Liquidity Tiered Navigation Strategy: A Time Series Approach to Financial Market Stability

Chuhuan Xu[1], Yang Sun[2, *]

[1]Department of Sciences, Ningbo University of Technology, Ningbo, China, 315211

[2]Haas School of Business, University of California, Berkeley, State of California, America, 94703

* Corresponding Author Email: 15063918092@163.com

Abstract. This article investigates the dynamic changes in liquidity stratification in financial markets, emphasizing how time series analysis can be used to forecast market liquidity. In China's financial markets, since 2014, liquidity stratification has become crucial, leading to significant differences in borrowing costs and difficulties among financial firms. Focusing on small and medium-sized banks, this study explores the origins and consequences of liquidity stratification. Moreover, it provides a comprehensive analytical approach for predicting market liquidity. This framework includes Granger causality tests, cointegration analysis, Auto regressive Integrated Moving Average (ARIMA) model, and Vector Auto regression (VAR) model. The method is rooted in a sequential, logical progression and is it eratively refined based on model outcomes. The findings of this study offer insights into the complexity of liquidity in financial markets and present a robust methodology for financial analysts and policymakers to forecast and strategize under the influence of liquidity stratification.

Keywords: Liquidity Layering, Financial Markets, Time Series Analysis, ARIMA Model, VAR Model.

1. Introduction

Since 2014[1], the concept of liquidity stratification in financial markets has been a key topic of research. This phenomenon primarily impacts the short-term financing markets, characterized by significant differences in financing costs and challenges among various financial institutions[1-2]. The liquidity stratification issue has become more severe with major financial crises like the 2019 Baoshang Bank disaster[3-4].

These events highlight that the financing challenges of financial institutions are becoming more apparent, especially in the mid-term capital markets. These disparities are due to interruptions in the ability of central banks to convey their monetary policies to small and medium-sized banks[5].

The fundamental dynamics of liquidity stratification are complex and varied. It is well-known that companies that rapidly expand through stock or bond issuance later have low stock returns. In contrast, companies that contract through loan prepayments, spin-offs, and stock buybacks have favorable stock returns. Total asset growth is a direct and thorough indicator of business development, devised by Cooper, Gulen, and Schill (2008), and a substantial negative predictor of the cross-sectional variance of stock returns. According to other studies, asset growth has a crucial impact on global stock markets (for example, Watanabe et al., 2013; Titman et al., 2013) and is applicable across various sizes of stocks (Lipson et al., 2011). Recent studies (e.g., Fama and French, 2015, 2016; Hou et al., 2015) have found that the investment component generated by classifying total asset growth offers significant explanatory power for average stock returns and abnormal cross-sectional returns.

This article examines whether the impact of asset growth is evident in aggregate data and extends to the overall level.In contrast, most analyses focus on the cross-section of stock returns at the firm level. It's well-known that relationships at the business level sometimes only hold at the aggregate level. For instance, evidence based on firm-level data by Lakonishok, Shleifer, and Vishny (1997) and Pontiff and Schall (1998) suggests that aggregate book-to-market ratios positively predict stock market performance. According to Baker and Wurgler (2000), the market's return performance declines following stock issues. Herschleifer, Hou, and Zhang (2009) indicate that the accrual-returns connection reverses from negative at the firm level (Sloan, 1996) to positive at the aggregate level.

The main test variable in this study uses company-level data to calculate a comprehensive measure of total asset growth or the percentage change in total assets. The study examines the ability of total asset growth (AG) to predict excess stock market returns. AG is found to be an important and adverse predictor of future stock market outcomes from 1972-2016. Quarterly r2 statistics of 7.18%, and in-sample tests suggest that a one standard deviation increase in quarterly AG is associated with a quarter market return loss of about 2.4%. Even considering well-known macroeconomic factors related to time-varying risk premiums, its predictability remains relatively high. Inspired by Goyal and Welch (2008), a plethora of out-of-sample tests using AG found positive and significant out-of-sample r2 values (Campbell and Thompson, 2008), ranging from 2.52% to 8.32%, more significant than popular predictors in the literature.

