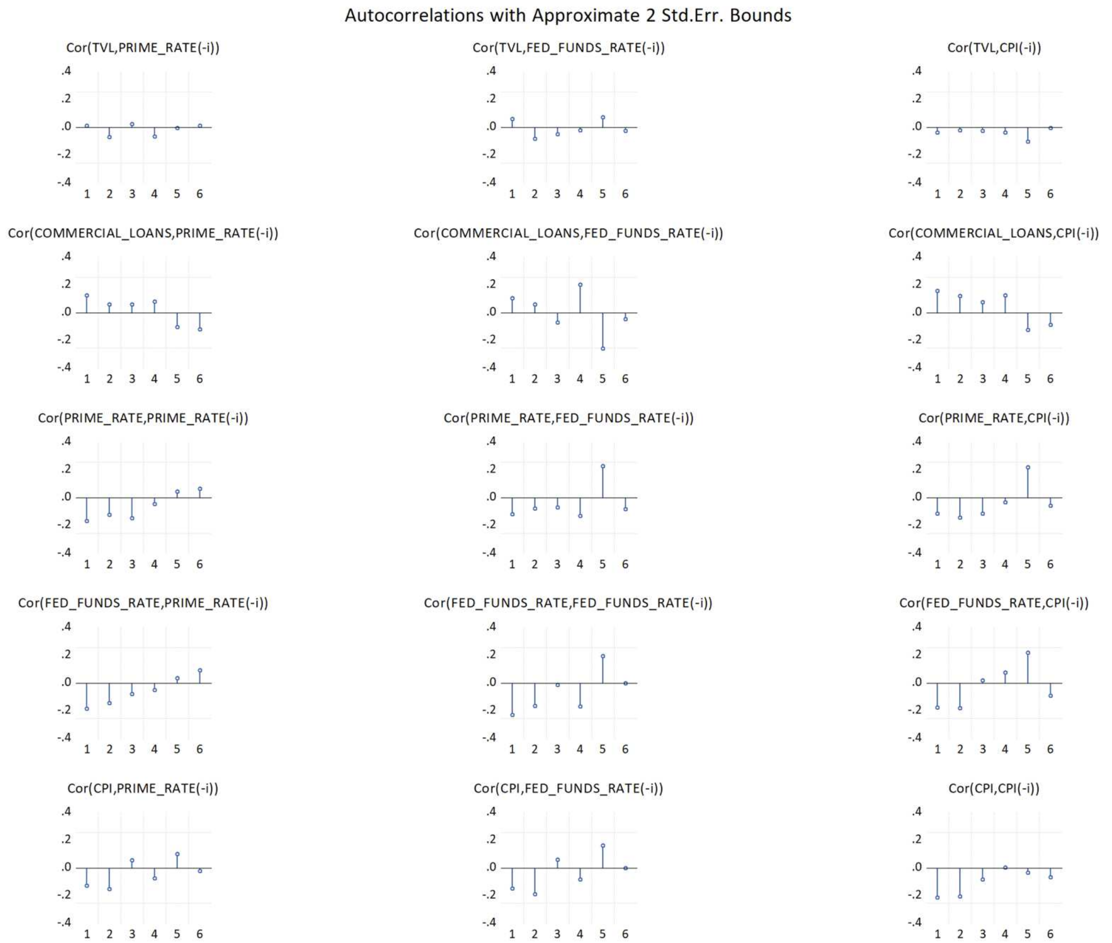

Figure 2. Partial display of residual cross-correlations of model variables

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Table 3. Residual serial correlation LM tests for the USA

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	63.38876	49	0.0811	1.385235	(49, 70.4)	0.1041
2	45.08504	49	0.6326	0.885473	(49, 70.4)	0.6710
3	50.12664	49	0.4285	1.013557	(49, 70.4)	0.4734
4	52.32644	49	0.3461	1.071635	(49, 70.4)	0.3905
5	48.99241	49	0.4734	0.984139	(49, 70.4)	0.5178
6	44.71628	49	0.6473	0.876371	(49, 70.4)	0.6849

2 onwards, the p-values increase significantly, indicating the absence of significant autocorrelation and suggesting that the model captures the dynamics of the financial time series well beyond the initial lag.

The UK data (Appendix D, Table D2) indicate no significant serial correlation in most lags, with the exception of lag 2, where p-values are 0,0179 (LRE* stat) and 0,0205 (Rao F-stat), suggesting the presence of autocorrelation at this point. This may indicate specific temporal dependencies that are not accounted for by the model at lag 2. However, the absence of significant autocorrelation at other lags suggests that the model generally captures the dynamics of the financial time series well.

3.3. Granger causality test

A Granger causality test for the VAR model was conducted to analyze the relationships between TVL in DeFi and other economic variables for the US, India, and the UK for the period July 2018 to January 2024.

Granger causality tests for the US (Table 4, Table 5) show that none of the financial variables (commercial loans, prime rate, Fed rate, CPI, bank liabilities and capital, bank deposits) causes a statistically significant Granger change in TVL, as evidenced by high p-values. Similarly, TVL does not condition the significance of any of these variables, with the exception of CPI, which has a p-value closer to traditional significance levels, but still not below the common threshold of 0.05. In the US, the VAR model indicates no short-term predictive causality between TVL and traditional financial sector indicators, assuming that changes in these variables are relatively independent in the short run.

