Firm Liquidity and the Origins of Aggregate Fluctuations in a Network Economy

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Abstract

This paper investigates how microeconomic origins of liquidity shocks at the firm level influence aggregate output and financial stability in a network economy with inter-sectoral linkages. We use firm-level balance sheet data to construct two liquidity measures: the quick ratio, capturing firms' internal short-term liquidity, and a network-based measure, capturing inter-sectoral network structure of liquidity flows derived from receivables and payables. Using sector-level aggregates, we apply a Structural Vector Autoregression (SVAR) model to examine the dynamic responses of GDP, the repo rates, the quick ratio, and the network measure to liquidity shocks. We further decompose forecast error variance to assess the relative contribution of each shock to business-cycle fluctuations. The main results indicate that the network effect is the dominant driver of business-cycle fluctuations, followed by the quick ratio, with both outweighing the remaining endogenous variables. The findings are relevant for macroprudential oversight, highlighting the importance of monitoring firms' liquidity imbalances and network structure for financial stability and economic resilience.

Keywords: Firm liquidity, business cycle, macroeconomic fluctuations, Structural VAR, input–output linkages, intersectoral networks.

JEL classifications: E32, E44, E52, G20, G32.

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1 Introduction

Financial and monetary markets are typically characterized by the level of liquidity firms require to meet obligations, which generally involve assets and liabilities with relatively short maturities or durations. In an economy where firms engage in frequent trading and hold short-term assets and liabilities, access to liquid assets – such as cash or highly liquid securities – is crucial for ensuring operational continuity and financial stability (Beck et al., 2022). Liquidity, in this context, refers to the ease and speed with which an asset can be converted into cash without incurring significant loss in value (Gallagher and Andrew, 2003; Tracy and Tracy, 2014; Vernimmen et al., 2022). This raises the question of how disruptions to firm liquidity propagate through an economy and ultimately shape macroeconomic fluctuations and financial stability.

Sufficient liquidity enables firms to cover short-term obligations, manage working capital, and respond to unexpected financial needs, while also supporting efficient asset trading and price discovery. When liquidity evaporates, markets experience increased volatility, spread widening, and funding stress, which can escalate into broader economic crises (Erel et al., 2021; Jordà et al., 2021). In financial networks characterized by interdependencies and time-sensitive commitments between economic agents, delays in payment settlements or disruptions in liquidity flows can generate cascading effects (Gatti et al., 2009; Acemoglu et al., 2012; Carvalho, 2014; Glasserman and Young, 2016), manifesting as liquidity shortages, credit risks, and systemic instability within a network economy where firms trade and interact with one another (Acemoglu et al., 2015, 2017; Altinoglu, 2021).

The systemic consequences of liquidity breakdown were vividly demonstrated during the Global Financial Crisis (GFC) of 2008, when disruptions in short-term funding markets triggered widespread financial distress, credit contraction, and severe macroeconomic downturns(Gorton, 2008, 2009; Lou and Sadka, 2011). Since then, a growing body of research has documented a strong link between liquidity conditions and business cycles (Bernanke and Blinder, 1988; Krishnamurthy, 2010; Bigio, 2015; Adrian et al., 2017), with particular emphasis on the interactions among financial intermediaries, firm balance sheets, and macroeconomic instability (Chung and Chuwonganant, 2014). Understanding these dynamics in modern financial systems is crucial for promoting financial resilience and mitigating the risk of liquidity-driven crises (Langley, 2014; Thakor, 2015; Jordà et al., 2021).

This study investigates the origins of aggregate fluctuations in a network economy arising from *liquidity shortages* and their propagation mechanisms.[1] The contribution of this research is twofold. First, it identifies which liquidity-related *structural* shocks, rooted in firm-level balance-sheet

[1]This paper henceforth uses the terms "fluctuation", "cyclical fluctuation", "business cycle", and "cycle" interchangeably.

conditions, drive cyclical fluctuations in a network economy and addresses the question, "how does the economy respond to shocks to liquidity-related variables?" The study distinguishes itself from Altinoglu (2021), who models a trade-credit network based primarily on accounts receivable and payable, by incorporating the full set of short-term balance-sheet items relevant to liquidity management. More generally, relative to granular and production-network approaches that take *idiosyncratic* micro-level shocks as primitives and study how they generate aggregate fluctuations through size heterogeneity and network propagation, often without explicitly incorporating balance-sheet liquidity measures (Gabaix, 2011; Baqaee and Rubbo, 2023), this paper brings firm-level liquidity measures directly into the empirical analysis of business-cycle fluctuations. Furthermore, whereas these studies rely on theoretical models or regression-based approaches to trace the propagation of idiosyncratic shocks, this paper employs a Structural VAR framework to identify aggregate structural shocks with microeconomic origins and to quantify their dynamic propagation. Second, the study evaluates the relative contribution of liquidity shocks to business-cycle fluctuations, quantifying the share of cyclical variation attributable to liquidity-related shocks compared to the remaining structural drivers in the system.

The analysis considers a network economy in which firms allocate part of their short-term assets to meet current obligations – covering goods, labor, and investments – and trade the remaining portion through inter-firm markets in the form of accounts receivable and payable to manage liquidity needs. Firms may also access the money market to borrow additional resources for refinancing or bridging liquidity shortfalls.[2] In such an economy, firm-level liquidity constraints can cascade through both financial linkages and production networks, amplifying macroeconomic volatility. To examine these effects empirically, the study employs a Structural Vector Autoregression (SVAR) model estimated on U.S. data, which enables the joint identification of structural innovations and the tracing of their propagation through impulse response functions and forecast error variance decompositions (Lütkepohl, 2005; Kilian and Lütkepohl, 2017).[3] The quarterly liquidity data are derived from the balance sheets of the top 100 U.S. firms in the $S\&P100$ index over the period 2006 to 2020. The sectoral network and liquidity ratio are then constructed for the core sectors of the U.S. economy. These are combined with the repo rate and Gross Domestic Product (GDP) to capture monetary and output effects, respectively. The specification also includes standard macro-financial controls (the federal funds rate, CPI, money supply, and the U.S. dollar exchange rate) each an important driver of aggregate liquidity conditions. The cyclical components of all endogenous variables are extracted using the Hodrick–Prescott (HP) filter and applied to the

[2]Although non-financial firms rarely borrow directly from money markets, their funding behavior is indirectly influenced by intermediaries; this relationship is captured through the network structure, following the approach in Altinoglu (2021).

[3]The term "structural" reflects the assumption that the relationships between the variables are grounded in the underlying economic structure and can be used to identify the sources of the innovations.

SVAR model to isolate business-cycle fluctuations arising from liquidity movements.[4]

Overall, this paper highlights the central role of liquidity in financial markets and the importance of understanding how liquidity shortages originate and propagate through interconnected firms. The findings can inform policymakers, regulators, and market participants seeking to manage liquidity risks and design frameworks that mitigate the adverse effects of liquidity-driven disruptions. The remainder of the paper is organised as follows; Section 2 explains the related literature about the liquidity issues and aggregate fluctuations as well as the background about the SVAR model and the approaches for the identifications of the model. Section 3 describes the data and model specification. The empirical results are explained in Section 4. The paper concludes with a summary of findings and policy implications.

2 Related Literature

The related literature of the paper is mainly covered in two parts. The first part explains the studies around liquidity issues and business cycles, and the second subsection elaborates on the Structural Vector Autoregression (SVAR) models and different approaches of identification.

2.1 Microeconomic Origins of Business Cycles

The concept and the level of liquidity is crucial for the entire economy as it is strictly associated with the ability to meet short-term obligations and respond to unexpected events (Gallagher and Andrew, 2003). Business cycles and market volatility are strictly related to liquidity, and the interaction of the two has been the topic of interest in macro-finance research in the economy (Krishnamurthy, 2010; Bigio, 2015; Adrian et al., 2017). In monetary economics and macroeconomics, liquidity addresses to the availability and accessibility of money or cash in an economy and its effect on economic determinants including inflation, spending, investment, etc. Liquidity in this context is defined by the ease with which money is used for trades and transactions as well as for the response of the monetary system to changes in demand for money in the economy and can be measured by the volume or amount of money in circulation (Tracy and Tracy, 2014; Vernimmen et al., 2022).

There is a lot of research on the origins of liquidity issues from different points of view. One line of literature discusses the level of liquidity based on the types of financial assets in the market including bonds and stocks, commodities, real estate etc. There are studies that have focused mainly

[4] Hodrick and Prescott (1997) propose the HP filter as a tool for decomposing time series into trend and cyclical components. Details are provided in Section 3.1 and Appendix 2.

on stock liquidity (Brogaard et al., 2017; Naik and Reddy, 2021), some studies discuss bond liquidity and its role in financial crises (Chen et al., 2007; Dick-Nielsen et al., 2012), and some focus only on commodity volatility and its returns on market liquidity and liquidity risk (Zhang and Ding, 2018; Zhang et al., 2019). He et al. (2018) also developed a model to investigate the connection between asset liquidity and market volatility in the real estate market.

Another strand of the literature studies the market structure in the provision of liquidity. They argue how liquidity arises from the behavior and interactions of market participants and financial intermediaries (Chung and Chuwonganant, 2014). Gorton (2008), Gorton (2009), and Cetorelli et al. (2012) for instance are limited to the role of financial intermediaries in providing liquidity and also for their potential systemic disruption. Lyons (1995) and Krishnamurthy (2010) have also pursued to investigate the underlying mechanisms and channels that drive the provision and demand of liquidity including trading costs, information asymmetry, and market volatility. Rupponen (2023) also shows how frictions in the credit markets affect business cycles. Understanding the origins of liquidity is essential for clarifying how liquidity is influenced by different factors and how it affects market outcomes.

Other studies have expanded on studying micro-level mechanisms and micro-foundations of driving liquidity supply and demand. Lyons (1995) assesses the structure of the market in providing liquidity to the foreign exchange market. They find the significant role of asymmetric information and the effectiveness of market interventions in market volatility and market failures in the foreign exchange market. The paper also explains the market players are willing to supply liquidity under the conditions in which the cost and the price movement volatility of liquidity provision are low. Tyagi (2000) also designs a liquidity provision model in loan markets and sheds light on how the banking system evaluates the benefits and costs of supplying liquidity to borrowers. Baqaee and Rubbo (2022) focuses on an economy in which shocks originate at the producers' side and propagate, generating aggregate fluctuations.

There is another line of literature that discusses liquidity from a monetary point of view, where the central banks inject money into the economy through financial instruments like different types of interest rates or printing fiat money. Kiyotaki and Moore (2019) discuss the role of government policy on asset prices and liquidity through open-market operations. Jessop (2013) highlight the role of fiat money in lubricating an economy and discuss that the liquidity is generated not from the balance sheet of firms in the economy but from the balance sheet of central banks. Calvo (2012) also argue the destructive role of CB intervening in the market and printing the fiat money (see also Goodhart (2011) and Brunnermeier and Schnabel (2015)).

The connection between liquidity and the business cycle is also another strand of literature that has substantial implications for the whole health of the economy. The important early study by Bernanke and Blinder (1988) found that liquidity crises can contribute to market volatility and economic recessions. They examine that changes in credit conditions can result in volatility of aggregate demand and output. They also established that the interbank market's frictions can lead to liquidity shortage and spillover throughout the whole economy. Bernanke and Gertler (1986) developed the framework to assess the impact of liquidity shocks and its fluctuations in unemployment, investment, and output. Their finding shows that liquidity shock contributes more to the industries and sectors that depend on external financing and have high levels of debt.

Other studies build upon these works and discuss the micro origins of liquidity and how they associate with the business cycle. They mainly discuss the role of the banking system and financial intermediaries in providing and managing liquidity in the economy. Acharya and Viswanathan (2011) explain the role of financial sectors' regulation and structure in determining the magnitude of liquidity in the economy or in rolling over the liquidity shortage throughout the economy. Financial institutions could hold more liquid assets during times of stress and uncertainty. This liquidity hoarding behavior may aggravate the liquidity stress during economic downturns since they may not be willing or able to provide liquidity to other counterparties. They also suggest that bank leverage may result in moral hazard and thus liquidity shortage. Cetorelli and Peristiani (2012) and Cetorelli et al. (2012) similarly examine the contribution of liquidity in the banking system during the Great Financial Crisis (GFC) in 2007-8. They illustrate that banks experience higher losses once they save lower amounts of liquidity during the financial crisis and this can again lead to less lending. The decline in lending then can play a negative role on the whole economy and thereby trigger the recession. Some studies focus on the role of financial intermediaries' capital structure and liquidity provision in business cycles (Begenau, 2020; Jordà et al., 2021). Some also analyze the microstructure of markets to determine market prices or the behavior or the role of market participants on the business fluctuations (Bernanke and Gertler, 1986; Li et al., 2021).

This paper contributes to the strand of the literature that investigates the origins of shocks to the business cycle. A growing literature examines the contribution of shocks to aggregate fluctuations, building upon foundational work of Cochrane (1994) and progressing with Gabaix (2011), Foerster et al. (2011), Acemoglu et al. (2012), Stella (2015), Atalay (2017), Altinoglu (2021), and Bai et al. (2024). Acemoglu et al. (2012) and Bigio et al. (2016) demonstrate how the network structure within an economy can drive fluctuations from idiosyncratic shocks using an input-output model. Bai et al. (2024) shows the causal effects of global supply chain disruptions on the macroeconomic outcomes. Altinoglu (2021) similarly models a network economy to understand the mechanism of fluctuations. However, it is restricted to the type of shock to the economy and addresses the importance of financial shock in the fluctuation, and he does not explain the dynamic of shock in the network. Overall, the literature shows constant attempts to understand the origins of fluctuation in the economy. This paper contributes to the literature by explaining the essential role of liquidity and its profound impact on economic business cycles. However, further exploration in this area is required to enhance how policymakers can better control economic volatility.

2.2 Structural VAR Model

The Structural Vector Autoregression (SVAR) model is widely used in macroeconomics and econometrics to analyze the relationships between economic variables. The SVAR model was first introduced by Christopher Sims in his 1980 paper, "Macroeconomics and Reality" (Sims, 1980a,b). Sims formulated a new macroeconomic model as a way to analyze the relationships between variables such as inflation, unemployment, and output in order to study the business cycle (Sims et al., 1986). Sims (1980a,b) suggest the SVAR tool as an alternative identification approach to analyse macro-model and overcome the false identification in macroeconomics. Bernanke (1986) and Shapiro and Watson (1988) developed a new class of SVAR econometric models to argue the business cycle and the relationship between money and income in the financial market. They focus more on the identification of the errors of the system that are taken as an exogenous shock, rather than identifying only the (autoregressive) coefficients.

After Sims (1980a,b) introduced the model, many studies used the model to address the business cycles in an economy and assess the dynamics of shocks. Some of the recent papers that apply the SVAR with the focus on liquidity and market interactions are da Silva Souza and Fry-McKibbin (2021), Múnera and Agudelo (2022) and Doojav et al. (2023). We also apply the SVAR model as one of the major means of extracting and analyzing information about the macroeconomy in order to quantify impulse responses of macroeconomic shocks (innovations) as well as investigate the contribution of different shocks to business cycles and forecast errors through decompositions of variance. To draw this information, first, a reduced form VAR model is fitted to summarize the data and then a SVAR model is carried out to interpret the data, where the errors of structural equations are taken as the economic shocks, and the parameters of these equations are estimated by restoring the information from the VAR representation. However, for any block of structural equations, recovering and estimating the structural equation shocks and parameters requires identifying restrictions in order to reduce the number of "free" parameters in the structural equations to the number that can be estimated and recovered from the data in the reduced form.

The identification issue is a crucial step in estimating the structural parameters of SVAR models and has been a topic of debate in the literature. There are different approaches for identifying the structural shocks in SVAR models, including long-run restrictions, sign restrictions, Cholesky identification, proxy variables, and external instruments. There is a strand of SVAR literature that focuses on different approaches of specifying the restrictions to perform an appropriate identification. Lütkepohl (2005), Ouliaris et al. (2016), and Kilian and Lütkepohl (2017) illustrate the steps to perform SVAR model and explain different types of identification to restrict the parameters with the focus on the AB model and sign restrictions. Gottschalk (2001) and Buckle et al. (2002) also assess different types of identification and address issues in imposing the restrictions. According to the literature, since we are focusing on the business cycle and short-term fluctuations, it is appropriate to use short-term identification methods such as the AB model and Cholesky identification rather than the long-term model, Vector Error Correction Model (VECM). This is not necessary and may be even obscure as it is possible that imposing long-term restrictions leads to unreliable results for investigating the business cycle. Sign restrictions involve imposing economic theory-based restrictions on the sign of the impulse response functions, while proxy variables and external instruments use exogenous variables to identify the structural shocks. There are also several advantages to proxy variables or external instruments such as limited validity, weak instruments, etc (Ouliaris et al., 2016).

To the best of our knowledge, there seems to be no recommendation on any specific approach, and some apply a mixed set of restrictions or a combination of the methods that are described above. However, overall in practice, without a particular context, any of the approaches can be employed depending on the preferences of the researcher and the context of the research. Sims (1980b) also discusses that "structural identification is not ordinarily needed and that false restrictions may not hurt." Among all the identification methods, we apply the Cholesky decomposition method as it is considered a good and reliable method for identifying structural shocks in SVAR models despite all the shortcomings (Lütkepohl, 2005). The Cholesky decomposition imposes a recursive structure on the model based on their economic theory which involves ordering the variables in the system. This approach assumes that the innovations propagate through the system in some specific order that is consistent with economic theory. Several research has shown that the Cholesky method leads to more accurate and robust results compared to other identification methods. Further, Kilian and Lütkepohl (2017) shows that the Cholesky identification method outperformed other approaches in a macroeconomic model in terms of accuracy and robustness. Furthermore, it is sufficient to implement and provide meaningful interpretable results.

3 Data and Empirical Model

This section is organized into two parts. Subsection 3.1 describes the data and the selection of endogenous and exogenous variables. It also explains the construction of the inter-sectoral network capturing the flow of funds between industries. Subsection 3.2 presents the SVAR model used to investigate the shocks driving cyclical fluctuations in the economy. The SVAR framework is employed to address two central questions: how does the economy respond to shocks to liquidity-related variables, and what is the contribution of each shock to business-cycle fluctuations? (Lütkepohl, 2005; Kilian and Lütkepohl, 2017).