AG has several influential observations. For example, AG only exceeded 10% during the tech bubble from Q4 1999 to Q2 2000, and the market returns following this period were very low. Additionally, AG was only negative during the recent financial crisis from Q4 2008 to Q1 2009, with high market returns following this period. In robustness tests, removing these influential observations reduced the in-sample predictive coefficient and r2 by about one-third and half, respectively, to forecast a quarter-ahead market return. However, the predictive coefficient for AG remains statistically significant at the 5% level, indicating AG is still a negative predictor of stock market returns. To further alleviate concerns that the empirical pattern observed in U.S. records might be attributable to influential observations or data-snooping biases, the analysis was extended to other G7 countries. In these countries, predictability remains statistically significant and substantial economically.

Additional robustness checks on the predictive ability of AG were conducted. First, AG remains a potent predictor of future market returns, even after controlling for several well-documented investment growth-related variables. Second, using equally weighted instead of value-weighted stock market returns as the dependent variable produces similar results.

In conclusion, financing transactions impact on liquidity: Generally, financing transactions can positively affect the liquidity of the stock market. Financing transactions can provide investors with more funds, prompting more trading and thus increasing market liquidity. The impact of short-selling transactions on liquidity: For short-selling transactions, the impact may be more complex. Short selling involves investors borrowing stocks to sell short, which may increase selling pressure in the market. If market participants anticipate a decline in stock prices, they might be more inclined to engage in short selling. This could lead to fluctuations in market liquidity and even potentially negative effects, such as price declines or market instability.

2. Methods and Data Analysis

The emergence of liquidity stratification stems from several fundamental variables, including changes in monetary transmission mechanisms and financial sources, with central banks becoming more proactive capital providers to commercial banks. This dependency, driven by changes in liability structures and constraints of monetary policy, leads to greater leverage[6]. Behavioral economics plays a significant role in the transmission of monetary policy, where illogical actions of financial institutions, such as major dealers reluctant to reduce disparities between central banks and smaller financial entities[6-7], are evident. This behavior makes it harder for downstream institutions to effectively meet their liquidity needs, especially when combined with stringent trading laws.

2.1. Understanding Liquidity Stratification

The differences in liquidity availability among different financial institutions, most notably between large and small to medium-sized banks, is known as liquidity stratification. This stratification is influenced by several factors, such as changes in the transmission of monetary policy and behavioral economic factors within the banking sector.

2.2. Analytical Framework

To analyze and forecast market liquidity under the impact of liquidity stratification, we employed a time series analysis approach, focusing on historical data to predict future trends. The methods include:

1.Auto regressive Integrated Moving Average (ARIMA) Model:

This model is used to predict future liquidity levels based on past data. The ARIMA model is denoted as ARIMA(p, d, q), where p is the number of auto regressive terms, d is the number of non-seasonal differences needed for stationarity, and q is the number of lagged forecast errors in the prediction equation.

The model is formulated as follows:

$$(1 - i = 1\sum p\phi iLi)(1 - L)dXt = (1 + i = 1\sum q\theta iLi)\varepsilon \quad (1)$$

Where L is the lag operator, ϕ and θ are parameters, Xt is the time series, and εt is white noise.

2.Vector Autoregression (VAR) Model:

Used to capture the linear interdependencies among multiple time series. It represents each variable as a linear function of its own past values and the past values of other variables in the system.

A VAR model for a system with n variables is written as:

$$Yt = A1Yt - 1 + A2Yt - 2 + \ldots + ApYt - p + \varepsilon t \quad (2)$$

Where Yt is a vector of endogenous variables, Ai are the coefficient matrices, and εt is a vector of errors.