For India, although p-values for the relationships between TVL and other financial indicators (loans, repo rate, CPI, total liabilities, aggregate deposits) generally exceed the 0.05 threshold (Appendix E: Table E1, Table E2), they are lower compared to the US, which indicates the presence of connections. Notably, loans, repo rate and CPI show p-values close to significance in predicting TVL, suggesting the potential predictive information content of these variables for TVL. The Indian financial system shows some degree of interdependence between TVL and key financial indicators, with credit, repo rates, and CPI almost reaching the threshold in Granger causality tests. This suggests a more interconnected financial environment where monetary policy (as represented by the repo rate) and inflation (CPI) may have predictive power in understanding TVL dynamics.

The UK Granger causality tests (Appendix E: Table E3; Table E4) reveal a Granger causality rela-

Table 4. Results of the Granger causality test (dependent variable – TVL) for the USA

Dependent variable: TVL			
Excluded	**Chi-sq**	**df**	**Prob.**
COMMERCIAL_LOANS	2.58036	5	0.7643
PRIME_RATE	1.801902	5	0.8758
FED_FUNDS_RATE	3.571306	5	0.6126
CPI	2.830278	5	0.7261
BANK_LIABILITIES_CAPITAL	1.225992	5	0.9424
BANK_DEPOSITS	2.930825	5	0.7106

Table 5. Granger causality test results (variable TVL affects other model variables) for the USA

Dependent variable	Excluded	Chi-sq	df	Prob.
COMMERCIAL_LOANS	TVL	1.180159	5	0.9468
PRIME_RATE	TVL	1.634305	5	0.8971
FED_FUNDS_RATE	TVL	0.923227	5	0.9685
CPI	TVL	4.533374	5	0.4754
BANK_LIABILITIES_CAPITAL	TVL	3.991729	5	0.5506
BANK_DEPOSITS	TVL	3.081813	5	0.6874

tionship between total liabilities and aggregate deposits TVL, as indicated by the p-value of 0.0254 and 0.0047, respectively. This means that these variables may contain predictive information for the UK TVL. TVL is found to have a relationship with credit score, highlighted by the low p-value (0.0000), which may indicate a strong predictive relationship. The UK data show a correlation between TVL and specific financial indicators such as total liabilities and aggregate deposits. This relationship suggests that fluctuations in banking sector liabilities and deposits may have a predictive relationship with TVL, highlighting the impact of banking sector stability and liquidity on TVL dynamics.

3.4. Impulse response function

An Impulse Response Function (IRF) analysis for a VAR model provides information on the response of each variable in the system to a shock (single standard deviation) in the TVL variable while considering the Cholesky sequence to rank the variables. This study analyzed the response of variables during the first ten periods after the shock in TVL, taking into account the presented standard errors.

For the US data (Figure 3), commercial loans increased to a peak of 0.001813 in period 4, indicating a lending response to TVL shocks. Meanwhile, the CPI rose marginally with a peak change of 0.000316 in period 8, indicating little inflationary pressure. The prime rate is showing a decrease, particularly by –0.002374 in period 6, which may reflect the easing of lending conditions. The Fed rate shows a significant downward adjustment with a maximum decrease of –0.025715 in period 4, indicating active monetary stimulus. Bank liabilities to equity ratio peaks at 0.000974 in period 4, while bank deposits increase by 0.001272 over the same period, reflecting the increasing stability or potential of the banking sector.

The results for India (Appendix F, Figure F1) indicate that loans show a notable peak increase of 0.001319 in period 2 before showing variation in response to TVL shocks. This variation indicates fluctuations in demand or supply for credit. The repo rate declined significantly with a significant fall of –0.016312 in period 6, indicating the central bank's intention to stimulate the economy. CPI responses are mixed, with a notable decrease of –0.000629 in period 2, suggesting the temporary effects of deflation. Total liabilities show growth, peaking at 0.001876 in period 7, and aggregate deposits increasing to 0.001867 in period 2, indicating the financial sector's response to takeovers and promotion of economic activity after TVL shocks.

For the UK, the IRF results (Appendix F, Figure F2) show that loans initially decreased with a minimum of –0.000926 in period 3, indicating a contraction in lending following TVL shocks. However, there is a slight positive response in period 10 with an increase of 0.000203. The bank rate is rising markedly, peaking at 0.052816 in period 7, indicating a significant tightening of monetary policy in contrast to the US and India. The CPI experiences significant volatility with a significant increase of 0.034378 in period 3, indicating strong inflationary pressures in response to TVL shocks. Total Liabilities and Aggregate Deposits both show contraction, with Total Liabilities down –0.001280 in period 4 and Aggregate Deposits down –0.001187 over the same period, suggesting a potential shift to more conservative financial positions in the banking sector.