3.1 Data Discription and Choice of Variables

The data are collected from firms' balance sheets and macro-financial sources to study liquidity dynamics and their aggregate implications. The empirical analysis distinguishes between *endogenous* variables, which are jointly modelled in the SVAR system, and additional *exogenous* controls.

The endogenous variables fall into three groups. First, we construct firm-based liquidity measures from the balance sheets of large U.S. firms: (i) the quick ratio, which captures internal short-term liquidity, and (ii) a network-based liquidity measure, which summarizes inter-firm (inter-sectoral) financial connections implied by accounts receivable and accounts payable. These variables are designed to capture both balance-sheet liquidity conditions and the structure through which liquidity stress can propagate. Second, we include a short-term interest rate (the repo rate) to proxy money-market funding conditions and the price of short-term liquidity. Third, we include a measure of aggregate real activity, based on output growth in U.S. industrial production, to capture economy-wide responses to liquidity shocks.

We also include the federal funds rate, money supply, inflation, and the dollar exchange rate as exogenous variables to account for common macroeconomic forces that may co-move with liquidity conditions and improve the results. The remainder of this subsection describes the construction and sources of each series. Descriptive statistics are reported in Table A.2 in Appendix A.

1. Firm balance-sheet data. The paper examines the ease with which firms can convert their short-term assets into cash to meet current obligations. To capture this, the analysis focuses on the liquidity ratio, which measures a firm's capacity to pay off its short-term liabilities using available liquid assets.[5] The liquidity data are derived directly from the balance sheets of the top 100 U.S. firms in the $S\&P100$ index over the period 2006Q1 to 2020Q4.[6] We consider both sides of the balance sheet, current assets and current liabilities, as standard liquidity ratio formulas require. These short-term items are then decomposed into two components: a network measure and a liquidity ratio. The network measure comprises accounts receivable and accounts payable, capturing inter-firm financial linkages. The liquidity ratio measures a firm's ability to cover its current liabilities using its remaining current assets, according to the following formula,

$$LR = \frac{CA}{CL} \tag{1.1}$$

[5]There are several measures of liquidity that can be used to assess a firm's maturity mismatch, such as the current ratio, quick ratio, and cash ratio. In this study, we focus on the quick ratio to assess firms' ability to meet short-term obligations (see further details in Vernimmen et al. (2022)).

[6]The data are collected from Datastream. The list of firms is available upon request.

where LR denotes the liquidity ratio, CA is the current assets, and CL is the current liabilities. More specifically, we use the concept of quick ratio in Equation 1.1 as one of the most important liquidity ratios to decompose the elements of a balance sheet;[7]

$$QR = \frac{C + CI + S + AR}{CL} \tag{1.2}$$

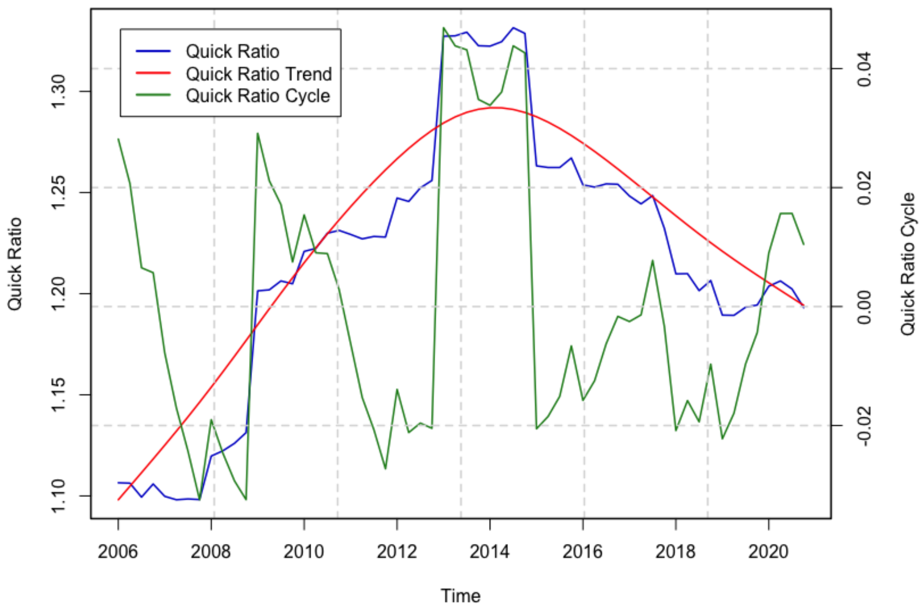
where QR denotes quick ratio, C is cash and its equivalents, CI is a current or short-term investment, S is marketable securities, AR is accounts receivable and CL is current liabilities. CL are short-term obligations that a firm is expected to settle within the current accounting period. For this study, the elements of current liabilities mainly include Account Payable (AP) and other current liabilities (such as wages payable, operating costs payable, short-term loans, taxes, accrued liabilities, dividends payable, etc.). We then isolate accounts receivable (AR) and accounts payable (AP) to construct the network effect, and the remaining elements capture another vital aspect of liquidity to discuss the liquidity dynamic (henceforth, for ease of reference and to simplify the discussion, we adopt the term 'quick ratio' to denote this residual liquidity measure).[8] Figure 1.1 plots the quick ratio as well as its corresponding trend and cycle components. The trend and cycle are calculated by the Hodrick–Prescott (HP) filter (see the details in Appendix 2).[9]

[7]There are several different liquidity ratios available depending on the purpose to evaluate the status of the debtor; current ratio, quick ratio (i.e., acid test ratio), operation cash flow ratio, working capital, working capital ratio, and absolute liquid ratio (see Vernimmen et al. (2022) for the details of each ratio). The quick ratio is chosen over other ratios as Madushanka and Jathurika (2018) shows the significant role of quick ratio in firms' performance compared to other liquidity ratios.

[8]We assume that other components of the balance sheet stay fixed and there is no minimum capital requirement as there are no constraints for non-bank and non-financial firms from the regulatory end (the Basell III). Non-financial firms in the US economy are not required to hold a minimum amount of capital. However, all firms need to maintain a sufficient level of financial resources to meet their financial obligations and continue to operate. This can include holding adequate cash reserves, maintaining a healthy debt-to-equity ratio, and having access to credit or other sources of financing.

[9]Hodrick and Prescott (1997) filter or HP decomposition is a popular tool in macroeconomics to study business cycles or fluctuation by decomposing the time series variables into the trend component and cycle component. In this paper, the cycle component is used in the model as the model requires the stationarity of the variables.

FIGURE 1.1: Quick Ratio: Level, Trend, and Cycle



Note: This figure depicts the time series of the endogenous variable quick ratio used in the model. It plots the quick ratio along with its corresponding trend and cyclical components, calculated using the Hodrick–Prescott (HP) filter as described in Appendix A.6. The left vertical axis shows the scale of the quick ratio, and the right vertical axis represents the scale of the cyclical component of the quick ratio. The horizontal axis shows the time period in years.

Data source: Calculated and plotted by the author using Datastream database.

2. Financial Network. The study also captures the network structure and interconnections among firms within the economy. Constructing the network for each period requires disaggregated data on liquidity flows between firms. To obtain these, the paper uses quarterly *liquidity-related balance-sheet data* for the top 100 U.S. firms from the Datastream database over the sample period. The relevant balance-sheet elements are current assets and current liabilities, as described earlier. For the network construction specifically, we use accounts receivable (AR) and accounts payable (AP) to develop a proxy for the financial linkages connecting firms.

Ideally, constructing the inter-firm network would require data on bilateral fund flows between firms, which are not available. To address this, the study creates a proxy for inter-sectoral trade flows by combining sector-level input-output data from the Bureau of Economic Analysis (BEA) with firm-level balance-sheet data from Datastream. The BEA database provides annual trade flows between sector pairs. Given the limited availability of liability breakdowns by individual counterparty, we aggregate the firm-level liquidity data to the sector level. This allows us to exploit the sector-by-sector input-output table from the BEA to decompose liabilities and examine the extent of financial linkages between sectors.[10]

[10]Main sectors of the study are as follows: Utilities, Manufacturing, Wholesale, Retail trade, Transportation, Information, Finance; insurance; real estate; rental; and leasing, Professional and business services, Educational services; health care; and social assistance, Arts; entertainment; recreation; accommodation; and food services.

Our model considers an environment with $N = 10$ sectors in which they interact with each other by creating obligations from their suppliers. To analyze the network effect of an economy, the paper first constructs the proxy matrix X of our financial network by a finite pair of set (N, E) using the balance-sheet firm-level data, where N is the nodes and E is the set of edges. In our network, the nodes are the top 10 big sectors and the edges represent flows of claims or the obligations of each firm to its counterparties. More precisely, our model considers an economy with N sectors, where each sector i holds the liabilities of its counterparties. Every financial linkage x_{ij} denotes the liabilities of i to j at every period for any $i, j \in \mathcal{N} = \{1, ..., N\}$. x_{ij} corresponds to accounts receivable in the liability side of the balance sheet of a firm. Thus, the pattern of liability holding for the firms across the economy at every period can be shown in the following form:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NN} \end{pmatrix}$$

These edges or linkages indicate the flow of claims to each sector, i.e. x_{ij} is the net amount that sector i owes to sector j. We then compute *net receivables* of a firm by $X^n = X^R - X^P$, where X^R is the receivable network, and X^P is the payable network and X^n is the net receivable with all the elements $x_{ij}^n \geq 0$.

After constructing the financial network, the paper uses different types of network analysis tools and metrics to gain a more complete understanding of the risk profile of a financial network. However, it is important to note that the volatility of a system can arise from a variety of sources and different types of shocks such as changes in market conditions, economic events, and shocks to individual nodes or groups of nodes. Additionally, although there are several network statistics that can provide useful insights into the risk of a financial network, none of them can provide a single network measure that can fully capture the volatility of a financial network since the risk of a financial network is a complex and multifaceted concept, and it highly depends on a range of factors such as network structure and topology, the level of interconnectedness, and the quality of the assets, liabilities, and one single metric cannot fully capture its complexity (Albert and Barabási, 2002; Gao et al., 2017).

The analysis therefore uses different metrics together with a combination of them to overcome the complexity issue, to capture the whole network effects, and to assess the susceptibility of financial networks to volatility and risk. The first type of network measure that we use is the first two moments of degree distribution (i.e., mean and variance), and the second part is our proposed network index that is built using two network centralities:

i. Moments of degree distribution: Network analysis methods provide a powerful framework for visualizing and analyzing the structure and dynamics of financial systems, including their volatility and systemic risk. One key tool is the degree distribution, which describes the distribution of connections (linkages) across nodes in the network and reveals how evenly or unevenly connected the nodes are (Jackson, 2010; Gai and Kapadia, 2010). The moments of the degree distribution offer summary statistics that capture important aspects of network topology. A network with a large mean or high variance in its degree distribution may be more prone to volatility, as small changes in the connectivity of a few key nodes can have disproportionate effects on the overall network structure.

This study uses the first two moments of the degree distribution to capture different aspects of the network's topology and potential systemic risk. The first moment, mean degree, measures the average number of connections per node in the network. In the context of financial networks, a higher mean degree indicates greater interconnectivity between sectors or industries, which can facilitate contagion and systemic risk if one sector experiences distress. The second moment, the variance of the degree distribution, captures the variability in the number of connections across nodes. A high variance implies that a small number of nodes have a very high level of connectivity, making the network more susceptible to disruptions originating from these systemically important nodes.

As these moments are restricted to the number of edges, they may not be so helpful as the volume of the edge matters. The analysis then uses the weighted moments of degree distribution. The weighted degree distribution of a directed network X provides the probability distribution of the total weights of all edges (incoming or outgoing) for each node i in the network. The weight here refers to the size of receivables associated with each node or industry in the network.[11] The mean and variance of degree here are different from the standard degree distribution since it takes the weights on the linkages between nodes into account. More specifically, the weighted distribution gives the average and variance weight of the edges connected to nodes with a given degree (Qiu et al., 2010). The weighted mean degree of the network is the average total weight of all the linkages/connections for all industries i in the network, where the weighted degree of a node is given:

$$\langle k \rangle_w = \frac{\sum_{i=1}^{N} w_i}{N} \tag{1.3}$$

where $\langle k \rangle_w$ is the weighted mean degree of the network, w_i is the weighted degree of node i, and N is the total number of nodes in the network. The network with a larger weighted mean degree shows that the nodes, on average, are connected to each other more strongly. This implies a higher degree

[11] Battiston et al. (2010) explains the structure of networks in finance and economics using the weighted degree distribution and calls the corresponding quantity as the strength of an edge.

of financial interconnectedness in the network. Figure 1.2a plots the mean degree distribution and its corresponding trend and cycle trends of the network.

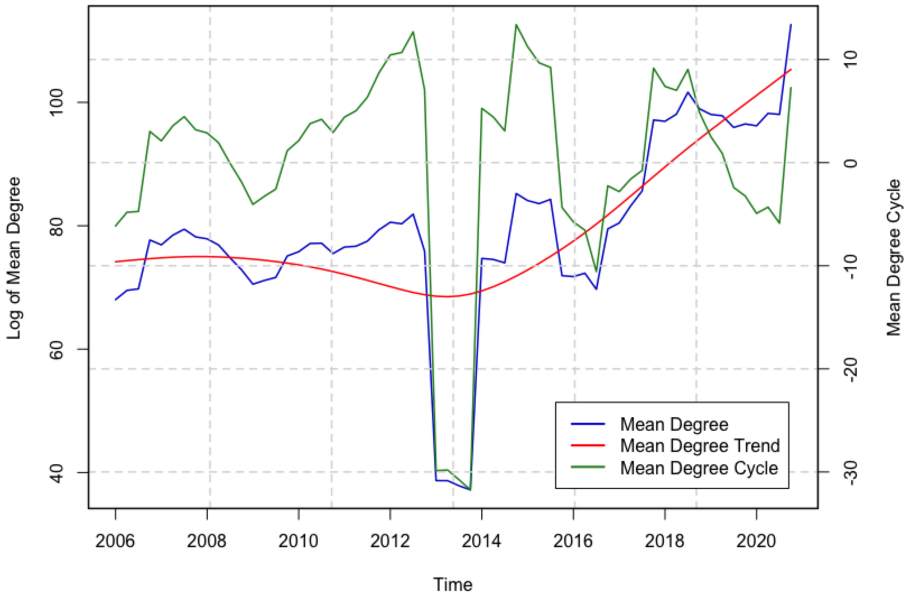
We also apply the *variance* of the weighted mean degree using the following formula:

$$\langle \sigma^2 \rangle_w = \frac{1}{N} \sum_{i=1}^{N} (k_i - \langle k \rangle_w)^2 \tag{1.4}$$

where $\langle \sigma^2 \rangle_w$ denotes the variance of the weighted mean degree, k_i is the weighted degree of node i, N is the total number of nodes, $\langle k \rangle_w$ is the weighted mean degree of the network. The variance of the weighted mean degrees can also provide some information about the structure of the network. A high variance explains that a few nodes (i.e., industries) have high-weighted degrees and dominate in the network while the majority of nodes are connected with low-weighted degrees. However, a low variance declares that the weighted degrees of nodes are relatively distributed more evenly across the network. Figure 1.2b shows the variance degree and its corresponding trend and cycle trends of the network.

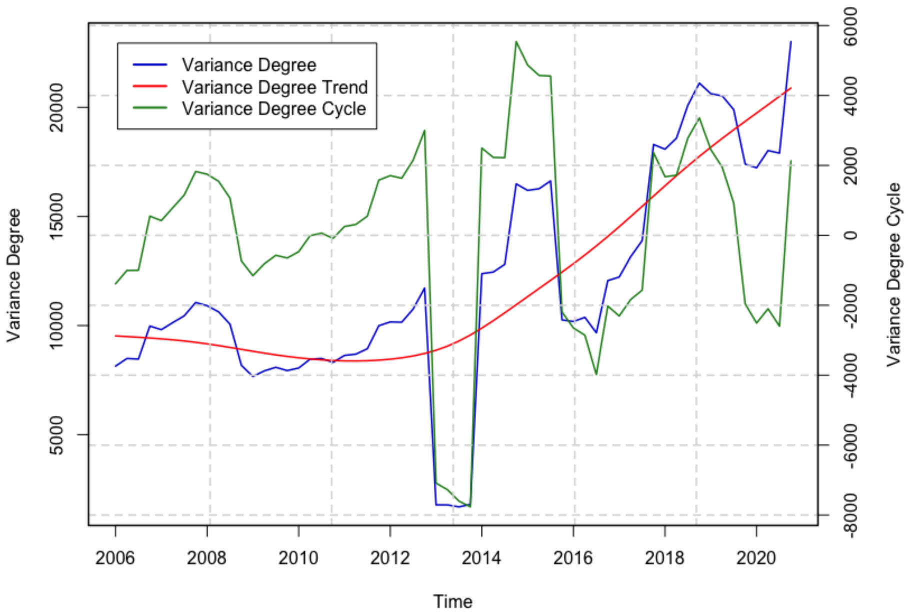
FIGURE 1.2: Weighted Degree Distribution: Level, Trend, and Cycle

(A) Mean Degree



Note: This figure depicts the time series of the endogenous variable mean degree distribution used in the model. It plots the mean degree distribution along with its corresponding trend and cyclical components, calculated using the Hodrick–Prescott (HP) filter as described in Appendix A.6. The left vertical axis shows the scale of the mean degree distribution, and the right vertical axis represents the scale of the cyclical component of the mean degree distribution. The horizontal axis shows the time period in years.

(B) Variance Degree



Note: This figure depicts the time series of the endogenous variable variance of the degree distribution used in the model. It plots the variance of the degree distribution along with its corresponding trend and cyclical components, which are calculated using the Hodrick–Prescott (HP) filter as described in Appendix A.6. The left vertical axis shows the scale of the variance of the degree distribution, and the right vertical axis represents the scale of the cyclical component of the variance of the degree distribution. The horizontal axis shows the time period in years.