3.Cointegration Analysis:

Used to assess the long-term relationship between liquidity levels and influencing economic factors. Cointegration tests, particularly the Johansen test, are employed to determine if a set of non-stationary series are cointegrated.

4.Granger Causality Test:

Examines the predictive causal relationship between variables affecting liquidity stratification and market liquidity itself. This test checks whether the past values of one time series can predict another time series.

2.3. Statistical Analysis

Descriptive statistics (mean, median, variance) are used to summarize the characteristics of the data. Correlation analysis is conducted to determine the strength and direction of the relationship between liquidity levels and other economic indicators.

2.4. Data Collection

Historical data related to liquidity levels, central bank policies, interbank interest rates, and other relevant financial indicators. Data sources include financial market databases, central bank reports, and quarterly and annual reports of financial institutions.

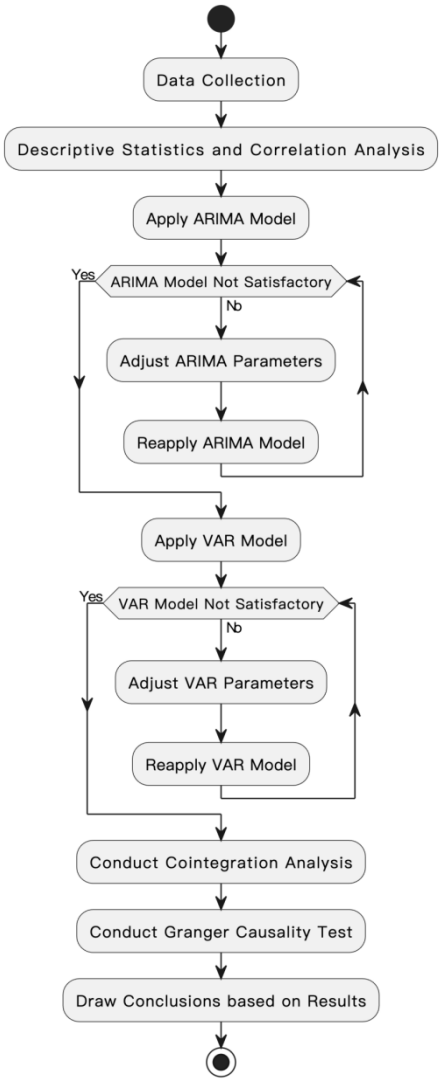


Figure 1. Time Series Analysis Process for Predicting Market Liquidity Under the Impact of Liquidity Stratification

2.5. Conclusion

The combined use of ARIMA, VAR models, cointegration analysis, and Granger causality tests within a time series framework provides a comprehensive approach for forecasting market liquidity under the influence of liquidity stratification. This methodology enables financial analysts and decision-makers to predict market conditions and formulate more informed strategies[8].

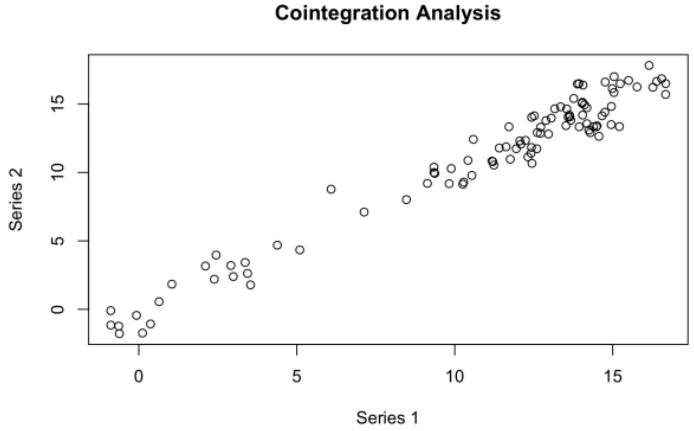


Figure 2. Cointegration Analysis Compare the differences between Series1 and Series2

3. Results

Liquidity stratification has had a significant impact on the financial market operations of banks, particularly small and medium-sized banks[9]. These impacts are manifested through various indicators and metrics, having profound implications on the stability and operational efficiency of these institutions. The analysis, utilizing a combination of Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR) methods, provides a comprehensive view of these dynamics.