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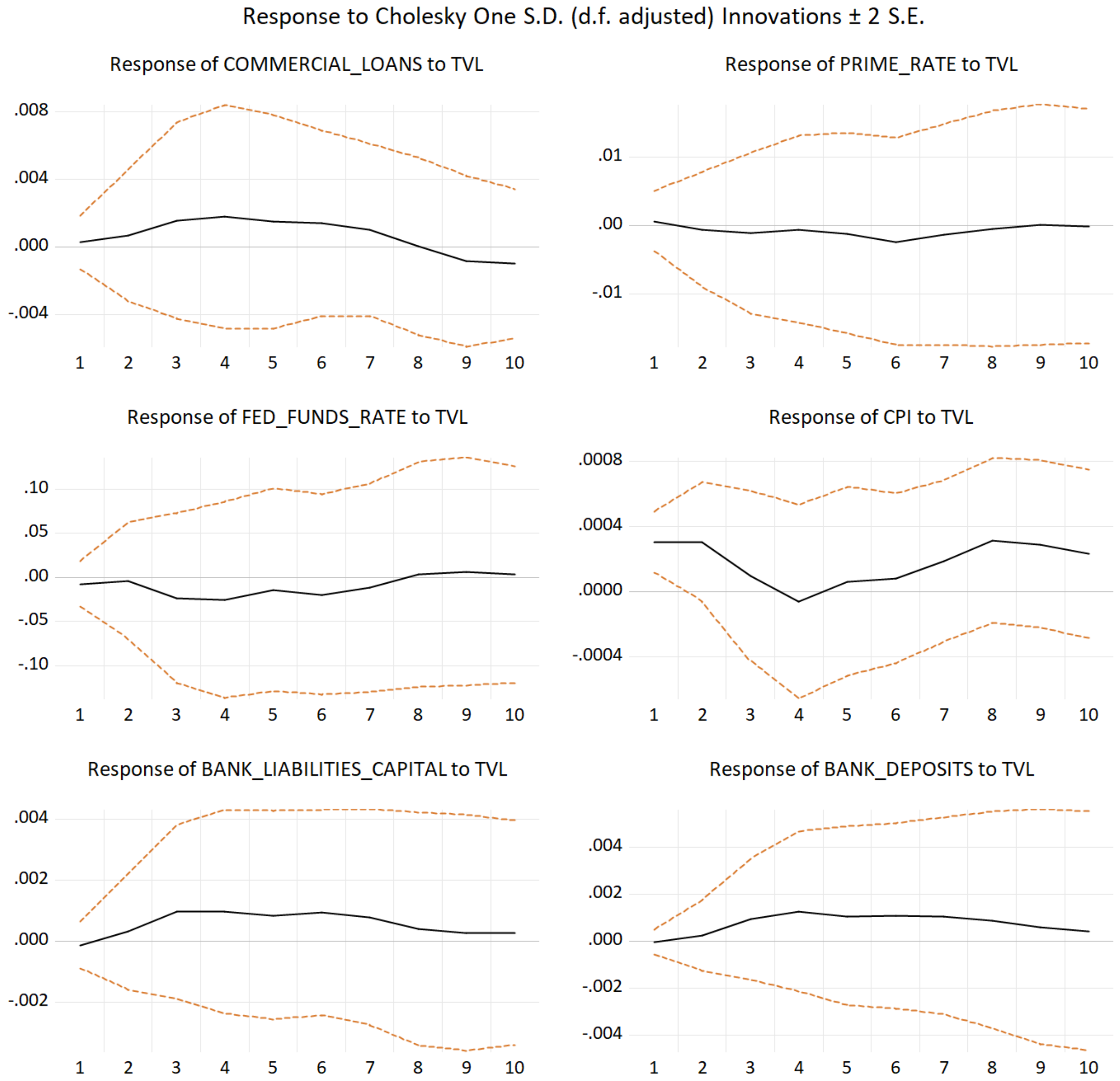

Figure 3. Response to Cholesky one S.D. (d.f. adjusted) innovations ± 2 S.E. (USA)

3.5. Variance decomposition using Cholesky factors

The analysis of variance decomposition for the variable Total Value Locked (TVL) and other variables of the VAR model makes it possible to estimate what percentage of each variable's variation can be explained by initial shocks in other variables of the system. Let us consider the results of variance decomposition for TVL and other variables over ten periods.

The US variance decomposition (Figure 4) indicates that while TVL initially accounts for all of the variance in its own forecast error, over time variables such as commercial credit, the prime rate, the Fed rate, and the CPI begin to explain some of the variance in TVL. This suggests little interaction between TVL and these financial indicators, indicating that changes in lending rates, monetary policy, and inflation have a measurable impact on the value captured in financial instruments. The increasing contribution of these variables over time underscores the interconnectedness of the financial system and the importance of monitoring a range of indicators for forecasting and policy analysis. The US financial environment is complex and interconnected, with monetary policy, lending rates, and inflation playing a minor role in influencing the dynamics of TVL and oth-