Data source: Calculated and plotted by the author using the Datastream database.

ii. Network index: Although network statistics can provide useful insights into the risk profile of a financial network, no single measure can fully capture its volatility or systemic risk (Albert and Barabási, 2002). To address this limitation, the paper combines multiple centrality measures to assess the susceptibility of financial networks to volatility and risk more comprehensively. Centrality measures are widely used in network analysis to identify the most important nodes and linkages in a network (Jackson, 2010; Eshraghi, 2023), and applying several centralities in conjunction offers a more complete picture of the network's risk profile.

Specifically, the paper proposes a composite index that captures the network effects of financial flows by taking the product of Katz centrality and edge betweenness centrality. This combination identifies nodes that are important both for their overall influence within the network, as captured by Katz centrality, and for their potential to control the flow of transactions, as measured by edge betweenness centrality (Katz, 1953; Freeman, 1977; Freeman et al., 2002; Brandes, 2008).[12] The resulting index identifies key nodes and intermediaries that are both influential and act as gatekeepers for transaction flows. By capturing the role of nodes that serve simultaneously as hubs and bridges between industries, the index helps assess the potential impact that changes to individual nodes, linkages, or groups of nodes may have on the overall structure and stability of the network (Chan-Lau, 2018).[13]

The analysis uses average network centralities to obtain the average influence of nodes in a network as a single metric to have a proxy of the whole network and can provide useful insights into the risk of a financial network. The average of all nodes can help identify which nodes are the most important or influential in the network, and thus which nodes may pose the greatest risk if they were to fail or experience distress.[14] The measure shows how strongly the influence of each node on average is affected (amplified or diminished) by the influence of other nodes, and thus how a shock to one node may ripple through the network (Thurner and Poledna, 2013; Huang and Wang, 2018; Cao et al., 2022).

$$\underbrace{n^{-1}\sum_{i=1}^{n} c_K(i) \times n^{-1} \sum_{s,t\in V} \frac{\sigma(s,t|i)}{\sigma(s,t)}}_{c_T(i)} = \beta\, \underbrace{n^{-1}\sum_{i=1}^{n} c_K(i)}_{c_K(i)} + \gamma\, \underbrace{n^{-1}\sum_{s,t\in V} \frac{\sigma(s,t|i)}{\sigma(s,t)}}_{c_B(i)} + \epsilon_N \tag{1.5}$$

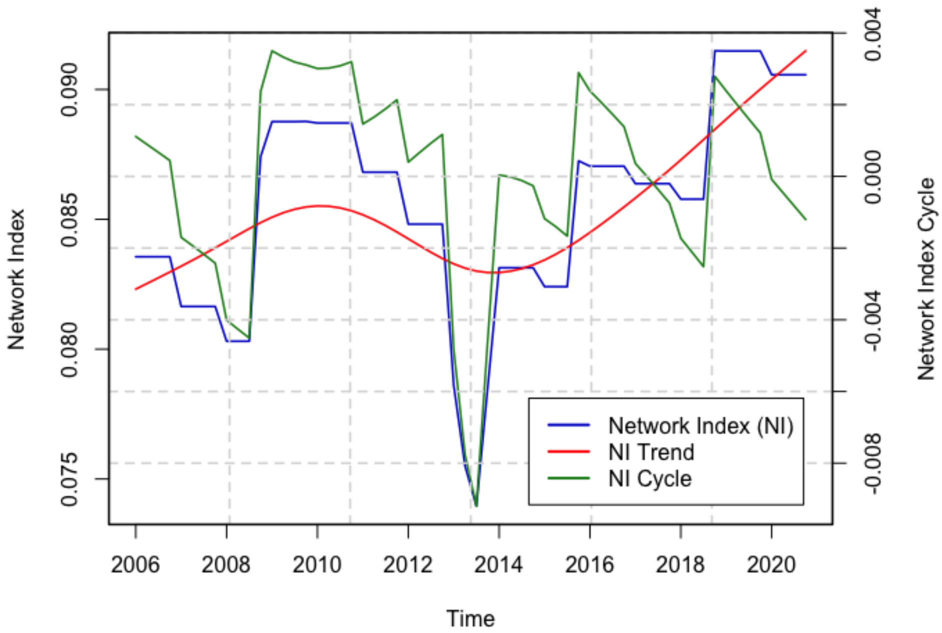
[12]Katz centrality and Google's PageRank are variants of eigenvector centrality. The advantage of Katz centrality over the other two is that it accounts not only for the influence of immediate neighbors but also for distant neighbors through the attenuation factor α.

[13]The product of network centralities is commonly used in studies seeking to capture different aspects of node or linkage importance simultaneously. Details of each centrality measure are provided in Appendix 1.

[14]In the literature, we discussed one of the main limitations of SVAR model that is by adding more endogenous variables to model, more restrictions required for the identification of the model. Therefore, we avoid using local centralities which report a measure for each node. Instead, we focus on global metrics that provide a single measure for the whole network.

where $\overline{c_K(i)}$ in the right-hand side denotes average Katz centrality and represents the nodes' effect and $\overline{c_B(i)}$ is the average edge betweenness centrality and captures the linkages effect (The definitions and details for each centrality are explained in Appendix 1). The estimated $\hat{\gamma}\overline{c_B(i)}$ then can reflect the 'pure' linkage effect and the estimated $\hat{\beta}\overline{c_K(i)}$ can capture the pure node effect. Since a network is a complex system and there may be a common effect from both $\overline{c_K(i)}$ and $\overline{c_B(i)}$, ϵ_N actually captures the common effect. We use the fitted value of the product of Katz and edge betweenness centrality, $\widehat{c_T(i)}$, to capture both the linkage effect and node effect. In this study, $\hat{\gamma}\overline{c_B(i)}$ can help to identify debt relationships that are important in connecting different groups or clusters of sectors in the network and $\hat{\beta}\overline{c_K(i)}$ can capture the important sectors in transmitting the debt. More details as well as information about $\hat{\gamma}$ and $\hat{\beta}$ can be found in Table A.1 in Appendix 1.

FIGURE 1.3: Network Index: Level, Trend, and Cycle



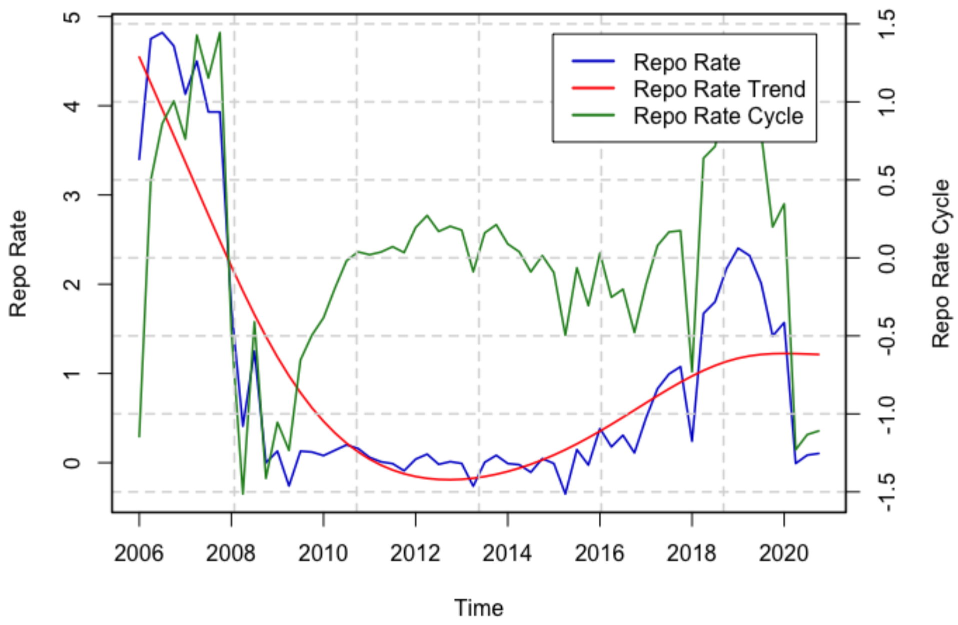
Note: This figure depicts the time series of the endogenous variable network index used in the model. It plots the network index along with its corresponding trend and cyclical components, computed using the Hodrick–Prescott (HP) filter as described in Appendix A.6. The left vertical axis shows the scale of the network index, and the right vertical axis represents the scale of the cyclical component of the network index.

Data source: Calculated and plotted by the author using the Datastream and the BEA datasets.

However, it is important to note that the volatility of a financial network is a complex and dynamic phenomenon that can depend on a range of factors beyond network structure and topology. Therefore, it is important to use network measures in combination with other analytical tools and to consider the specific context and characteristics of the network in question.

3. Repo rate. The *Repurchase Agreement (Repo) rate* is another variable that the analysis takes into account as it captures monetary shock in our system of economy. The repo rate is the interest rate that is concerned with liquidity as financial institutions can borrow and lend short-term funds in the money market. The Repo rate is endogenously determined by supply and demand in the money market and fluctuates throughout the day based on the availability of funds in the market and the demand for short-term financing by institutions (Nath, 2015; Fuhrer, 2018; Kozlowski and Jordan-Wood, 2022). The paper employs the quarterly repo rate for the sample time span from FRED. Figure 1.4 shows the quarterly time series of interest rate, its trend and cyclical movement in the US economy from 2006 to 2021.[15]

FIGURE 1.4: Repo Rate: Level, Trend, and Cycle



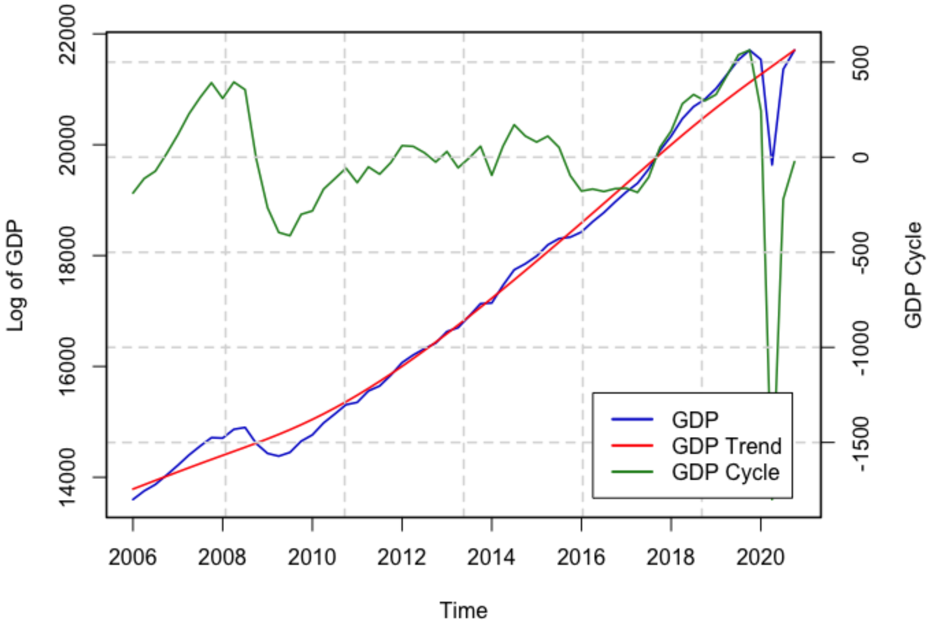
Note: This figure depicts the time series of the endogenous variable repo rate used in the model. It plots the repo rate along with its corresponding trend and cyclical components, which are computed using the Hodrick–Prescott (HP) filter as described in Appendix A.6. The left vertical axis shows the scale of the repo rate, and the right vertical axis represents the scale of the cyclical component of the repo rate. The horizontal axis shows the time period in years.

Data source: Calculated and plotted by the author using the Datastream.

4. Gross Domestic Production (GDP). The paper finally applies the *Gross Domestic Production (GDP)* to analyze the effect of liquidity and interest rate on the real output aggregate fluctuation and volatility (Bigio et al., 2016; Altinoglu, 2021). Figure 1.5 plots the quarterly time series of GDP and its corresponding trend and cycle components of the US economy from 2006 to 2021.

[15]We have three different types of interest rate. Similarly, the Secured Overnight Financing Rate (SOFR) is a benchmark interest rate to reflect the cost of borrowing money in the short-term funding markets. SOFR is a broad-based benchmark rate that is based on transactions in the repo market, specifically overnight loans collateralized by U.S. Treasury securities. However, the Repo rate is a more specific interest rate that reflects the cost of borrowing and lending cash in exchange for high-quality collateral such as U.S. Treasury securities or other types of securities. SOFR is calculated as a volume-weighted median of overnight Treasury repo transactions, while the Repo rate is determined by supply and demand in the repo market, where market participants negotiate borrowing rates based on the specific collateral being used and the perceived creditworthiness of the borrower. The SOFR may slightly be a better indicator of short-term funding costs as it covers a wider range of financial products. The reason we apply the repo rate over the SOFR is because of the availability of historical data. SOFR was introduced for the first time by the Federal Reserve Bank of New York in April 2018, while the repo rate has been available for a longer period of time, with the year going back to 2000.

Figure 1.5: GDP: Level, Trend, and Cycle



Note: This figure depicts the time series of the endogenous variable GDP used in the model. It plots GDP along with its corresponding trend and cyclical components, which are calculated using the Hodrick-Prescott (HP) filter as described in Appendix A.6. The left vertical axis shows the scale of GDP, and the right vertical axis represents the scale of the cyclical component of GDP. The horizontal axis shows the time period in years.

Data source: Calculated and plotted by the author using the FRED.

Exogenous variables. The paper found it desirable to include further exogenous variables in order to have more accurate results. The role of federal funds rates, money supply, consumer price index (CPI), and dollar exchange rates on liquidity and business cycles, and how policymakers can leverage these relationships to maintain economic stability have been a topic of interest for researchers and policymakers for decades. These variables and their interactions are expected to fundamentally impact the business cycle and macroeconomic outcomes, influencing the cost of borrowing and the availability of credit. Therefore, the variables are added to the model for the sample period under study. The summary statistics for the exogenous variables of interest can be found in Table A.2.

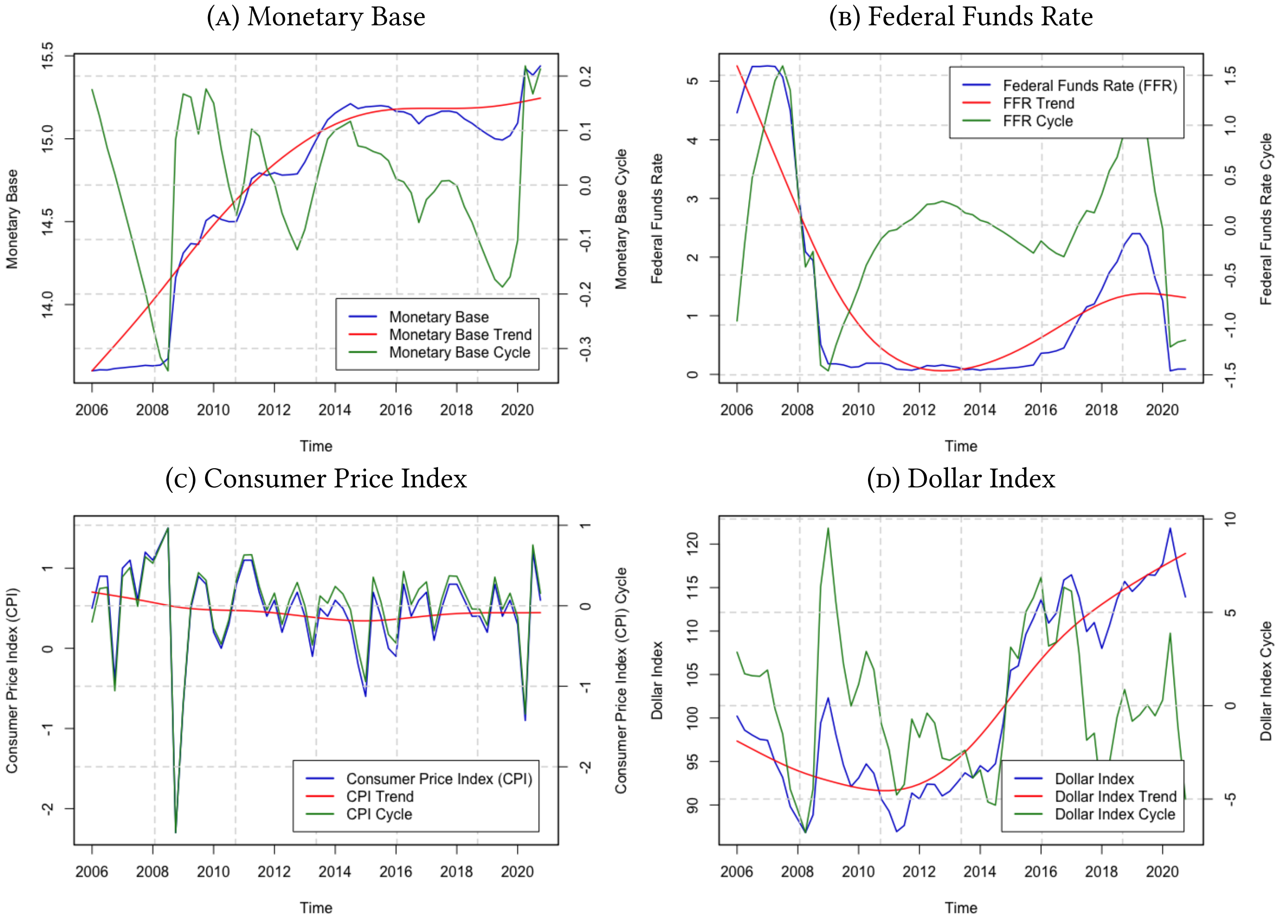
The *Federal Funds Rate (FFR)* is the interest rate at which banks lend money to each other overnight to meet reserve requirements. Interest rate plays a crucial role in determining the availability of credit and the cost of borrowing, which in turn affects the level of liquidity in the economy. For example, the Federal Reserve lowered interest rates to near zero to boost liquidity in the financial system during the global financial crisis of 2008 and stimulate economic activity. This policy helped to prevent a full-blown economic depression and promoted borrowing (Krishnamurthy and Vissing-Jorgensen, 2011; Altavilla et al., 2022). The FFR is applied as an exogenous variable as it is set by the Federal Reserve and serves as a benchmark for other interest rates in the economy. The federal funds rate has a significant impact on the business cycle, as it influences borrowing and spending decisions by households and businesses. Sims (2013), for example, shows how changes in the Federal funds rate can affect credit and spending and thereby economic activity. The paper also declares how the federal funds rate affects the yield curve, long-term interest rates, and investment decisions.