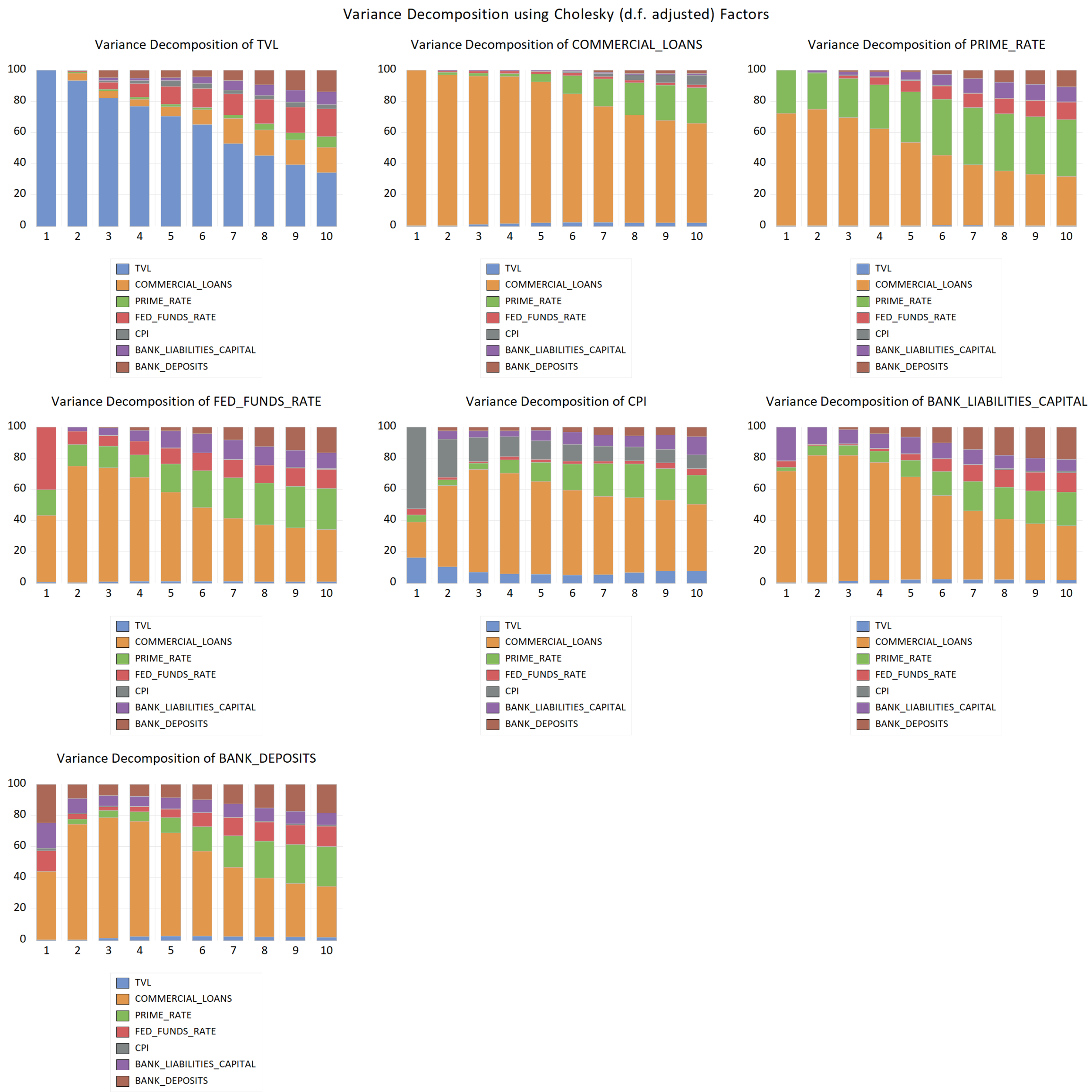

Figure 4. Analysis of variance distribution for VAR model variables (USA)

er financial variables. Policymakers and investors must consider a wide range of indicators to understand and predict changes in the financial market.

In India (Appendix G, Figure G1), the variance decomposition shows a slightly different situation, with the repo rate, borrowings, and CPI explaining a significant portion of the forecast error variance in TVL over time. This suggests that monetary policy (as indicated by the repo rate) and lending conditions (as reflected in loans) are significant drivers of financial market dynamics in India. The role of CPI in explaining the variance of TVL highlights the impact of inflation on investment decisions and the value of financial instruments. The Indian financial market is sensitive to changes in monetary policy, credit conditions, and inflation. Understanding the interplay between these variables is critical to predicting market changes and making informed financial decisions.

The variance decomposition for the UK (Appendix G, Figure G2) shows a significant contribution of the Bank Rate to forecast error variance of TVL and other variables over time, indicating a significant impact of monetary policy on the financial market. Unlike the US and India, the bank rate in Great Britain has a more pronounced impact

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on the dynamics of financial variables, including loans and CPI. This emphasizes the key role of the Bank of England's policy decisions in shaping the financial environment. The dynamics of the financial market of Great Britain are largely influenced by the decisions of the central bank regarding monetary policy, as evidenced by the contribution of the bank rate to the dispersion of TVL and other financial indicators. Effective monetary policy is the key to maintaining market stability and promoting economic growth. Stakeholders should closely monitor policy changes and their impact on the financial market.

The obtained results are consistent with existing studies regarding the impact of DeFi on the traditional banking system. Given that DeFi platforms offer higher deposit interest rates, this could compel banks to elevate their own rates to maintain competitiveness, potentially reducing their net interest margins. Moreover, the dynamic interest rates in DeFi may necessitate adjustments in the structures of bank interest rates (Castro-Iragorri et al., 2021).

The credit mechanisms of DeFi could encourage traditional banks to reevaluate their lending models and potentially adopt more inclusive lending criteria or develop similar technological offerings (Kaplan et al., 2023). DeFi platforms require substantial collateral to mitigate default risk, which might influence traditional banks to consider similar mechanisms or innovative credit products that reduce their risk exposure (Canales & Nanda, 2011). Banks may need to refine their liquidity management strategies to ensure they can meet withdrawal demands and other liquidity requirements effectively (Harvey et al., 2021).

CONCLUSION

The study considered how decentralized finance interacts with the traditional banking system and assessed the impact of DeFi on financial stability, regulatory policy, and the global financial ecosystem. A comprehensive analysis of financial markets in the United States, India, and the United Kingdom using vector autoregression (VAR) models, Granger causality tests, impulse response functions, and variance decomposition using Cholesky factors provides a detailed understanding of interdependencies and dynamics in these economies. The results highlight the key role of monetary policy, credit conditions, inflation and TVL in shaping the financial environment in these economic systems.

Different levels of Granger causality in the US, India, and the UK highlight the role of TVL in each country's economy. The UK shows the clearest causality, suggesting a closer integration between TVL and traditional banking metrics. The Indian results suggest potential relationships that warrant further investigation. In contrast, the US financial system shows no short-term predictive causality between TVL and the included financial indicators, possibly reflecting a more complex or indirect set of relationships not captured by this study.

In the US, India, and the UK, the IRF results illustrate the different ways in which TVL and other financial indicators interact in each country's economic and financial context. In the USA, the reaction of a stimulating monetary policy is demonstrated with a significant reduction in the Fed rate (to –0.025715) and an increase in commercial lending (to 0.001813). In India, monetary stimulus has been identified due to a reduction in repo rates (to –0.016312) and dynamic response of the banking sector with a marked increase in total liabilities and deposits. The UK has a contrasting monetary policy with a sharp increase in the Bank Rate (to 0.052816) and a mixed response in lending and deposits, suggesting a more conservative approach to financial stability in response to TVL shocks.

The analysis of variance decomposition in the US, India, and the UK highlights the importance of monetary policy, credit conditions, and inflation in influencing financial markets. Despite the similarity of factors influencing financial variables across countries, the magnitude and specificity of these influences differ, reflecting unique economic and regulatory environments.

This comparative analysis identifies critical factors influencing financial markets in the US, India, and the UK, with monetary policy, credit conditions, and inflation emerging as central themes in these economies. Despite the different economic contexts and regulatory environments of these countries, the interdependence of their financial systems reveals a commonality in the mechanisms governing market dynamics. For policymakers, financial analysts, and investors, the insights gained from this study underscore the importance of a comprehensive, multifaceted approach to understanding and navigating the global financial environment. Addressing this complexity and interconnectedness is essential to developing sound economic policies, making sound investment decisions, and promoting sustainable economic growth in an increasingly interconnected world.

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Writing – reviewing & editing: Serhiy Frolov, Iryna Shalyhina.

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APPENDIX A

Table A1. Descriptive statistics of input (raw) data for India

Metrics	TVL	Loans	Repo Rate	CPI	Total liabilities	Aggregate Deposits
Mean	45,114,032,864.11	11,536,644.62	5.25	160.91	2,748,128.75	15,706,452.61
Median	39,698,867,463.60	10,996,327.08	5.40	158.90	2,887,898.00	15,682,311.47
Maximum	189,345,628,417.74	16,213,389.48	45,418.00	186.30	3,424,815.65	20,681,803.11
Minimum	20,500.41	8,650,228.35	4.00	139.60	1,896,813.57	11,831,585.65
Std. Dev.	52,784,786,118.00	1,990,682.21	01.08	15.01	483,806.92	2,525,179.04
Skewness	1.16	0.81	–0.07	0.15	–0.35	0.27
Kurtosis	3.37	2.67	1.27	1.78	1.73	02.01
Jarque-Bera	15.53	7.69	8.43	4.40	5.88	3.55
Probability	0.00	0.02	0.01	0.11	0.05	0.17
Observations	67.00	67.00	67.00	67.00	67.00	67.00

Table A2. Descriptive statistics of input (raw) data for Great Britain

Metrics	TVL	Loans	Bank Rate	CPI	Total liabilities	Aggregate Deposits
Mean	45,114,032,864.11	2,626,410.40	1.46	4.15	4,182,251.28	2,688,601.66
Median	39,698,867,463.60	2,653,080.00	0.75	2.40	4,237,813.00	2,776,271.00
Maximum	189,345,628,417.74	2,771,772.00	5.25	11.10	45,74,871.00	2,987,929.00
Minimum	20,500.41	2,408,064.00	0.10	0.20	3,695,046.00	2,295,922.00
Std. Dev.	52,784,786,118.00	98,323.49	1.78	3.46	266,399.92	238,719.85
Skewness	1.16	–0.80	1.25	0.74	–0.56	–0.51
Kurtosis	3.37	2.46	2.96	02.06	02.01	1.64
Jarque-Bera	15.53	7.95	17.51	8.62	6.22	8.12
Probability	0.00	0.02	0.00	0.01	0.04	0.02
Observations	67.00	67.00	67.00	67.00	67.00	67.00

APPENDIX B

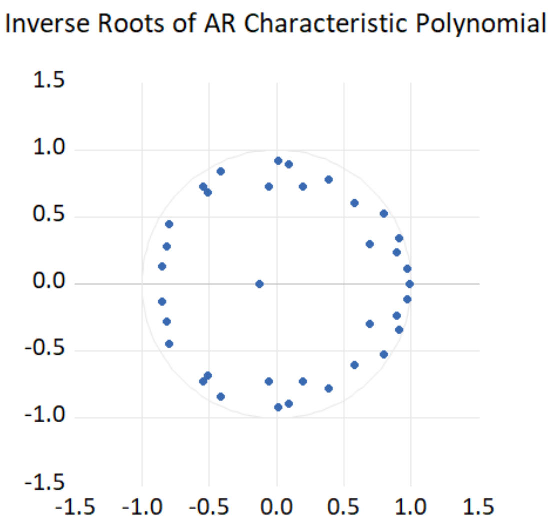

Figure B1. Inverse roots of AR Characteristic polynomial (India)

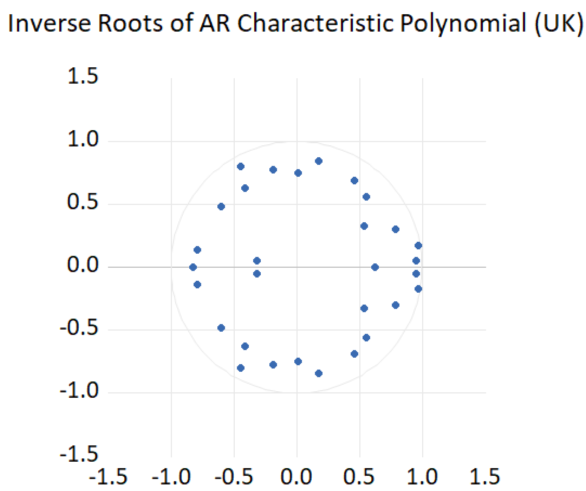

Figure B2. Inverse roots of AR Characteristic polynomial (UK)