The *money supply, or base,* is another exogenous variable that refers to the amount of money in circulation in the economy. This includes physical currency, bank deposits, and other liquid assets and is mainly controlled by the central bank. The money supply along with the interest rate has a significant impact on liquidity, as it impacts the availability of credit and the cost of borrowing. For instance, Benigno et al. (2020) study the relationship between monetary policy, bank credit, and liquidity. The study further discusses liquidity trap phenomena, where interest rates are close to zero, and central banks intervene in the market and increase liquidity by using unconventional monetary policy tools such as quantitative easing. Senhadji and Khan (2000) also discusses the role of money supply on liquidity and how the central bank manages the money supply through open market operations, reserve requirements, and discount rates.

The *dollar exchange rate* can also affect the liquidity and economy mainly through two channels. First, the dollar exchange rate has a profound impact on liquidity in the economy as the value of the U.S. dollar relative to other currencies can change the trade balance within economies and, in turn, affect the economic activity and liquidity in the economy as businesses finances and their access to sources of funds can vary. Furthermore, the exchange rate also affects the availability of credit in the economy. A high exchange rate can increase the attractiveness of foreign investment, leading to an inflow of capital into the U.S. economy. This can lead to increased credit availability and lower borrowing costs, thereby increasing liquidity in the economy. On the other hand, a low exchange rate can discourage foreign investment, resulting in lower credit availability and higher borrowing costs, which can reduce liquidity in the economy (Huang and Stoll, 2001; Bianchi et al., 2021). Hence, policymakers are mindful of the impact of the exchange rate on liquidity and implement effective measures to stabilize the currency, maintain economic stability, and promote sustainable growth. Central banks can intervene in currency markets to prevent excessive fluctuations in the exchange rate.

The paper also includes the *Consumer Price Index (CPI)*, a measure of inflation, which can track changes in the prices of goods and services over time. It has a significant impact on the business cycle, as it affects consumer purchasing power, business profits, and investment decisions (McCallum, 2001; Galí, 2015; Hommes and Lustenhouwer, 2019). Overall, federal funds rates, money supply, CPI, and exchange rates and their interaction play important roles in determining liquidity and economic activity.

Figure 1.6: Exogenous Variables: Level, Trend, and Cycle



Note: This figure depicts the time series of the exogenous variables used in the model. The variables are the monetary base, federal funds rate, consumer price index, and dollar exchange index. Each panel plots the original variable along with its trend and cyclical components, calculated using the Hodrick–Prescott (HP) filter as described in Appendix A.6. The left vertical axis of each panel shows the scale of the exogenous variable, and the right vertical axis represents the scale of the cyclical component.

Data source: Plotted by the author using the Datastream and the FRED datasets.

3.2 Structural Vector AutoRegressive (VAR) model

This section describes the structural VAR model, which is a widely used tool for analyzing the dynamic effects of variables of interest over time. Subsection 3.2.1 presents the model setup, explaining how the SVAR representation captures time-dependent dynamics and how the dynamic interactions among variables are analyzed by tracing the effect of a shock through the system. The identification challenges associated with the SVAR and the approaches used to address them are explained in Subsection 3.2.2. The model specification is presented in Subsection 3.2.3. Finally, we discuss two key outputs of the model, the Impulse Response Functions (IRFs) and the Forecast Error Variance Decompositions (FEVDs), in Subsections 3.2.4 and 3.2.5, respectively.

3.2.1 Model Setup

The SVAR models are an outstanding tool in macro-economics to investigate the impacts of shocks on a system of variables (Lütkepohl, 2005; Kilian and Lütkepohl, 2017). In these models, the unobserved structural innovations serve the information that is unrevealed or undisclosed in the reduced-form VAR model. The paper determines the system's responses to this type of isolated shock, which can be visualized by the impulse-response functions approach.

It is initially assumed we have the K dimentional multivariate VAR representation of order p, where the process of y_t is a sequence $\{y_t\}_{t=0}^{\infty}$ defined by the following linear p-order equation,

$$y_t = \mu + A_1 y_{t-1} + ... + A_p y_{t-p} + e_t \tag{1.6}$$

where $y_t = (y_{1t}, ..., y_{Kt})'$ indicates a $(K \times 1)$ vector of time series variables (endogenous variables), coefficient A_i $(i = 1, ..., p)$ are $(K \times K)$ matrix, and μ denotes the intercept coefficient and is mapping the variable of interest to its previous value $(t - p)$, which can be interpreted as the time-invariant deterministic terms.

3.2.2 The Identification Problem

The VAR model is a very useful method to explain impulse response functions and investigate the connection between our variables. The model, however, has shortcomings in its interpretation. The impulse responses are not unique and in general, the set of impulse responses that can impact the system is ambiguous and varying, so the non-sample information is required to choose the appropriate set from the underlying model (Lütkepohl, 2005). VAR representations are considered as reduced form models in econometric terminology, and it is essential to impose some structural restrictions in order to identify the shocks and accordingly investigate impulse response function and forecast error variance decomposition.

More specifically, the innovation e_t in Equation 1.6 may be correlated contemporaneously i.e. σ_e may not be a diagonal matrix. This implies that Φ_i matrices in Equation 1.12 will not represent the relationships between the endogenous variables correctly, hence there will be no isolated shocks in the system of equations which can make the interpretation of innovations in matrix e_t impossible. To overcome this issue, we need to identify the model's parameters and impose restrictions on the model in order to find economic insight and structural interpretation of the response of the variables. The choice of identification is one of the main challenges of this study since the approaches are quite arbitrary and thus unsatisfactory unless they build upon a theoretical model or there are specific justifications behind the approach. In Section 2.2 we reviewed the possible approaches to identify the impulses and the underlying SVAR model.

Our strategy to specify unique innovations and impulse responses is first to estimate a simple baseline model with the least restrictive identification method and then use other studies to build an alternative identification model and implement a robustness check to make solid arguments about the model under scrutiny. The departure point to build the identification scenarios is based on the following structural form model,

$$\mathsf{A}y_t = \mu + A_1 y_{t-1} + ... + A_p y_{t-p} + \mathsf{B}\epsilon_t \tag{1.7}$$

$$y_t = \mu + A_1^* y_{t-1} + ... + A_p^* y_{t-p} + \mathsf{A}^{-1}\mathsf{B}\epsilon_t \ , \qquad t = 1, ..., T \tag{1.8}$$

where $A_i^* = \mathsf{A}^{-1}A_i \ (i = 1, ..., p)$. The vector e_t contains reduced-form residuals or innovations at time t, which are assumed serially uncorrelated and follows $e_t \sim (0, \sigma_e^2)$ i.e., e_t is a white noise with mean $E(e_t) = 0$, time-invariant variance σ_e^2, and $cov(e_t) = \Sigma_e = \mathsf{A}^{-1}\mathsf{B}\Sigma_\epsilon\mathsf{B}'\mathsf{A}^{-1\prime}$. Also, the nonsingular $(K \times K)$ matrix B captures the contemporaneous effects of the structural shocks upon the variables of the system.

For analyzing the impulse response we are mainly interested in interpreting the unexpected part of the simultaneous equations system or shocks rather than specifying the relationship between the endogenous variables. We thus attempt to identify the structural shocks ϵ_t from the reduced form residuals or forecast errors e_t in Equation 1.6. This implies the following relation,

$$e_t = \mathsf{A}^{-1}\mathsf{B}\epsilon_t \tag{1.9}$$

meaning that the reduced form error e_t can be considered as linear functions of the structural shocks ϵ_t with which the relationships between the reduced form residuals are characterized using the covariance matrix $cov(e_t) = \Sigma_e = \mathsf{A}^{-1}\mathsf{B}\Sigma_\epsilon\mathsf{B}'\mathsf{A}^{-1\prime}$ in Equation 1.7, where Σ_ϵ is the covariance matrix of the structural shock ϵ_t. The structural shocks of the model are considered uncorrelated Σ_ϵ, and thereby it is a diagonal matrix. If the errors are correlated, it is hard to measure directly the impact of any change in an error since the shock cannot be kept constant when a shock occurs. This is required for a meaningful impulse-response analysis (Lütkepohl, 2005; Kilian and Lütkepohl, 2017).

Yet, with no further model specification, the equation of Σ_e holds for every matrix A and B which decomposes the variance-covariance matrix Σ_e. Thus, additional restrictions are required to construct a unique matrix A and B. The identification of matrix B enables us to find economic insight and structural interpretation on the response of the variable of interest. After estimating the VAR model in Equation 1.6, the estimated reduced-form residual $\hat{e}_t$ and the corresponding estimated $\hat{\Sigma}_e$ is the first step for the subsequent identification methods.

Once we specify the number of lag length p for the VAR(p) model, the restrictions are imposed to estimate the structural parameters. The SVAR parameters are not identified without the restrictions, i.e. it is not possible to solve uniquely the structural parameters A, B, A and Σ_e given values of the reduced form parameters Σ_ϵ and A^*. From the Relation 1.9 we have $\frac{K(K+1)}{2} = 10$ equations while there are $K^2 = 16$ elements for each matrices A and B. This implies that with $K = 4$ the overall number of $2K^2 - \frac{K(K+1)}{2} = 22$ restrictions on the matrices A and B are required to obtain the exact identification. we have imposed the just-identified restriction in order to avoid over-simplifying and placing too many restrictions on the system.

The *baseline model scenario* for the identification is to leave out the matrix A by setting the A $= I_K$ and only identify the diagonal matrix B where the diagonal elements reflecting the standard deviation of the error terms of the system of equations. The uncorrelated diagonal matrix provides a straightforward and transparent choice to identify the structural shocks and an easy simple way to interpret the impulse response results and explain the underlying dynamics of the system. This also allows the model to avoid any biasedness rooted in the wrong determination of the immediate impact of endogenous variables in matrix A.

The *second scenario* of the identification follows the standard approach where the relations between shocks arise due to instantaneous correlations between endogenous variables. This implies that we look at the system such that each variable depends on the contemporaneous effects of other variables instead of having a variable that only depends upon past values of other variables. The matrix B can be still considered as an uncorrelated diagonal matrix as we had in the first scenario. Given that the structural shocks are uncorrelated and there are 12 zero restrictions on B matrix, there are 10 additional restrictions are required to identify the full model. The diagonal is normalized to 1 and the off-diagonal is restricted based on the related literature of the study. We use just-identifying restrictions as represented in the form of the following structural matrix A and B. As discussed earlier in 3.2.2, it is impossible to estimate all the coefficients in matrix A without some restrictions. Our approach to identifying the parameters of matrix A is to make the system recursive, as it is proposed by Wold (1951).[16]

The paper extracts the choice of restriction by the studies done on the relationships between the variables of interest. The restrictions imposed on matrix A are similar to Cholesky restrictions and are consistent with the studies done so far. Some research has been conducted about the relationship between the financial network centrality and liquidity ratios. The relationship between account receivables/payables and other short-term elements of the balance sheet is complex and interconnected. Changes in one element can affect the levels of others, which can potentially affect the firm's ability to meet its short-term obligations. However, the elements A_{12} and A_{21} are primarily

[16]The combination of triangularity and uncorrelated shocks is a numerical method for estimating a recursive system, which is known as the Cholesky decomposition. In this method, the ordering choice of variables is identified by theoretical or institutional ideas (Wold, 1951; Lütkepohl, 2005; Kilian and Lütkepohl, 2017).

identified by the studies of Allen and Gale (2000) and Acharya and Yorulmazer (2008) which show highly connected institutions may be more susceptible to contagion and liquidity risk, which can lead to a sudden withdrawal of funding and a loss of liquidity. We also use Altinoglu (2021) argument about the role of network effects on the output in order to identify A_{13}, A_{23}, A_{31}, and A_{32}. $\mathsf{A}_{14} = 0$ and $\mathsf{A}_{24} = 0$ are assumed as no contemporaneous impact since the repo rates are determined endogenously but not vice versa (Téllez-León et al., 2021). The elements A_{34} and A_{43} are also inspired by Taylor (1993).[17] This argument and the corresponding reduced form residuals Equation 1.9 can be specified as the following matrix form;

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{pmatrix} \begin{pmatrix} e^{N} \\ e^{LR} \\ e^{GDP} \\ e^{R} \end{pmatrix} = \begin{pmatrix} b_{11} & 0 & 0 & 0 \\ 0 & b_{22} & 0 & 0 \\ 0 & 0 & b_{33} & 0 \\ 0 & 0 & 0 & b_{44} \end{pmatrix} \begin{pmatrix} \epsilon^{N} \\ \epsilon^{LR} \\ \epsilon^{GDP} \\ \epsilon^{R} \end{pmatrix} \tag{1.10}$$

3.2.3 Model Specification

This segment characterizes the estimation strategy by specifying the model and identifying shocks and impulses in order to produce reasonable results. Our corresponding SVAR representation of Equation 1.7 then can be formulated as:

$$\mathsf{A}\, \mathcal{C}(Y_t) = \alpha + \sum_{i=1}^{p} A_p\, \mathcal{C}(Y_{t-i}) + \delta\, \mathcal{C}(X_t) + \mathsf{B}\, \epsilon_t \tag{1.11}$$

where $Y_t = (N_t, LR_t, GDP_t, i_t)'$ for the period $2006Q1$ to $2020Q4$. Y_t is the vector of the U.S. macro-financial time series variables, the real GDP (GDP_t), an overnight repo rate (i_t), liquidity ratio (LR_t), and the network indices (N_t) are the variables of interest that are explained in Section 3.1. Since further generalizations of the model are desirable in practice and help to have better results, we also include further stochastic variables in addition to the deterministic part. X_t is a vector of unmodeled exogenous variables representing the money supply provided by the U.S. central bank, federal funds rate, dollar exchange rate, and inflation rate, respectively, for our sample period. These are the variables that are expected to affect the macroeconomic outcomes.[18] $\mathcal{C}(\cdot)$ denotes the time series cycle calculated by the HP filter explained in Appendix 2. Note that, as the process y_t shows

[17] The identification of A and B are mainly determined by the theoretical background as there is no unique structure. The second scenario is built under some assumptions based on the related literature. For some cases, a different way of restrictions was imposed, and found negligible differences in results. Nevertheless, there is some degree of uncertainty in the second identification approach, and the structure of matrix A is only applied to check the robustness of the base scenario.

[18] In this study we do not intend to calculate the dynamic multipliers of the exogenous variables or investigate the impulse responses to innovation for the exogenous variables. The exogeneity is only specified by incorporating the exogenous variables in the structural equation.

unit root process (further explanation can be seen in Section 4), we use the cycle component of the time series $\mathcal{C}(\cdot)$ and is compatible with a stationary generation process. Moreover, the number of lags can be determined by the selection criteria that are explained further.

Note that as part of the data processing and cleansing technique, all the variables are normalized by min-max normalization, i.e. $Y_t = \frac{Y - Y_{min}}{Y_{max} - Y_{min}}$. The main reason is to make the variables homogeneous over all records and fields in order to improve the data quality.[19]

3.2.4 Impulse-Response Functions (IRFs)

Impulse response functions investigate the effect of isolated shocks on the variables of the model with respect to a particular response lag (delay). The response matrices of Equation 1.6 can be characterized with recursive substitution given starting at some infinite time i,

$$\mathsf{A}A(L)y_t = \mu + \mathsf{B}\epsilon_t \tag{1.12}$$

$$y_t = \mathsf{A}^{-1}A(L)^{-1}\mu + A(L)^{-1}\mathsf{A}^{-1}\mathsf{B}\epsilon_t \tag{1.13}$$

$$= \nu + \Phi(L)\mathsf{A}^{-1}\mathsf{B}\epsilon_t = \nu + \sum_{i=0}^{\infty} \Phi_i \mathsf{A}^{-1}\mathsf{B}\epsilon_{t-i} = \nu + \sum_{i=0}^{\infty} \Theta_i \epsilon_{t-i} \tag{1.14}$$

where the reduced form lag polynomial is defined as $A(L) = I - A_1 L - A_2 L^2 - ... - A_p L^p$, and ν denotes the unconditional mean of observable variables. The $\Theta_i (= \Phi_i \mathsf{A}^{-1}\mathsf{B})$ summarizes the information of dynamic parameters in Φ_i ($i = 1, 2, 3, ...$) and of the structural matrix $\mathsf{A}^{-1}\mathsf{B}$. Matrix Θ_0 then represnts matrix $\mathsf{A}^{-1}\mathsf{B}$. Thus, the elements of Θ_i can be interpreted as the responses of the system to structural shocks ϵ_t. Here we wish to investigate the effect of a unit change in a structural shock on the relevant variables. Then, the effects of a change in the initial shock on y_t has the following dynamic,

$$\frac{\partial y_t}{\partial \epsilon_{t-i}} = \Theta_i \tag{1.15}$$

This shows that the dynamic multiplier Θ_i depends solely on the time lag i, which represents the number of periods that separate the occurrence of the disturbance ϵ_{t-i} from the observation of the output variable y_t. However, the multiplier is independent of the specific observation time t. This implies that the value of Θ_i remains constant regardless of which time period t is the output observation y_t, and the dynamic relationship between the disturbance and the output remains stable over time.

[19]The min-max normalization is chosen over the z standardization $Y_t = \frac{Y - mean(Y)}{std(Y)}$ to avoid any presumptions about the distribution of the data (see Ali et al. (2014) and Asesh (2021) to find some helpful application of data preprocessing normalization techniques).