APPENDIX C

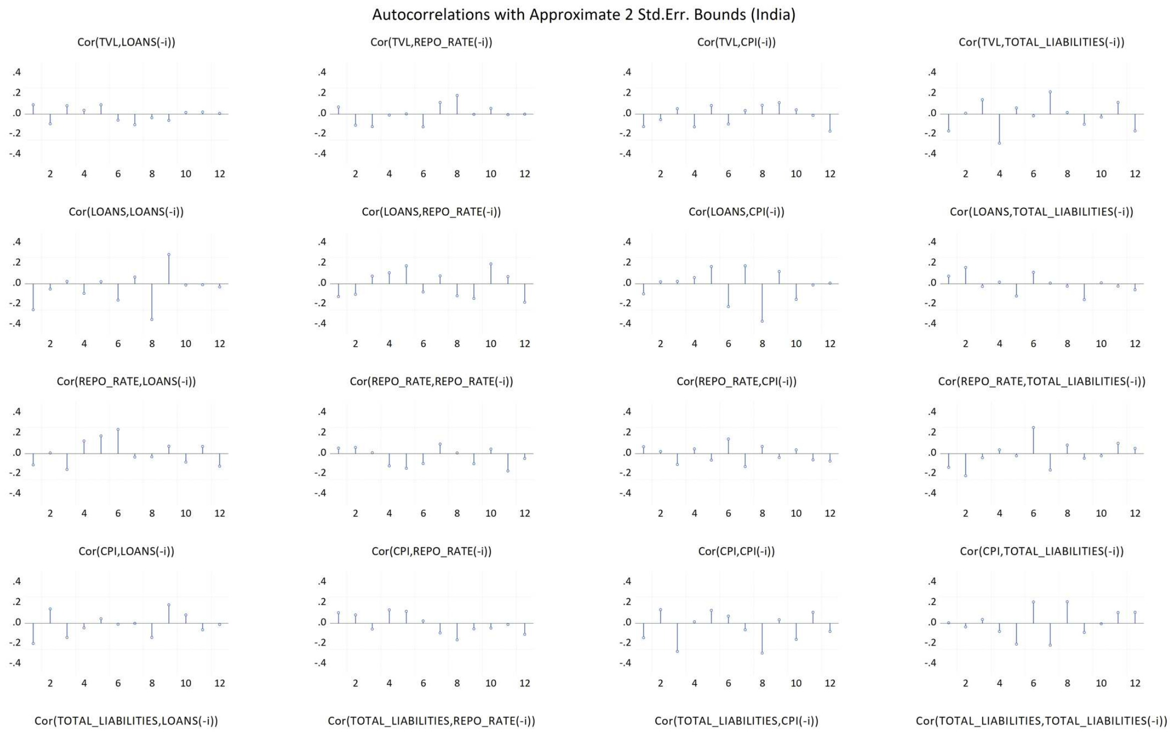

Figure C1. Partial display of residual cross-correlations of model variables for India

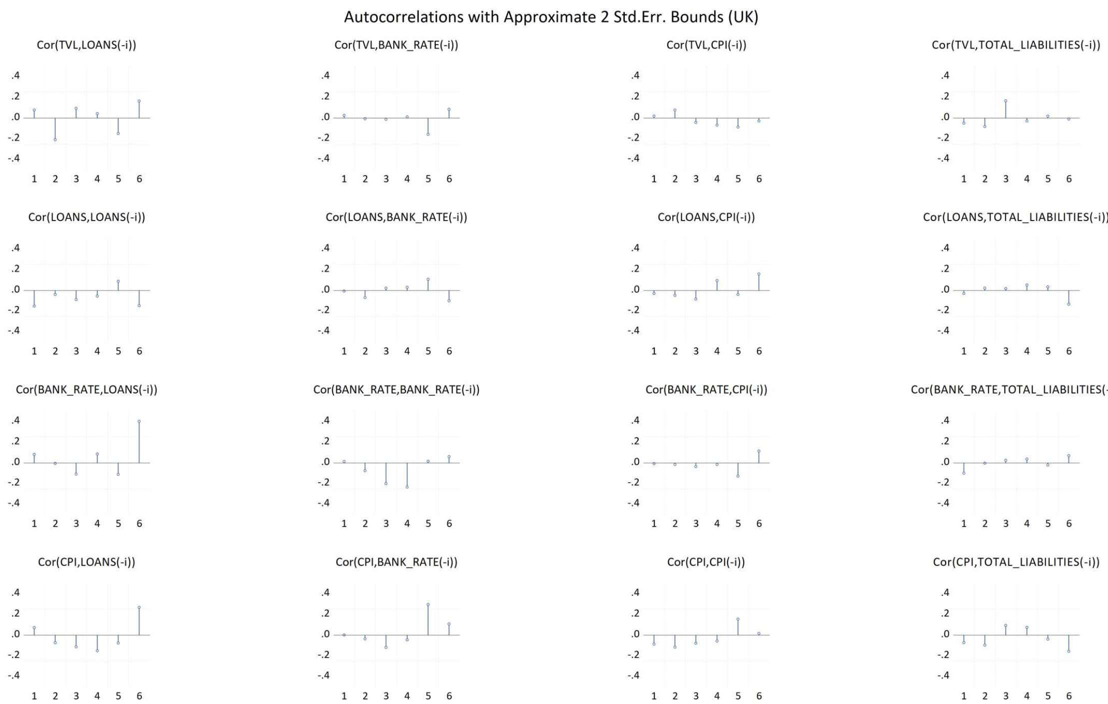

Figure C2. Partial display of residual cross-correlations of model variables for Great Britain

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APPENDIX D

Table D1. Residual serial correlation LM tests (India)

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	76.69340	36	0.0001	2.847467	(36, 59.8)	0.0002
2	38.18275	36	0.3705	1.069872	(36, 59.8)	0.4010
3	34.04917	36	0.5617	0.926786	(36, 59.8)	0.5901
4	28.80255	36	0.7974	0.755912	(36, 59.8)	0.8149
5	20.77299	36	0.9801	0.515980	(36, 59.8)	0.9824
6	32.56529	36	0.6327	0.877269	(36, 59.8)	0.6588
7	26.48438	36	0.8767	0.684050	(36, 59.8)	0.8885

Table D2. Residual serial correlation LM tests (UK)

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	34.13975	36	0.5573	0.939702	(36, 90.6)	0.5718
2	56.01170	36	0.0179	1.718805	(36, 90.6)	0.0205
3	33.56961	36	0.5847	0.921436	(36, 90.6)	0.5989
4	49.44900	36	0.0670	1.468189	(36, 90.6)	0.0739
5	42.07677	36	0.2245	1.204302	(36, 90.6)	0.2379
6	45.29963	36	0.1377	1.317442	(36, 90.6)	0.1483

APPENDIX E

Table E1. Granger causality test results (dependent variable – TVL) for India

Dependent variable: TVL			
Excluded	**Chi-sq**	**df**	**Prob.**
LOANS	9.789401	6	0.1338
REPO_RATE	10.36381	6	0.1101
CPI	10.14248	6	0.1188
TOTAL_LIABILITIES	8.222444	6	0.2223
AGGREGATE_DEPOSITS	4.842340	6	0.5642

Table E2. Granger causality test results (TVL variable affects other model variables) for India

Dependent variable	Excluded	Chi-sq	df	Prob.
LOANS	TVL	7.569628	6	0.2714
REPO_RATE	TVL	6.124840	6	0.4094
CPI	TVL	10.69257	6	0.0984
TOTAL_LIABILITIES	TVL	3.749844	6	0.7105
AGGREGATE_DEPOSITS	TVL	6.221014	6	0.3989

Table E3. Granger causality test results (dependent variable – TVL) for the UK

Dependent variable: TVL			
Excluded	**Chi-sq**	**df**	**Prob.**
LOANS	6.578621	5	0.2539
BANK_RATE	9.334133	5	0.0965
CPI	4.634114	5	0.4621
TOTAL_LIABILITIES	12.78925	5	0.0254
AGGREGATE_DEPOSITS	16.91101	5	0.0047

Table E4. Granger causality test results (variable TVL affects other model variables) for the UK

Dependent variable	Excluded	Chi-sq	df	Prob.
LOANS	TVL	27.49814	5	0.0000
BANK_RATE	TVL	2.259515	5	0.8122
CPI	TVL	2.336675	5	0.8009
TOTAL_LIABILITIES	TVL	10.01969	5	0.0747
AGGREGATE_DEPOSITS	TVL	3.252929	5	0.6611