3.2.5 Forecast Error Variance Decompositions (FEVD)

Forecast Error Variance Decomposition (FEVD) explains the relative contribution of each structural shock to the variation of the variables of interest. The technique helps in analysing the relative importance of different shocks in explaining the fluctuations of the variables over a forecast horizon h. The FEVD formula for a given variable y_{kt} with respect to the shock ϵ_{it} at a specific forecast horizon h is typically written in the form:

$$FEVD_{ki}(h) = \frac{\sum_{j=0}^{h-1} \Theta_{ki,j}^2}{\sigma_k^2(h)} \tag{1.16}$$

where $\Theta_{ki,j}$ represents the element in the k-th row and i-th column of the matrix Θ_j at lag j, so the numerator implies quantifies the contribution of a specific structural shock to the forecast error variance of a variable y_{kt} at a specific forecast horizon h. The denominator $\sigma_k^2(h)$ is the h-step ahead forecast error variance of the k-th variable and can be computed by $\sigma_k^2(h) = \sum_{j=0}^{h-1} \sum_{i=1}^{K} \Theta_{k_i,j}^2$, which is the sum of squared contributions from all structural shocks across lags up to $h-1$. Additionally, the h-step ahead forecast error for the multivariate time series y_t is a linear combination of the structural shocks ϵ_{t+1} to ϵ_{t+h}, and can be presented mathematically as $y_{t+h} - y_{t|t}(h) = \Theta_0 \epsilon_{t+h} + \ldots + \Theta_h \epsilon_{t+1} = \sum_{j=0}^{h-1} \Theta_j \epsilon_{t+h-j}$ (more detailes can be found in Lütkepohl (2005)).

4 Empirical Results

This section reports the steps for estimating the SVAR model. This starts with explaining the model specification including the lag selection, stationary, and stability tests in Segment 4.1. Additionally, analysis of impulse response functions and forecast error variance decomposition have been explained afterward in 4.2 and 4.3, respectively.

4.1 Model Specification

The first step of implementing SVAR model is to decide on the orders of $AR(p)$ model and specify the lag length p by applying different information criteria; Different model selection criteria such as Akaike Information Criterion (AIC), Hannan-Quinn (HQ), Schwarz (SC), and Akaike's Final Prediction Error (FPE) criterion are carried out to select the length of p. Table 1.1 reports the selection criteria and their corresponding scores suggested by each criterion for the AR orders of 1 to 5 (see Table A.3a and A.3b in Appendix A to see the scores for each selection criteria). They propose orders of 1 or 4 based on different selection criteria since these orders minimize each criterion. We apply AIC and FPE criteria over the HQ and SC as they result in less parsimonious specifications with more parameters. Thus, the results were obtained using criteria AIC and FPE where $p = 4$ is suggested, and it is also more compatible with the quarterly sample size of $T = 60$.

TABLE 1.1: The best AR lag length order suggested by each criterion

Selection criterion	**AIC(n)**	**HQ(n)**	**SC(n)**	**FPE(n)**
AR order	4	1	1	4

Note: Table reports the selection criteria and their corresponding scores for the AR orders of 1 to 5.

The second step is to analyze the stationarity of the data generating process. This is a necessary assumption in time series SVAR analysis to keep the statistical properties of the time series (e.g., mean and variance) constant over time (Lütkepohl, 2005; Kilian and Lütkepohl, 2017). We apply Augmented Dickey–Fuller (henceforth: ADF) test to check the null hypothesis of having a unit root against the alternative of having the stationarity of the data. Table A.4 in the Appendix shows the original variables compared to the cycle of variables in y_t for AR order selected by the model selection criteria. Since all original variables contain the time-varying patterns and non-stationary trend, we perform the Hodrick and Prescott (1997) method explained in Appendix A.6 and use the cycle component as the transformation method to study the business cycles and fluctuations in the system. The results suggest that the HP cycle trend for the GDP, repo rate, quick ratio, and network indices reject the null hypothesis of unit root at a 5% significant level, and thereby, the cyclical part of the variables are stationary.

After the specification of the lag length p and unit root test, we estimate the SVAR model using the U.S. macro-financial time series explained in Section 3.1. The multivariate VAR then contains the real GDP (GDP_t), a repo interest rate (i_t), quick ratio (QR_t), and the network index (NI_t). Hence, the vector of time series variables for the sample period $2006Q1$ to $2020Q4$ is $y_t = (PR_t, QR_t, GDP_t, i_t)'$. Finally, using the reduced form VAR(4), we estimate the structural parameters by imposing the just-identifying restriction identified in Section 3.2. The results of estimating the structural coefficients (parameters) are reported by following matrix A and B,

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \underset{(0.46)}{0.94} & 1 & 0 & 0 \\ \underset{(0.0009)}{-0.06} & \underset{(0.039)}{0.013} & 1 & 0 \\ \underset{(0.001)}{-0.28} & \underset{(0.004)}{-0.24} & \underset{(0.19)}{-0.012} & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.119} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.17} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.07} \end{pmatrix} \tag{1.17}$$

where each element represents a parameter estimate with the corresponding p-values reported in parentheses.[20] The matrix A in Equation 1.17 captures the contemporaneous relationships between the endogenous variables. Based on the estimated matrix A, the coefficient of 0.94 for the relationship between QR_t and NI_t has a p-value of 0.46, which exceeds conventional significance levels (such as 0.05), indicating that this relationship is not statistically significant. In contrast, the effects of GDP_t on NI_t and of GDP_t on QR_t, with coefficients of -0.06 and 0.013 respectively, are both statistically significant. The coefficients linking i_t to NI_t and QR_t have p-values of 0.001 and 0.004 respectively, confirming statistical significance for both relationships. However, the relationship between i_t and GDP_t is not statistically significant at the conventional level, with a p-value of 0.19.

The matrix B reports the estimated standard deviations of the shocks or errors for NI_t, QR_t, GDP_t, and i_t, respectively. Therefore, the diagonal elements of B not only represent the estimated standard deviations of the errors but also directly determine the magnitude of the shocks' impact on each variable in the system. Higher standard deviations indicate greater unpredictability or variability in the shocks and, subsequently, a larger potential influence of these shocks on the variable in question. According to matrix B, the highest volatility respectively associated with the network effect, quick ratio, GDP, and interest rates with the elements of 0.119, 0.17, 0.09, 0.07 on the diagonal. After all, note that what we are mainly interested in is interpreting the unexpected part of the simultaneous equations system or shocks in matrix B rather than specifying the relationship between the endogenous variables in matrix A although estimated parameters of matrix A contribute to the accuracy of the results. Once we identify and estimate the structural model and its corresponding parameters, the effects of the shocks ϵ_t can be analyzed by the impulse response function in the next Section 4.2.

4.2 Impulse Response Functions (IRFs) Analysis

Impulse response functions investigate the effects of shocks (i.e., impulses) in the system of equations. IRFs trace out a change (here, two standard deviation shocks) to endogenous variables of the system and their effects on all the endogenous variables while holding other factors and shocks fixed.[21] This part concentrates on shocks by first, identifying the relevant shocks and then

[20] Robustness results for alternative identification scenarios are provided in Appendix 4.4.1.

[21] The decision to employ a two-standard-deviation shock rather than a moderate one-standard-deviation shock was grounded in multiple considerations. Given the research's focus on variables with short-term dynamics, where one-standard-deviation changes are common, opting for a stronger shock became desirable. The magnitude of shocks aimed to delve into the system's response to significant disruptions that might not be adequately captured by a single standard deviation shock. Considering potential severe economic scenarios, employing larger shocks facilitates a more comprehensive grasp of the system's dynamics and resilience. Furthermore, the use of a larger shock allows for the evaluation of the system's stability and robustness in extreme conditions. This choice aligns with the objective of stress testing and assessing the system's reaction to extraordinary events, enabling a more realistic appraisal of potential outcomes in high-stress scenarios.

by describing the response of the system to them using analyzing the propagation mechanism of shocks through the impulse responses and investigating the forecast error variance decomposition.

Two standard deviation shocks are introduced to the endogenous variables through the error terms in Equation 1.6. These shocks simultaneously affect all the variables of interest. The immediate effects of the shocks are evident not only in the same time period but also in subsequent periods, as our $VAR(4)$ system incorporates lagged variables up to four periods. This means that the current and past four periods' values jointly contribute to explaining the variables' behavior. $VAR(4)$ model also employed Bootstrap resampling to tackle the uncertainty in estimating Impulse Response Functions (IRFs). This technique generates a distribution of potential IRF outcomes by creating numerous resamples (here, 1000 times) from the original dataset. These samples capture variations in the data and help assess the robustness of the IRF estimates.

Figure 1.7 visualizes the impression of the dynamic interaction through the system and shows graphically the response of variable i to a two standard deviation shock (forecast error) in variable k. More specifically, we shed light on the patterns of fluctuations including the magnitudes and lengths of responses to the key endogenous variables. Figure 1.7 shows the effects of *two standard deviations* shocks to the variables from the channel of network effect, quick ratio, interest rate, and the GDP of the US economy. All the variables shown in Figure 1.7 contain only temporary (transitory) shocks rather than permanent shocks. However, some of the transitory shocks are quite persistent and take a long time to make any changes. The graph represents that all the variables' responses occur at the same time because of the contemporaneous effect in matrix A.

Figure 1.7 represents that the largest responses in the whole system are for the past values of the endogenous variables itself. With a two-standard deviation impulse, the largest responses are captured by the liquidity ratio (i.e., quick ratio) and the network effect with 0.2 and 0.15, respectively. The GDP and the interest rate (i.e., repo rate) come after, both with 0.1 percent. However, the GDP by far is the most volatile variable among all the endogenous variables within the 20 periods. The GDP shock also is the last variable in which the fluctuation dies away.

Within all the interest rate impulses, the largest innovation is from the past values of the interest rate itself. The impulse to repo rate (i.e., interest rate) increases the repo rate significantly up to about 0.1 percent. However, the impulse tapers off immediately within 5 quarters. The liquidity ratio, network effect, and the GDP respectively have the biggest fluctuations in the range of -0.05 and 0.05, and they all converge to zero almost after 10 periods. The GDP response and impulse from and to the interest rate have the smallest fluctuations in the whole system.

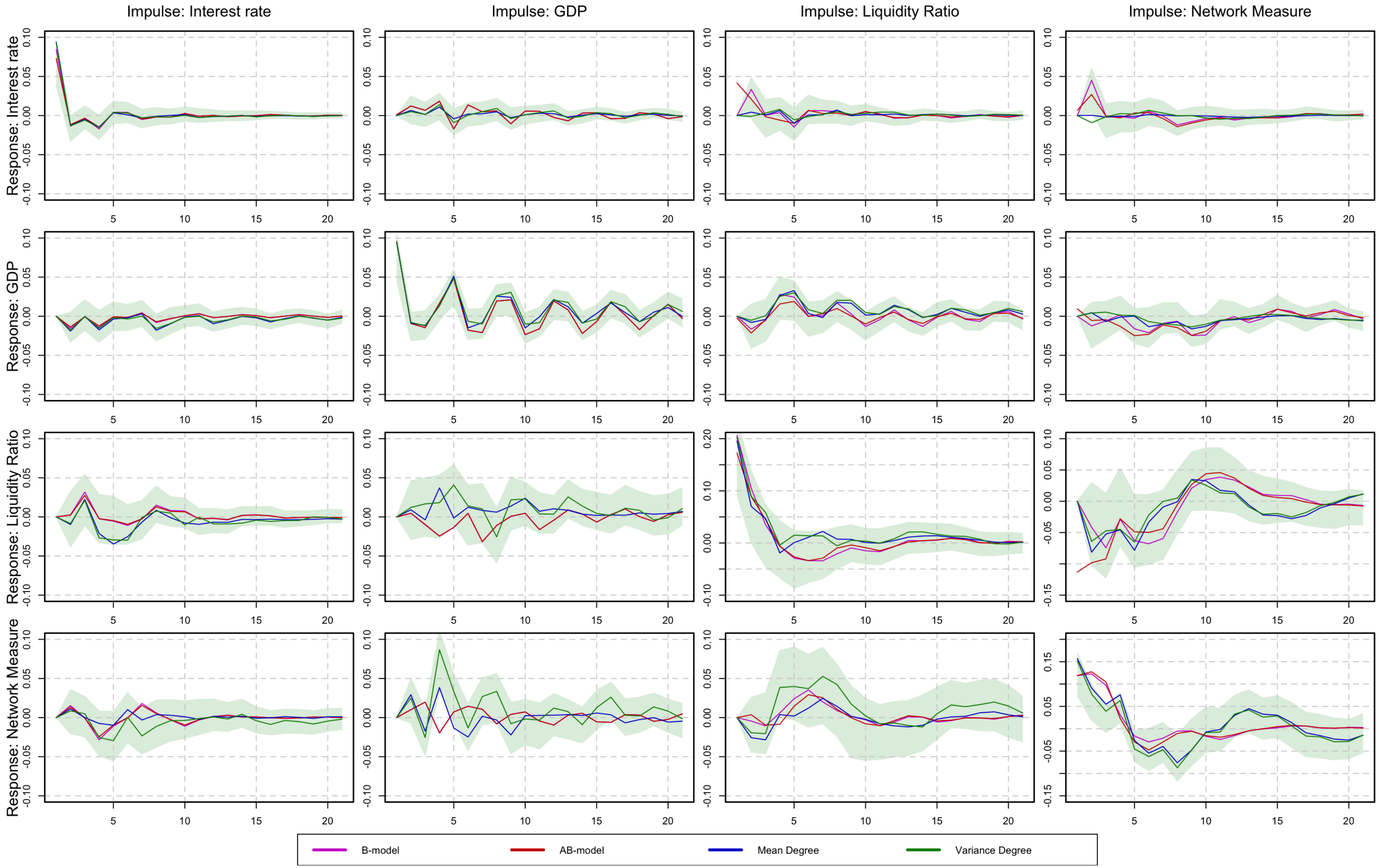
The second column of Figure 1.7 shows the response of our endogenous variables to the 2 standard deviation output shock. In terms of the output impulse, the biggest fluctuation is for the past values of the output itself with the range of -0.05 and 0.05, and it dies out after fluctuating around the baseline after 20 periods. The second volatile response is for the liquidity ratio within the range of -0.04 and 0.04 and fluctuated for about 15 quarters and then faded away. Although the variance degree of the network is the strongest between the liquidity ratios with the jump to more 0.05 and dies longer, the other indices of the network effects show less suffered by the output shock. The least volatile response is when the output impulse generates negligible fluctuation in the interest rate.

The third column of Figure 1.7 shows the response of our endogenous variables to the 2 standard deviation liquidity ratio (i.e., quick ratio) shock. Although the biggest effect is for the past values of the liquidity ratio itself, the impulse tapers off very quickly after 5 quarters. The network effects capture the second largest effects, but it takes longer for the fluctuations to converge to zero, almost 10 periods. Compared to the other variables, the GDP response has experienced more fluctuations than the other variables and it lasts about 20 periods to fade away. The first panel in the quick ratio impulses shows negligible volatile indicators within all the variables of interest.

Regarding the network effect, after the past values of network indicators, the most fluctuations happen for the liquidity ratio (i.e., quick ratio) response with the range of -0.08 and 0.05. This can be explained by the firm's approaches to switching between the methods of financing. The GDP response comes next with mild changes in the range of -0.025 and 0.01 compared to the interest rate (i.e., repo rate) response with negligible fluctuations. The output changes fade away longer than the repo rate where the fluctuation dies out quickly after the 3 periods. The biggest innovation in the financial data is concerned with liquidity ratio and network effects when the structural liquidity ratio shocks and network effects shock are seen to induce the variable itself for the first period and then it tapers off to zero after 5 quarters.

The Bootstrap resampling method is also employed to account for uncertainty in the estimation of IRFs in the above SVAR model. The resampling method generates a distribution of potential IRF outcomes by generating 1000 resamples from the original dataset. For each of these resampled datasets, the SVAR model is re-estimated, and corresponding Impulse Response Functions are computed and depicted collectively in Figure 1.7. To quantify the uncertainty surrounding the estimated IRFs, a 95% Confidence Interval (CI) is constructed, which signifies that there is a 95% probability that the actual IRFs lie within the calculated error bands (see the light green band around the line charts). By generating these resampled IRFs, the bootstrap procedure reveals the extent of variability and potential errors that can arise in our IRF estimates. The error bands serve as visual representations of the range within which the true IRFs are likely to be situated.

Figure 1.7: Impulse Response Functions Across Identification Scenarios



Note: This figure shows the Impulse Response Functions (IRFs) for the four identification scenarios and the endogenous variables of interest: the repo rate, real GDP, the quick ratio, the network index, the mean degree distribution, and the variance of the degree distribution. Each panel contains four lines, each corresponding to an identification scenario. The vertical axis of each panel shows the magnitude of the impulse responses, and the horizontal axis represents the horizon over which each shock persists. A 95% confidence interval (CI) is included to capture the uncertainty surrounding the IRFs.

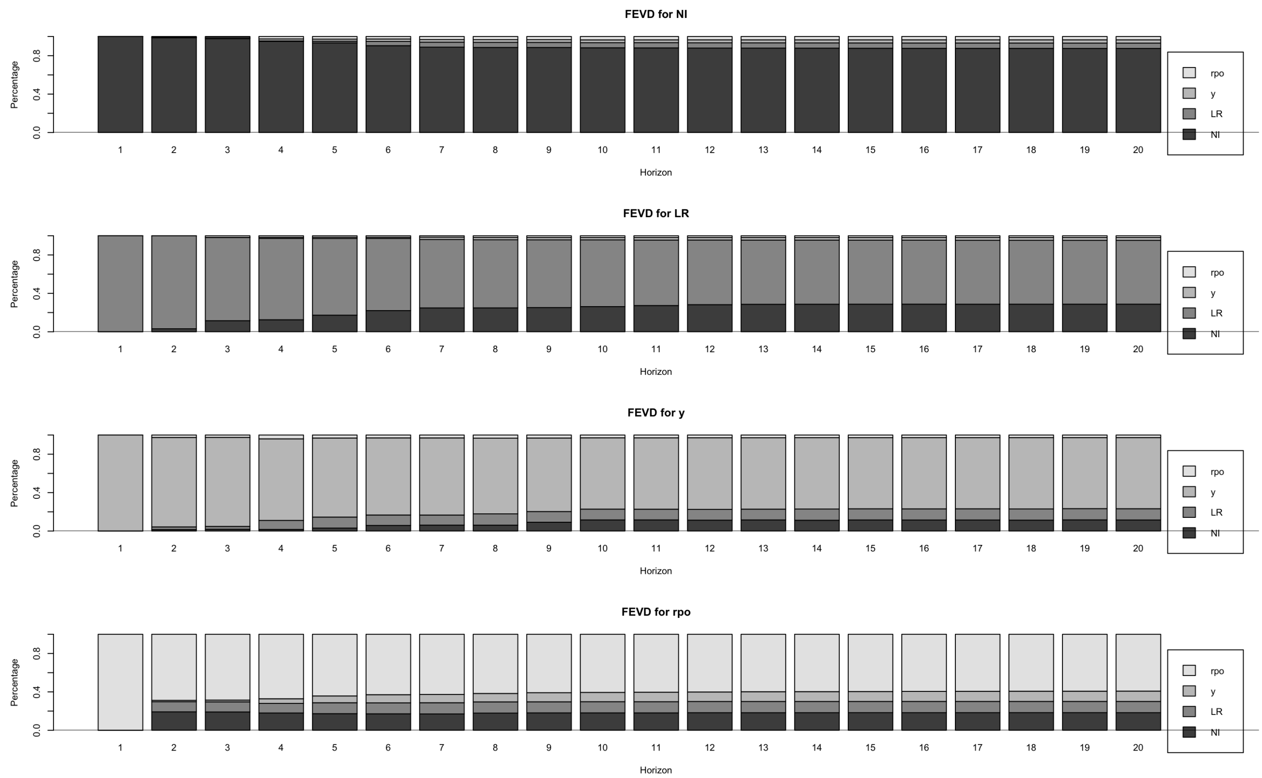
Data source: Calculated and plotted by the author.

4.3 Forecast Error Variance Decomposition (FEVD) Analysis

This study estimates the FEVD along with the impulse response functions. The FEVD is a component of structural analysis that reports the proportion of variation in the endogenous variables that is explained by each structural shock. Specifically, it decomposes the variance of the forecast error into the contributions of specific structural shocks to each variable. Intuitively, this reveals the importance of each shock and how much it explains of the variation in each variable over time. The FEVDs of the system under study are reported in Table 1.2, estimated using the VAR representation in Equation 1.6 to identify the driving forces of cyclical fluctuations. The variance decomposition provides insight into the relative impact of structural innovations in the network economy by quantifying the proportion of total variance in each variable attributable to each innovation.

Similar to impulse response functions in 4.2, FEVDs are generally presented graphically in a bar graph to visualize the proportion of variances. Figure 1.8 illustrates the variance decomposition for each variable, including 'network index,' 'repo rate,' 'liquidity ratio,' and 'GDP,' with respect to our designated variable of interest. This visualization serves to provide a graphical representation of the information presented in Table 1.2. The figure shows the composition of the error variance across innovations to all the variables of interest at each time period. For the network/ liquidity ratio/GDP/interest rate system, about 68% of the 1-st step forecast error variance of repo rate (i.e., interest rate) is accounted for by own innovations and about 19% is accounted for by network effects. For long-term horizon 20 period forecasts, 59 percent and 18% of the forecast error variance are accounted for interest rate and network effects, respectively. For any forecast horizon, the quick ratio and GDP innovations combined contribute less than 20% to the forecast error variance of interest rate. In the entire horizon, the quick ratio varies from about 10 to 12%. However, the output shock started in the 2-nd step forecast error with only 1% and increased to around 10% for the long-term horizon 20.

Figure 1.8: Forecast Error Variance Decomposition (FEVD)



Note: This figure reports the forecast error variance decomposition (FEVD) for the B-model specification using the endogenous variables: the repo rate (rpo), real GDP (y), the quick ratio (LR), and the network index (NI). Each panel presents bar charts showing the share of the h-step-ahead forecast error variance attributable to each structural shock. The vertical axis reports the variance share, and the horizontal axis shows the forecast horizon h.

Data source: Calculated and plotted by the author using FRED.

Regarding the GDP, we observe that more than 90% of the variations in GDP can be explained by the output shock in the first 3 time period. As we move further on to the next periods in the long term, the share of variation in GDP explained by output innovation goes on decreasing to approximately 75% by time period 20. On the contrary, approximately 1% of the 2-st step error variance of the output is accounted for by centralities' impulses, and this proportion goes further and stabilizes after the 10 time period at about 11%. Similarly, the quick ratio's contribution is about 0.02 and grows to 11% in the longer horizon. The repo rate shock has a negligible share among the other impulses. The interest rate shocks rank 4rd among all the shocks. we observe only small fractions of the error variances of GDP are explained by the interest rate impulses with less than 3%.

We similarly construct FEVD for quick ratio in response to all the variables' innovations under study. The main proportion of variations in the quick ratio is explained by its own effect by capturing the whole impact at the first step. As innovation moves further, it drops significantly to about 66% by time period 20. The remaining proportion of forecast error variance in liquidity ratio can be reported by the other variables - repo rate, GDP, and network effect - with less than 13% combined by 4th periods in the short-term to around 30% in period 20. Concerning the forecast error in network effect, the centralities' shock contributes the most to the volatilities of receivables/payables with more than 95%. As the horizon expands, the network impact reduces to about 87%, and this thereby substitutes with other variables innovations, mainly quick ratio. Quick ratio ranks second in explaining variations of the network with a maximum of 5 percent. The smallest fractions of the error variances of network centralities are related to the repo rate and GDP, where their shock stands third and fourth in explaining the changes in network centralities with the range of 0.003 to 3%.

Overall, the results highlight the role of network effects and the quick ratio among the liquidity-related variables. Among the self-innovation variables, the highest variations are accounted for by the network effect, quick ratio, GDP, and repo rate, with averages of approximately 93%, 83%, 81%, and 64%, respectively. For non-self-innovations, the highest proportion of variation is observed in network data and quick ratios. Regarding the second-highest rank in system fluctuations, there is no consensus among the robustness checks of the results. The baseline scenario shows a high proportion of fluctuations in the interest rate (i.e., repo rate) derived from the network data. However, other results demonstrate a high variation in the quick ratio concerning GDP fluctuations.

Table 1.2: FEVD: Repo Rate, GDP, Quick Ratio, and Network Index

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Network effect	Quick ratio	GDP	Repo rate
Repo rate	1	0.00	0.00	0.00	1.00
	2	0.19	0.10	0.01	0.68
	3	0.19	0.10	0.01	0.68
	4	0.18	0.10	0.04	0.67
	5	0.17	0.11	0.07	0.64
	10	0.18	0.11	0.09	0.60
	20	0.18	0.12	0.10	0.59
GDP	1	0.00	0.00	1.00	0.00
	2	0.01	0.02	0.93	0.02
	3	0.01	0.02	0.92	0.02
	4	0.01	0.09	0.84	0.03
	5	0.03	0.11	0.82	0.03
	10	0.11	0.11	0.74	0.02
	20	0.11	0.11	0.74	0.02
Quick ratio	1	0.00	1.00	0.00	0.00
	2	0.03	0.96	0.00	0.00
	3	0.11	0.86	0.001	0.01
	4	0.12	0.84	0.01	0.01
	5	0.17	0.79	0.01	0.01
	10	0.26	0.69	0.02	0.01
	20	0.28	0.66	0.02	0.01
Network effect	1	1.00	0.00	0.00	0.00
	2	0.98	0.00	0.003	0.007
	3	0.97	0.003	0.012	0.005
	4	0.95	0.003	0.02	0.02
	5	0.93	0.01	0.02	0.02
	10	0.88	0.05	0.02	0.03
	20	0.87	0.05	0.03	0.03

Note: This table reports the Forecast Error Variance Decomposition (FEVD) for the B-model specification using the endogenous variables: the repo rate, real GDP, the quick ratio, and the network index at a forecast horizon of $h = 20$.

Data source: Calculated and plotted by the author using FRED.

5 Concluding Remarks

This study has examined the dynamics of liquidity in a network economy, with a particular focus on the composition of firms' short-term assets and liabilities. The analysis highlights the importance of adequate liquidity conditions for firms to meet short-term obligations and absorb unexpected disturbances in the U.S. economy. The primary objective of the paper has been to investigate the dynamic components of liquidity movement within a network economy where firms engage in active trading and possess short-term assets and liabilities. The paper also evaluates the contribution of structurally identified liquidity-related shocks in explaining fluctuations in key macroeconomic and financial variables.

To address these objectives, the analysis looks closely into the origins of aggregate fluctuations within a network economy that may arise from liquidity changes and related forces. The paper focuses on analyzing the liquidity dynamics in the U.S. economy using repo rates, GDP, quick ratio, and the network measure of receivables/payables accounts. These variables are analyzed within a Structural Vector Autoregression (SVAR) framework to investigate their dynamic interactions and to identify liquidity disturbances with microeconomic origins, stemming from firm-level balance-sheet conditions and inter-sectoral linkages. Although the empirical model is estimated at the sectoral level, the identified shocks reflect liquidity disturbances rooted in firm-level behavior rather than purely aggregate or policy-driven shocks. To improve the accuracy of impulse response functions and forecast error variance decompositions, the analysis incorporates additional exogenous variables that are important drivers of liquidity conditions in the economy, including the Federal Funds Rate (FFR), Consumer Price Index (CPI), money supply, and the U.S. dollar exchange rate. These variables capture monetary policy conditions, price dynamics, and broader liquidity forces operating at the macroeconomic level.

The analysis begins by identifying the relevant innovations within the variables of interest and describe the response of the system to two standard deviation shocks, analyzing the propagation mechanisms of shocks through the Impulse Response Functions (IRFs). By analysing the impulses and responses of the variables in Figure 1.12, the paper quantifies the short-term effects of liquidity shocks on interest rates, GDP, quick ratio, and the network measure. The findings of this study are extensive; here we highlight the key results. Following two-standard-deviation shocks, the largest responses in the system are predominantly driven by each variable's own past innovations. Among all endogenous variables, the strongest immediate responses are observed for the quick ratio and the network measure, with peak responses of approximately 0.20% and 0.15%, respectively. GDP and the repo rate exhibit smaller initial responses, both around 0.1%. Despite its relatively smaller initial response, GDP emerges as the most volatile variable in the system, with fluctuations dissipating more slowly over time. These dynamics suggest that liquidity shocks originating in firms' balance sheets and network positions generate persistent, but transitory, effects on aggregate economic activity.

The paper further assesses the importance of each shock in explaining the variations observed in the endogenous variables by decomposing the Forecast Error Variance (FEV) and determining the proportion of shocks throughout the entire system. By quantifying the contribution of innovations to the overall forecast errors in Table 1.2, this analysis will shed light on the relative importance of liquidity dynamics in shaping the behavior of markets. The findings underscore the importance of the network measure and the quick ratio in the aggreagte fluctuations of the economy. The proportion of variation explained by own shocks is highest for the network measure (approximately 93%), followed by the quick ratio (83%), GDP (81%), and the repo rate (64%). With respect to cross-variable effects, the network measure and the quick ratio account for the largest shares of non-self innovations. In particular, a substantial fraction of repo rate fluctuations is explained by shocks originating from the network measure. These findings indicate that liquidity conditions embedded in firm-level networks and balance-sheet positions play an important role in transmitting liquidity shocks to funding markets and real economic activity over the business cycle.

The study acknowledges the limitations of the model specification in analyzing shocks and carefully considers the underlying assumptions when interpreting the results. The reliability of the findings is further validated through robustness checks employing alternative identification strategies and different network measures. Specifically, the study applies both AB-model and B-model identification schemes to account for contemporaneous and non-contemporaneous effects. Furthermore, the analysis employs various network centrality measures and moments of the degree distribution to capture the importance of different nodes and linkages within the network. This approach enables an examination of the role of specific firms and their interconnectedness in the network economy.

Overall, the results underscore the relevance of micro-origin liquidity disturbances in shaping aggregate fluctuations within a network economy, highlighting the importance of monitoring network-based liquidity indicators alongside traditional balance-sheet measures. The findings contribute to the broader literature on granular and network-driven fluctuations and offer insights for policymakers and market participants concerned with liquidity risk, macroeconomic stability, and systemic resilience. Future research should first develop a theoretical framework consistent with the empirical analysis and then extend the approach by refining the SVAR identification strategy and endogenizing variables that are currently treated as exogenous.

APPENDIX:
Complementary Materials for Liquidity Origins of Aggregate Fluctuations

1 Network Centralities

This part mainly explains the network centralities, Katz centrality and edge betweenness centrality, used to construct the network index in Section 3.1. We also provide the details of the network index including the effect of each centrality on the network index. This is what we referred to as pure node effect and pure linkage effect.

Katz centrality: We use *Katz centrality* as a node centrality to capture the relative influences of a node within the netwok. Katz is basically a measure of the "influence" of a node in the adjacency matrix A (here, associated with the directed network X in Section 3.1) that takes into account both direct and indirect linkages.[1] It computes the relative influence of a node within a network by measuring not only the number of the immediate neighbors (first degree nodes) but also all other nodes connected to the immediate neighbors. Connections made with distant neighbors are, however, penalized by an attenuation factor α. Katz centrality is mathematically defined as:

$$c_K(i) = \sum_{k=1}^{\infty} \sum_{j=1}^{n} \alpha^k (A^k)_{ji} \tag{A.1}$$

where the element at location (i, j) of A^k (i.e., X^k) reflects the total number of paths of k degree connections between nodes i and j. $(A^{[k]})_{ij}$ indicates the presence or absence of a financial transaction or connection between nodes. More specifically, if there is a financial transaction or interaction between node i and node j, then the entry A_{ij} is positive liability amount. On the other

[1] Katz centrality is a variant of eigenvector centrality. The advantage of Katz centrality compared to eigenvector centrality is that the former considers the indirect connections as well.

hand, if there is no direct financial interaction between nodes (i.e., sectors), then A_{ij} would be zero. The attenuation factor α controls the influence of indirect connections and penalizes the further apart than the immediate node. A typical choice for α is between 0 and 1, where factors closer to 1 give more weight to distant connections, while values closer to 0 emphasize more on local connections (Katz, 1953). This study gives more weight to the local financial interation and choose the default moderate value of $\alpha = 0.1$.

We used the Average Katz Centrality (AKC) to address the global Katz centrality due to the identification problem explained in Section 3.2. The AKC is simply the mean of Katz centralities over all nodes in the network, given by:

$$\overline{c_K(i)} = \frac{1}{n} \sum_{i=1}^{n} c_K(i) \tag{A.2}$$

where $\overline{c_K(i)}$ is the AKC, and n is the number of nodes (i.e., sectors). In a financial network context, Katz centrality can help identify institutions that are important in the flow of debt and financial relationships, even if they do not have high degree or direct connections to other institutions. The AKC can provide a summary measure of the overall influence of institutions in the network.

Edge Betweenness Centrality (EBC): EBC measures the importance of edges in the directed network X based on the number of shortest paths between pairs of nodes that pass through those edges. The EBC is often used to identify the ranking of edges based on their contributions as "bridges" (i.e., important connectors) between different parts of a network.

$$c_B(i) = \sum_{s,t \in V} \frac{\sigma(s,t|i)}{\sigma(s,t)} \tag{A.3}$$

This shows the formula that calculates the betweenness centrality of a specific edge i by summing up the fraction of all-pairs shortest paths that pass through i, where $\sigma(s,t|i)$ denotes the number of paths passing through edge i, and $\sigma(s,t)$ is the number of shortest (s,t)-paths. In this study, edge betweenness centrality can help to identify debt relationships that are important in connecting different group or clusters of sectors in the network (Freeman, 1977; Freeman et al., 2002).

The average edge betweenness centrality (AEBC) that is used to calculates the global edge network effect is simply the mean of edge betweenness centrality over all edges in the network, given by:

$$\overline{c_B(i)} = \frac{1}{n}\sum_i c_B(i) \tag{A.4}$$

where $\overline{c_B(i)}$ is the AEBC, and n is the number of nodes (i.e., sectors). In a financial network context, edge betweenness centrality can help identify debt relationships that are important in connecting different groups or clusters of institutions in the network. The AEBC can provide a summary measure of the overall importance of debt relationships in the network.

Once we define the centrality measures we use in Equation 1.5 to indentify the network effect of the sectors in the US economy, Table A.1 exhibits the regression results for Equation 1.5.

Table A.1: Network effect

	Dependent variable:
	Network effect
$\overline{c_K(i)}$	0.837***
	(0.049)
$\overline{c_B(i)}$	0.257***
	(0.017)
Constant	−0.193***
	(0.017)
Observations	60
R^2	0.863
Adjusted R^2	0.858
Residual Std. Error	0.003 (df = 57)
F Statistic	179.581*** (df = 2; 57)
Note:	*p<0.1; **p<0.05; ***p<0.01

Note: Table reports the regression applied to construct the network index, which is fitted value of $c_T(i)$, $\widehat{c_T(i)}$, explained in Section 3.1. $\overline{c_K(i)}$ denotes the average Katz centrality and $\overline{c_B(i)}$ is the average edge betweenness centrality.

According to Table A.1, the Equation 1.5 can be written in the following form,

$$c_T(i) = -0.193 + 0.837\ \overline{c_K(i)} + 0.257\ \overline{c_B(i)} \tag{A.5}$$

2 The Hodrick and Prescott (HP) Filter

The HP filter for the first time introduced by Hodrick and Prescott (1997) as a popular tool in macroeconomics to decpmpose a time series from raw data, especially in business cycle theory.[2] The

[2]Hamilton (2018) critisizes the choice of λ and the ability of the HP filter to derive cycles when none exist and proposes his own approach to decompose the data. However, Hodrick (2020) later simulates both filters and shows that

reasoning filter decomposes a time series y_t into two components; a trend or growth component g_t and a cyclical component c_t.

$$y_t = g_t + c_t \tag{A.6}$$

The decomposition solves for the growth component to minimize the sum of the squared deviations of the actual series y_t from the growth component g_t, and subtract it from the product of penalty λ and the sum of the squares of the trend component's second differences.

$$\underset{g}{min} \sum_{t=1}^{T} (y_t - g_t)^2 + \lambda \sum_{t=2}^{T-1} [(g_t - g_{t-1}) - (g_{t-1} - g_{t-2})]^2. \tag{A.7}$$

The second term attempts to penalize changes in the rate of growth. λ captures the magnitude of the penalty for the variations in growth rate of the trend component. In this paper, the λ is 1600 as Hodrick and Prescott (1997) suggests for the quarterly data.

both approaches Hamilton (2018) and Hodrick and Prescott (1997) work properly although the efficiency of them varies under different conditions and based on the complexity of the model. This paper uses the first difference approach and Baxter and King (1999) filter to avoid any mistake. Under the sensivity analysis, the results is very similar. However, we chooses HP filter over Hamilton (2018) and Baxter and King (1999) as the former is less restrictive compared to the other two methods that drop some observation during the filtering. HP filter has also advantage of smoothing the noise compared to the first difference.