APPENDIX F

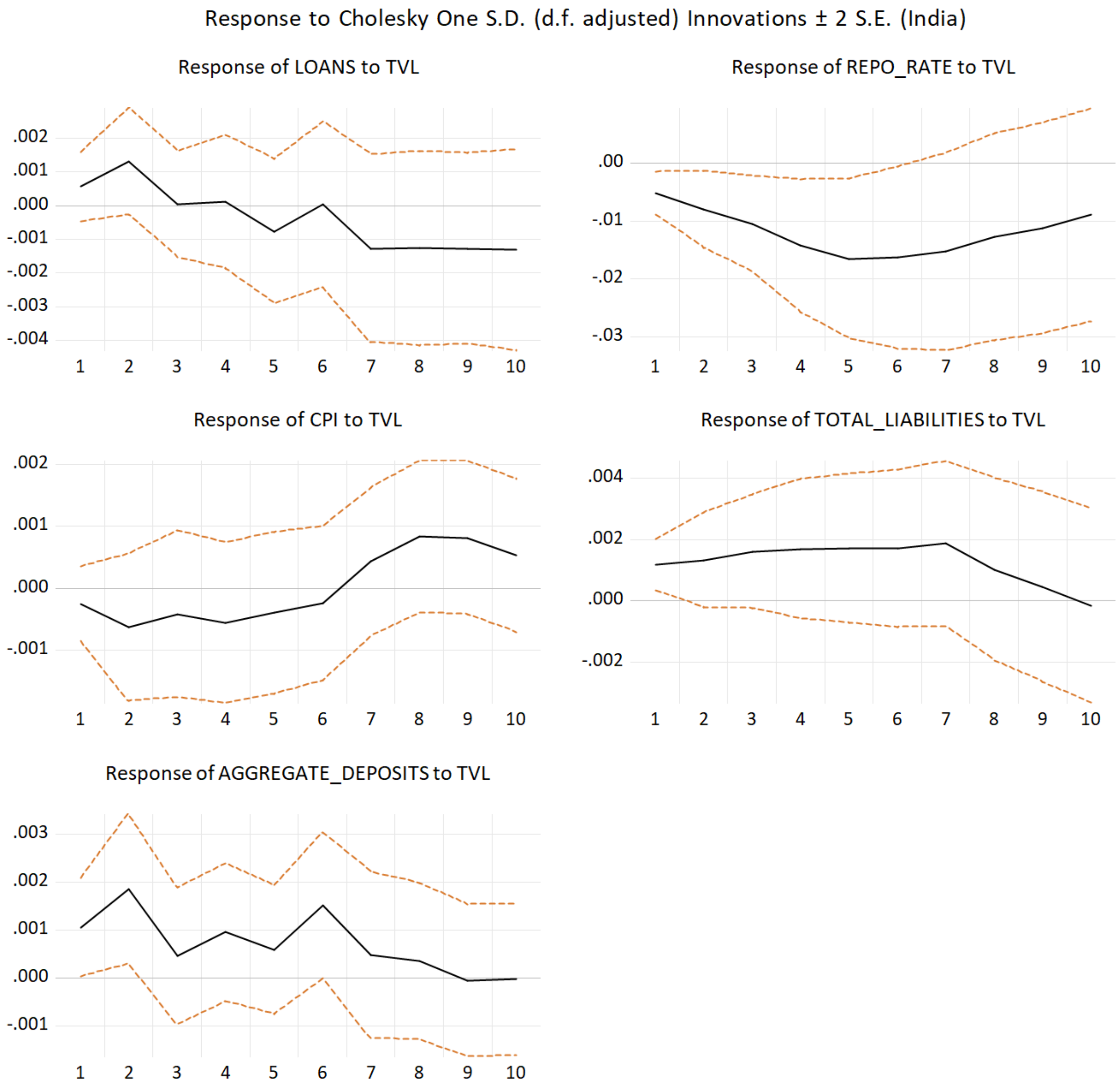

Figure F1. Response to Cholesky one S.D. (d.f. adjusted) innovations ± 2 S.E. (India)

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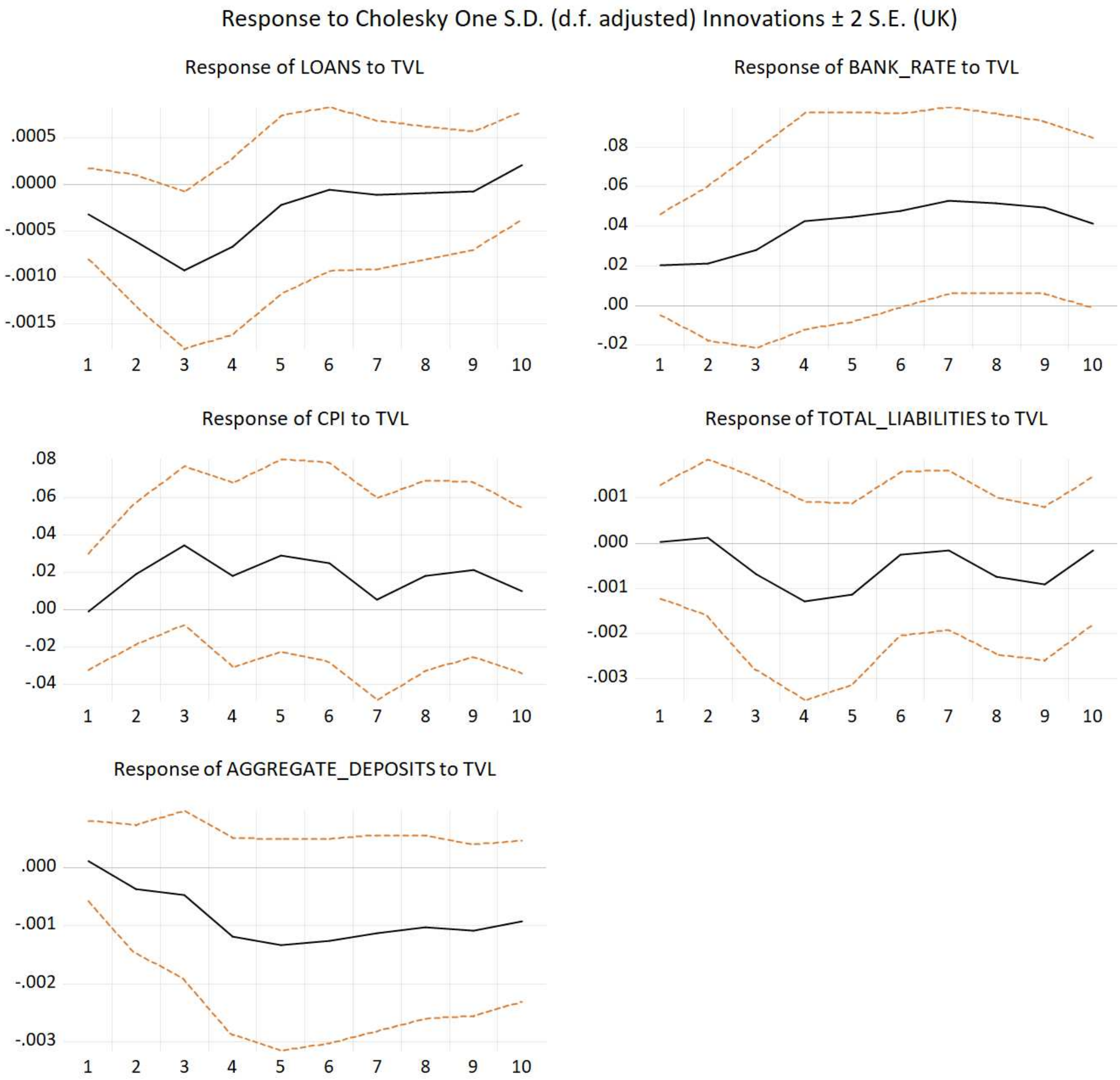

Figure F2. Response to Cholesky one S.D. (d.f. adjusted) innovations ± 2 S.E. (UK)

APPENDIX G

Figure G1. Analysis of variance decomposition for VAR model variables (India)

Figure G2. Analysis of variance decomposition for VAR model variables (the UK)

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