2.1 Summary Statistics Table

TABLE A.2: Applied Variables and Summary of their Statistics

Type of Variables	Variables	Min	1st Qua.	Median	Mean	3rd Qua.	Max	Source
Endogenous Variables	log(GDP)	16.14	16.27	16.40	16.39	16.49	16.61	Calculated from FRED
	Repo rate	0.07	0.12	0.20	1.21	1.85	5.26	FRED
	Quick ratio	1.098	1.193	1.225	1.217	1.254	1.331	Datastream
	Mean degree	37.20	73.72	77.60	78.94	84.52	112.61	Calculated from Datastream
	Variance degree	1689	8491	10411	11886	16327	23015	Calculated from Datastream
	Network index	0.061	0.083	0.086	0.084	0.088	0.091	Calculated from Datastream
Exogenous Variables	Log of Monetary base	13.60	14.47	14.97	14.70	15.16	15.44	FRED
	Federal funds rate	0.06	0.12	0.19	1.23	1.92	5.26	Datastream
	Consumer price index	-2.30	0.30	0.50	0.46	0.80	1.50	FRED
	Dollar exchange rate	86.81	92.55	98.08	101.43	111.62	121.84	FRED

Note: Table reports the variables applied in the study and summary of their statistics for the sample period of $2006Q1$ to $2020Q4$.

3 Model Specification

3.1 The AR model selection criteria

TABLE A.3: The AR model selection criteria

(A) The selection criteria scores for the AR orders

Selection criterion	AR orders				
	1	2	3	4	5
AIC(n)	-2.549	-2.510	-2.483	-2.593*	-2.574
HQ(n)	-2.514*	-2.452	-2.403	-2.489	-2.448
SC(n)	-2.459*	-2.360	-2.273	-2.323	-2.244
FPE(n)	$8.5e^{-7}$	$1.2e^{-6}$	$1.7e^{-6}$	$6.1e^{-7*}$	$8.2e^{-7}$

(B) The best AR lag length order suggested by each criterion

Selection criterion	**AIC(n)**	**HQ(n)**	**SC(n)**	**FPE(n)**
AR order	4	1	1	4

Note: Table reports the selection criteria and their corresponding scores for the AR orders of 1 to 5.

3.2 Augmented Dickey Fuller (ADF) unit root tests

TABLE A.4: ADF unit root tests for the time series variables of interest

Variable	No. of lagged differences	Test statistic	Critical value
GDP	0	-4.352	0.01
	3	-1.9199	0.60
$\mathcal{C}$**(GDP)**	0	-11.707	0.01
	3	-4.6217	0.01
Repo rate	0	-5.295	0.01
	3	-2.2844	0.45
$\mathcal{C}$**(Repo rate)**	0	-10.167	0.01
	3	-4.8361	0.01
Quick ratio	0	-0.9973	0.93
	3	-1.176	0.90
$\mathcal{C}$**(Quick ratio)**	0	-7.3861	0.01
	3	-3.1472	0.11
Network index (NI)	0	-2.8454	0.23
	3	-3.3945	0.06
$\mathcal{C}$**(NI)**	0	-7.3683	0.01
	3	-5.6684	0.01
Mean degree	0	-2.3424	0.34
	3	-3.3945	0.06
$\mathcal{C}$**(Mean degree)**	0	-6.2683	0.02
	3	-5.6684	0.01
Variance degree	0	-3.0051	0.43
	3	-2.3745	0.07
$\mathcal{C}$**(Variance degree)**	0	-7.7943	0.02
	3	-4.7354	0.01

Note: Table reports Augmented Dickey Fuller (ADF) unit root tests for the variables of interest for the sample period of $2006Q1$ to $2020Q4$. $\mathcal{C}(\cdot)$ denotes the time series cycle calculated by the HP filter explained in Appendix 2.

4 Model Diagnostics

Model diagnosis is also performed to evaluate the goodness of fit and the validity of required assumptions in the SVAR model. We use the following procedures to assess whether the model output adequately represents the data and whether any issue in data can be problematic.

4.1 Stability Test for VAR model

For the time series variables y_t in equation (1.7), the stability of the VAR representation can be determined by calculating the roots of the following equation:

$$(I_n - A_1 L^1 - A_2 L^2 - ...)y_t = A(L)y_t \tag{A.8}$$

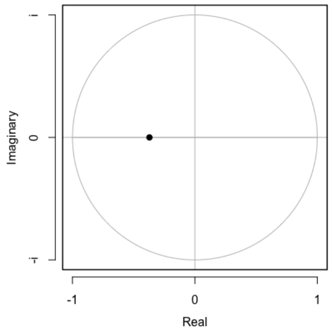
if we define the characteristic polynomial as:

$$\Phi(z) = (I_n - A_1 L^1 - A_2 L^2 - ...) \tag{A.9}$$

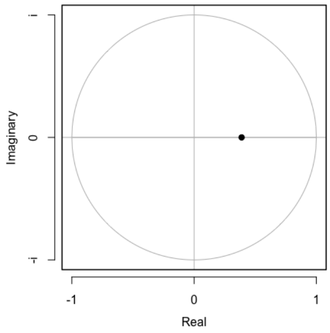
Then the necessary and sufficient condition for stability of model is that all characteristic roots of $\Phi(z)$ lie within the unit circle. Figure (A.1) shows the stability unit circle with inverse roots of AR characteristic polynomial. It confirms the stability condition of VAR system as the inverse toots are all inside of the circle, i.e. the roots are less than one, and thereby the system is stable.

Figure A.1: Stability Test for VAR model

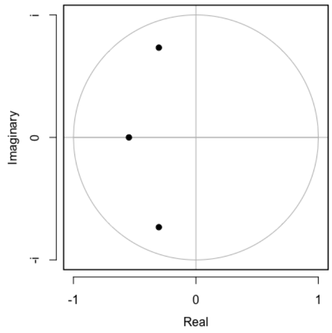
(A) Mean degree



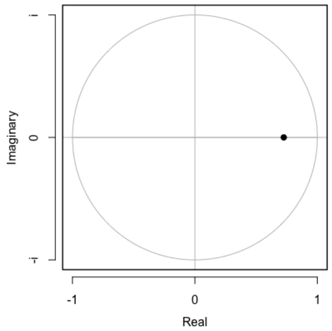
(B) Variance Degree



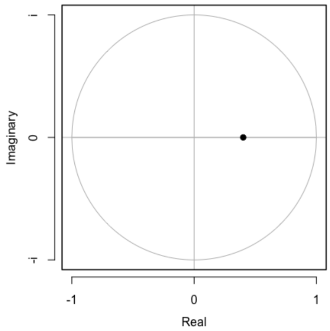
(C) Network Index



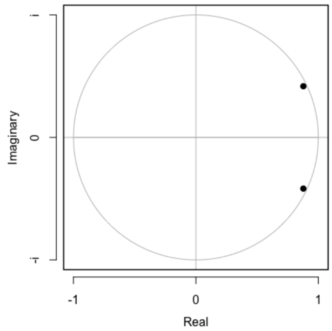
(D) Liquidity Ratio



(E) Real GDP



(F) Repo Rate



Note: Figure represents the stability unit circle with the inverse roots of AR characteristic polynomial.
Data source: Plotted by author using the databases explained in the data table.

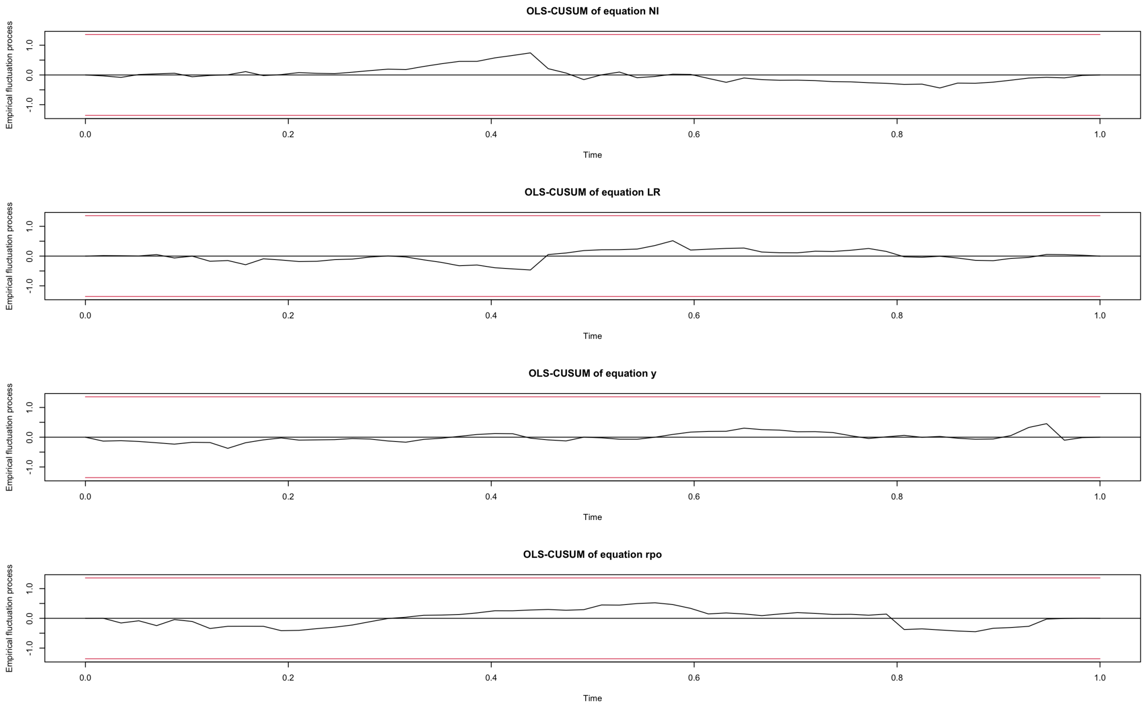
4.2 Structural Break

In this subsection we test for the stability of the system to examine whether the model remains stable over time periods or any structural breaks can be detected in the relationships between key variables of interest. This is required to ensure that the estimated relationships or parameters of the SVAR model hold over time. This can provide insights into the overall health of an economy and identify structural changes that may have occurred.

We use the OLS CUSUM (Ordinary Least Square Cumulative Sum Test) test to detect structural changes or instability in a model over time. The test statistic (CUSUM statistic) is calculated for the OLS regression model at different proportions of data, ranging from 0% to 100%. The proportion of data used for the test increases gradually as we move across the x-axis from 0% to 100%, and the

CUSUM statistic is computed at each proportion and shown in the y-axis. The Figure A.2 shows the model stable as CUSUM statistic fluctuates around zero and does not crosses or exceeds the critical values (confidence interval) as the proportion of data increases, showing no significant structural breaks or instability.

FIGURE A.2: Stability Test for Structural Breaks



Note: Figure represents stability testing to assess the stability of relationships between the variables of interest over different time periods. The y-axis plots the CUSUM test statistics, and the x-axis is the proportion of data used for the test. As the CUSUM statistic line does not break the confidence interval (the red line), we can conclude that the model is stable over the time.

4.3 Residual Analysis

Residual analysis is an important step in the evaluation of a SVAR model and involves examining the residuals obtained from the estimation of SVAR. This is to assess the properties of estimation and ensures the model representative meet the assumptions.

Autocorrelation analysis: The autocorrelation test, also known as the serial correlation test, is tested to check if there is any presence of correlation between the residual of different lags. Serial correlation occurs when the residuals are correlated with the residuals within the data over the time, which violates one of the assumptions of the VAR model. The residuals of the model are the differences between the observed values and the predicted values, and ideally there should be no systematic patterns or correlations available in them. I used the Ljung-Box test and Portmanteau test to detect whether there are any significant correlations in the residuls at different lag orders.

The Ljung-Box test in Table A.6 is used to assess the presence of autocorrelation in the residuals of a model. The test statistic of the model follows a chi-squared distribution under the null hypothesis of no autocorrelation. The high p-values ($p > 0.05$) in the test suggests that there is no strong evidence to reject the null hypothesis of no autocorrelation in the residuals. Hence, we can conclude that there is no significant autocorrelation present in the residuals for the lag order tested (in this case, up to lag 10) for the variables of interest in the SVAR model.

Table A.5: Results of the Box-Ljung Test

Variable	**test statistic Q**	**df**	**p-value**
Repo rate	4.45	10	0.92
GDP	6.50	10	0.77
Quick ratio	9.12	10	0.52
Network effect	9.92	10	0.45
Mean degree dist.	5.33	10	0.86
Variance degree dist.	8.11	10	0.61

Note: Table reports the results of the Box-Ljung test. The null hypothesis in the Box-Ljung test is that there is no autocorrelation in the dataset. The test statistic Q is calculated based on the sample autocorrelation function (ACF) values. The p-value is compared to a significance level ($\simeq 0.05$) to make decision.
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

The Portmanteau Test is also performed as it is specifically designed to check for serial correlation in the residuals of a time series model. With a p-value of 0.61, the test suggests that there is insufficient evidence to reject the null hypothesis, indicating that we fail to reject the null hypothesis and thereby the model's residuals show no significant autocorrelation. This implies that the residuals of the VAR model are independently distributed and no significant autocorrelation detected in the model's residuals.

In summary, the Box-Ljung and Portmanteau Test suggests that the VAR model provides a good fit to the data because of no evidence of significant autocorrelation in the residuals. Even though we tested the autocorrelation using the two test, we find it desirable to examine the residuals visually

Table A.6: Results of the Portmanteau Test (asymptotic)

Variables	**Chi-squared**	**df**	**p-value**
B model	137.11	144	0.61
AB model	136.11	128	0.27
Mean degree	147.32	128	0.11
Variance degree	139.93	128	0.22

Note: Table reports the results of the Portmanteau Test (asymptotic). Test Statistic (Chi-squared) measures the discrepancy between the observed autocorrelation of the residuals. The degrees of freedom (df) in the test is determined by the number of lags used in the autocorrelation calculation. The p-value is the probability of observing the test statistic under the assumption that the null hypothesis of no autocorrelation in the residuals.
Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

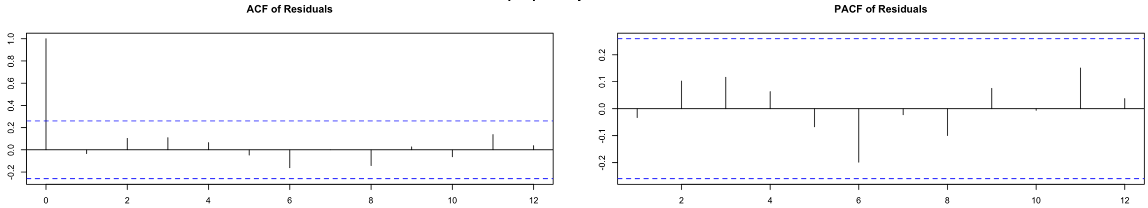
to ensure the absence of any residual patterns that may affect the accuracy and validity of the model in Figure A.3. The figure also shows and confirms that there is no pattern in the ACF plot.

Heteroskedasticity Analysis: We also attempt to check the presence of heteroskedasticity in the residuals to detect whether the variance of the estimated residuals changes systematically over time. The ARCH (Autoregressive Conditional Heteroskedasticity) test is applied for heteroskedasticity to the residuals of the VAR mdel to examine the presence of conditional heteroskedasticity in the time series data.[3] The ARCH test's results is shown in Figure A.3 for the all the variables. The plot indicates no heteroskedasticity in the residuals of the VAR model.

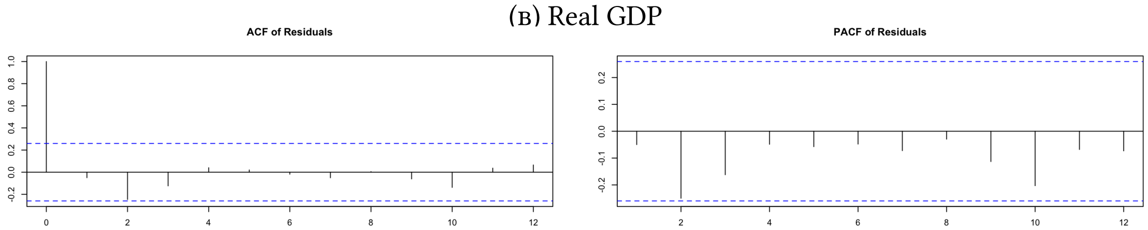
[3]The ARCH model is a time series model for capturing conditional heteroskedasticity, which allows for the variance of the current innovation to be modeled based on past observations or their conditional variances.

Figure A.3: ARCH (Autoregressive Conditional Heteroskedasticity) Test for Heteroskedasticity

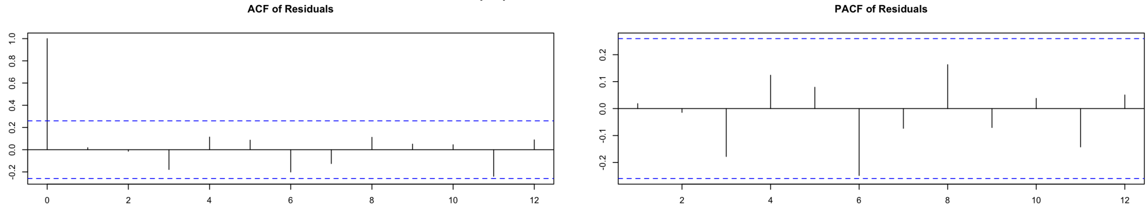
(a) Repo Rate



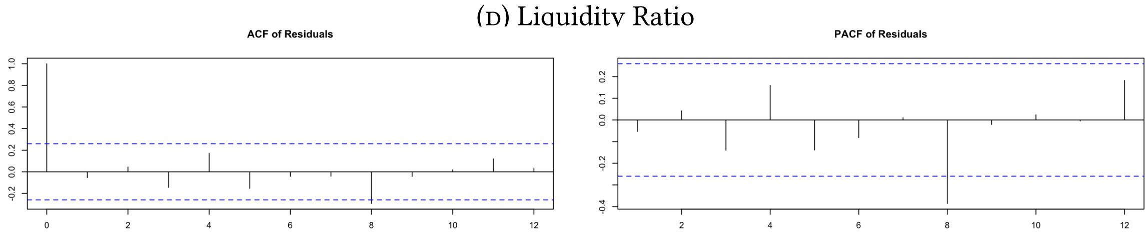
(b) Real GDP



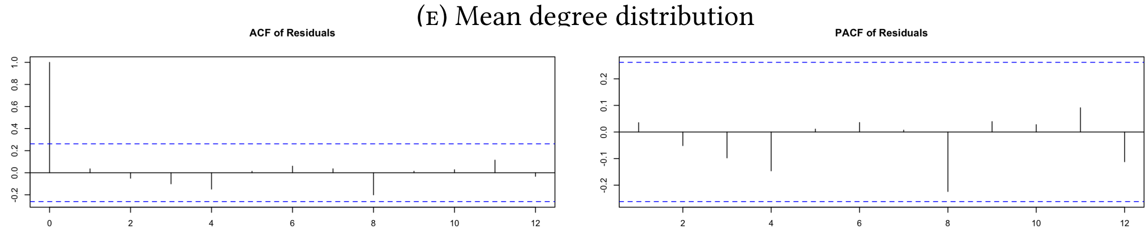
(c) Network Index



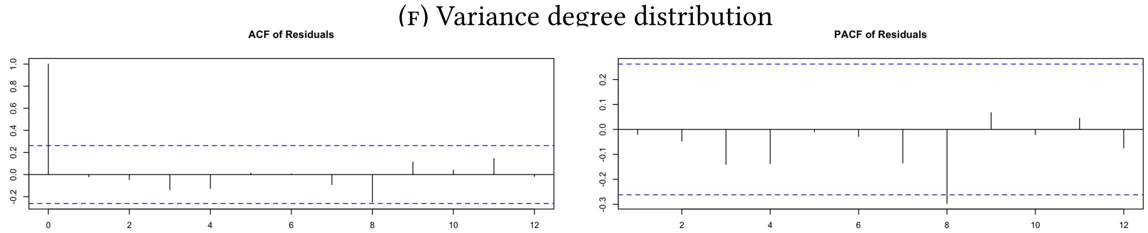
(d) Liquidity Ratio



(e) Mean degree distribution



(f) Variance degree distribution

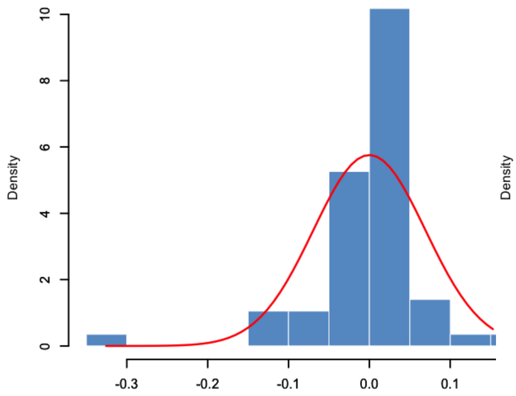


Note: Figure represents the ACF and PACF of residuals for the first 12 lags of VAR model to check the heteroskedasticity of the residuals.

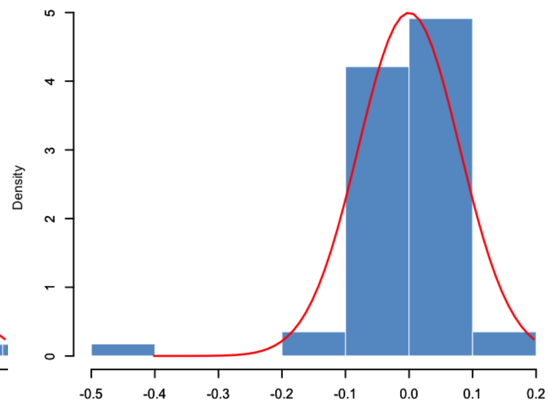
Normality Analysis: This step examines the distributional properties of the residuals to assess whether it is normal. The histogram of the residuals in Figure A.4 shows skewness in the tale of the histogram which implies the presence of slight non-normality. To overcome this issue, we apply two approaches: first, we employ the non-parametric Generalized Method of Moments (GMM) method instead of traditional linear models for estimating VAR parameters to relax the normality assumption. GMM does not require specifying the distribution of the errors and accommodate non-normal error distributions by allowing for more robust and efficient parameter estimation while relaxing some of the restrictive condtions (Hansen, 1982; Hall, 2004). Secondly, we employ Bootstrap robust methods for inference, which provides more reliable estimates and confidence intervals even in the presence of non-normality (Bickel and Freedman, 1984; Berkovits et al., 2000).

Figure A.4: Histogram of the Residuals

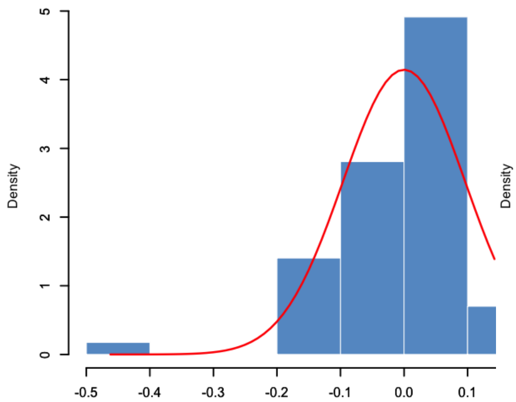
(a) Repo Rate



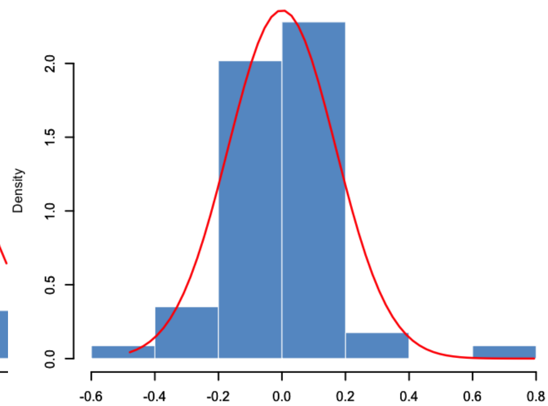
(b) Real GDP



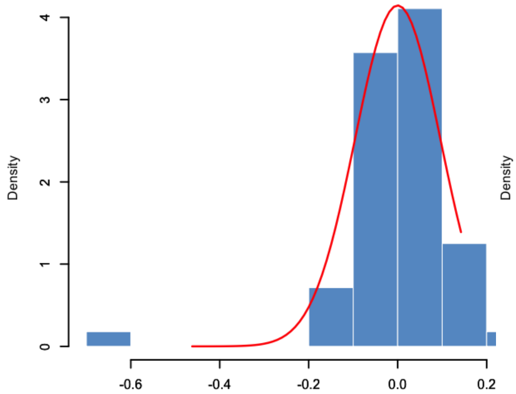
(c) Network Index



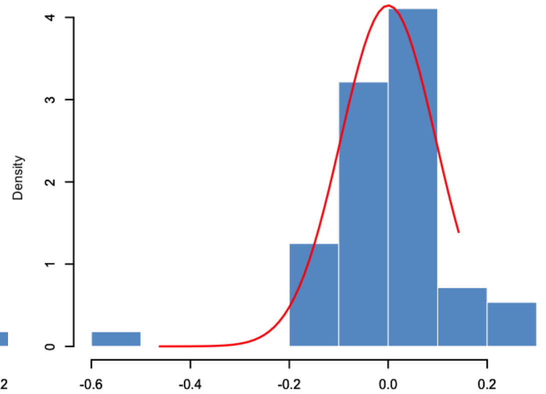
(d) Liquidity Ratio



(e) Mean Digree Distribution



(f) Variance Digree Distribution



Note: Figure represents the histograms of residuals taken from VAR model to check the normality condition.

4.4 Sensitivity Analysis

4.4.1 Model Parameters

B-model:

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.11} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.20} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.08} \end{pmatrix} \tag{A.10}$$

AB-model:

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ \underset{(0.46)}{0.94} & 1 & 0 & 0 \\ \underset{(0.0009)}{-0.06} & \underset{(0.039)}{0.013} & 1 & 0 \\ \underset{(0.001)}{-0.28} & \underset{(0.004)}{-0.24} & \underset{(0.19)}{-0.012} & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.119} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.17} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.07} \end{pmatrix} \tag{A.11}$$

Mean degree distribution:

$$\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.15} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.19} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.09} \end{pmatrix} \tag{A.12}$$

Variance degree distribution:

$$
\mathsf{A} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \text{ and } \mathsf{B} = \begin{pmatrix} \underset{(0.00)}{0.15} & 0 & 0 & 0 \\ 0 & \underset{(0.00)}{0.20} & 0 & 0 \\ 0 & 0 & \underset{(0.00)}{0.09} & 0 \\ 0 & 0 & 0 & \underset{(0.00)}{0.09} \end{pmatrix} \tag{A.13}
$$

4.4.2 Model Covariance Matrix

We examine the symmetric covariance matrix A.14 (multiplied by 100), denoted as Σ_e, between the error terms to understand the relationships between endogenous variables and the transmission mechanisms of shocks in the system. For the interest rate/output/liquidity ratio/network system, the innovation or white noise covariance matrix in the system is,

$$
\Sigma_e = \begin{pmatrix} 1.42 & -1.34 & 0.11 & 0.08 \\ \bullet & 4.25 & -0.15 & 0.64 \\ \bullet & \bullet & 0.91 & 0.01 \\ \bullet & \bullet & \bullet & 0.71 \end{pmatrix} \tag{A.14}
$$

where each element in Σ_e represents the covariance between the error terms of two respective variables. The diagonal elements of Σ_e denote the variances of the individual error terms while the off-diagonal elements show the covariances between different pairs of error terms. The square roots of the variances represent the magnitude of the innovations, so we follow up on a structural shock of $\sqrt{4.25} = 2.06$ (tracing an unexpected two standard deviation increase) in liquidity ratio since the standard deviation of e_{2t} is 2.06. The high size of the standard deviation for the liquidity ratio 2.06 reflects the high magnitude of the innovations within the system. The innovation related to the network effect, represented by $\sqrt{1.42}$, is the second highest among the variables. The GDP and repo rate with $\sqrt{0.91}$ and $\sqrt{0.71}$ show mildest innovations in the system, implying that GDP and the repo rate are less sensitive to sudden changes.

Equation Σ_e also reports that the strongest correlation is available between $e_{1,t}$ and $e_{2,t}$ with -1.34, showing a very strong positive correlation between the network effect and remaining sources of liquidity. The correlation 0.64 is the second strong correlation between the quick ratio and the repo rate. Other off-diagonal elements report relatively weak correlation between the innovations. GDP and the network effects, for instance, shows the lowest correlation in the system, which reflects the lack of significant correlation between certain pairs of error terms, such as between the GDP and the network effects (0.01), implies that a shock in GDP/network effect may not be accompanied by a shock in network effect/GDP in the same period.[4]

B-model:

$$\Sigma_e = \begin{pmatrix} 0.013 & -0.0129 & 0.0009 & 0.001 \\ \bullet & 0.041 & -0.0005 & 0.004 \\ \bullet & \bullet & 0.009 & -0.0004 \\ \bullet & \bullet & \bullet & 0.0068 \end{pmatrix} \tag{A.15}$$

AB-model:

$$\Sigma_e = \begin{pmatrix} 0.014 & -0.013 & 0.001 & 0.0008 \\ \bullet & 0.042 & -0.0014 & 0.006 \\ \bullet & \bullet & 0.009 & 0.0008 \\ \bullet & \bullet & \bullet & 0.007 \end{pmatrix} \tag{A.16}$$

Mean degree distribution:

$$\Sigma_e = \begin{pmatrix} 0.024 & -0.025 & 0.0007 & 0.0003 \\ \bullet & 0.038 & -0.0006 & 0.0042 \\ \bullet & \bullet & 0.009 & -0.0003 \\ \bullet & \bullet & \bullet & 0.008 \end{pmatrix} \tag{A.17}$$

[4]In Appendix 4.4.2, we present the robustness check for alternative scenarios and different network indices. Notably, the variance-covariance matrices for the B model, AB model, mean degree, and variance degree exhibit remarkable similarity.

Variance degree distribution:

$$\Sigma_e = \begin{pmatrix} 0.023 & -0.024 & -0.0012 & 0.0001 \\ \bullet & 0.041 & -0.0003 & 0.003 \\ \bullet & \bullet & 0.009 & -0.0003 \\ \bullet & \bullet & \bullet & 0.008 \end{pmatrix} \tag{A.18}$$

4.4.3 Forecast Error Variance Decomposition (FEVD)

Table A.7: Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/network effect system for AB model

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Network effect	Quick ratio	GDP	Repo rate
Repo rate	1	0.006	0.24	0.0002	0.74
	2	0.09	0.25	0.017	0.63
	3	0.08	0.25	0.02	0.63
	4	0.08	0.24	0.05	0.61
	5	0.08	0.24	0.08	0.59
	10	0.10	0.22	0.11	0.54
	20	0.11	0.22	0.12	0.53
GDP	1	0.009	0.00	0.98	0.00
	2	0.01	0.04	0.92	0.01
	3	0.01	0.04	0.92	0.01
	4	0.02	0.06	0.87	0.03
	5	0.06	0.07	0.83	0.02
	10	0.14	0.07	0.75	0.02
	20	0.14	0.07	0.76	0.02
Quick ratio	1	0.30	0.69	0.00	0.00
	2	0.37	0.62	0.00	0.00
	3	0.43	0.55	0.00	0.01
	4	0.43	0.54	0.009	0.01
	5	0.44	0.53	0.011	0.01
	10	0.47	0.49	0.02	0.01
	20	0.49	0.46	0.02	0.01
Network effect	1	1.00	0.00	0.00	0.00
	2	0.99	0.00	0.00	0.00
	3	0.98	0.00	0.01	0.00
	4	0.95	0.00	0.02	0.017
	5	0.95	0.00	0.02	0.01
	10	0.90	0.04	0.02	0.02
	20	0.90	0.04	0.03	0.02

Note: Table reports Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/quick ratio/network effect system for 20 time periods.

Table A.8: Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/mean degree system

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Mean degree	Quick ratio	GDP	Repo rate
Repo rate	1	0.00	0.00	0.00	1.00
	2	0.00	0.002	0.004	0.99
	3	0.0004	0.002	0.004	0.99
	4	0.0005	0.006	0.017	0.97
	5	0.0006	0.01	0.018	0.96
	10	0.0009	0.021	0.02	0.95
	20	0.002	0.022	0.02	0.94
GDP	1	0.00	0.00	1.00	0.00
	2	0.002	0.006	0.95	0.03
	3	0.006	0.008	0.94	0.03
	4	0.006	0.072	0.86	0.06
	5	0.004	0.12	0.82	0.04
	10	0.04	0.13	0.75	0.06
	20	0.04	0.14	0.74	0.06
Quick ratio	1	0.00	1.00	0.00	0.00
	2	0.13	0.86	0.001	0.001
	3	0.16	0.81	0.001	0.01
	4	0.19	0.76	0.02	0.017
	5	0.26	0.68	0.02	0.03
	10	0.28	0.63	0.03	0.04
	20	0.31	0.60	0.036	0.04
Mean degree	1	1.00	0.00	0.00	0.00
	2	0.95	0.019	0.02	0.003
	3	0.92	0.03	0.029	0.003
	4	0.90	0.03	0.05	0.003
	5	0.90	0.03	0.05	0.005
	10	0.89	0.039	0.06	0.006
	20	0.89	0.04	0.059	0.006

Note: Table reports Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/quick ratio/mean degree system for 20 time periods.

Table A.9: Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/liquidity ratio/variance degree system

Forecast error in	Forecast horizon h	proportions of FEV h periods ahead accounted for by innovations in			
		Variance degree	Quick ratio	GDP	Repo rate
Repo rate	1	0.00	0.00	0.00	1.00
	2	0.009	0.0001	0.002	0.98
	3	0.009	0.001	0.003	0.98
	4	0.009	0.007	0.02	0.95
	5	0.009	0.01	0.03	0.94
	10	0.016	0.014	0.04	0.92
	20	0.02	0.019	0.05	0.90
GDP	1	0.00	0.00	1.00	0.00
	2	0.001	0.002	0.96	0.03
	3	0.004	0.002	0.95	0.03
	4	0.004	0.06	0.88	0.05
	5	0.003	0.11	0.84	0.039
	10	0.03	0.14	0.77	0.05
	20	0.03	0.15	0.76	0.05
Quick ratio	1	0.00	1.00	0.00	0.00
	2	0.07	0.91	0.002	0.001
	3	0.10	0.87	0.007	0.008
	4	0.13	0.83	0.011	0.019
	5	0.18	0.75	0.034	0.03
	10	0.19	0.70	0.05	0.04
	20	0.21	0.67	0.06	0.04
Variance degree	1	1.00	0.00	0.00	0.00
	2	0.97	0.01	0.02	0.002
	3	0.93	0.02	0.03	0.0029
	4	0.84	0.049	0.089	0.01
	5	0.80	0.07	0.09	0.03
	10	0.78	0.13	0.05	0.03
	20	0.78	0.13	0.05	0.029

Note: Table reports Forecast Error Variance Decomposition (FEVD) of the interest rate/GDP/quick ratio/variance degree system for 20 time periods.

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