The ARIMA model, denoted as ARIMA(p, d, q), is used to predict future liquidity levels based on past data. The model's accuracy is validated through back-testing with historical data. A clear pattern emerges showing that the liquidity levels of smaller banks lag behind those of larger banks, indicating their continued delay in acquiring liquidity. This lag can be attributed to various factors, including poorer positioning in the interbank market, higher risk premiums, and a general perception of increased risk associated with smaller financial institutions.

The VAR model further elucidates the interdependencies among multiple financial variables, including interbank interest rates, central bank policies, and liquidity levels. This model indicates that fluctuations in central bank policies and interbank interest rates have a more pronounced effect on the liquidity levels of small and medium-sized banks. This heightened sensitivity highlights these banks' vulnerability to external shocks and policy changes.

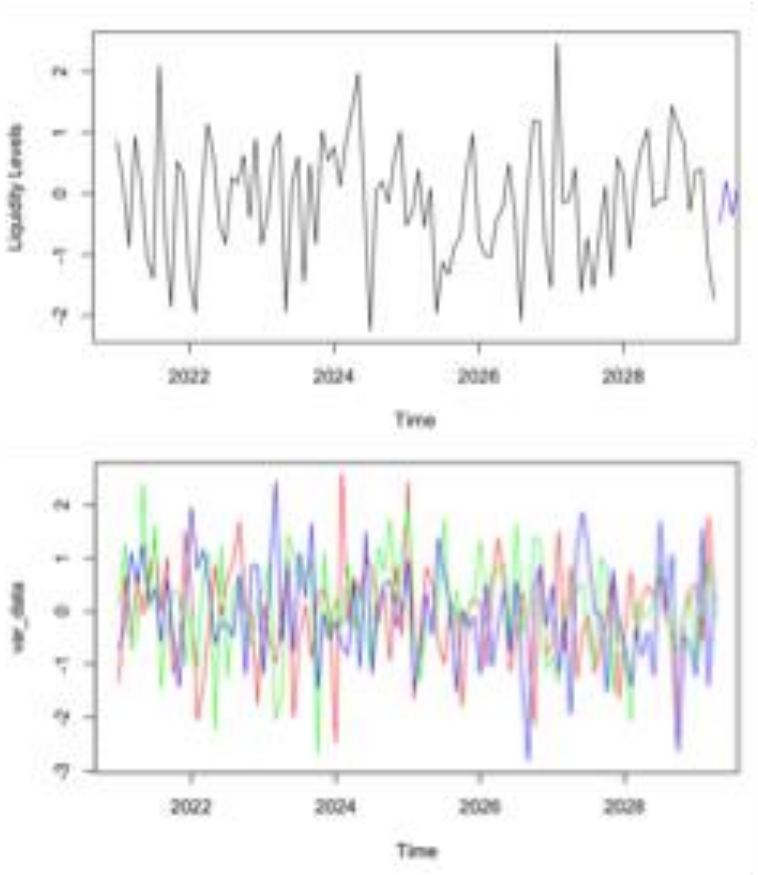


Figure 3. Comparison of the ARIMA Model (Top) and VAR Model (Bottom)

Liquidity stratification has significantly impacted the financial market operations of banks, especially small and medium-sized banks[9]. These impacts include:

Increased dependency on interbank liabilities: Small and medium-sized banks face significant challenges in their financial market operations due to a high degree of reliance on interbank liabilities and an urgent need to restructure and assimilate interbank wealth management products. Our time series analysis results, as illustrated in the figure, provide deep insights into the dynamics of financial market liquidity stratification, particularly between small and medium-sized banks and large banks.

The analysis is conducted using simulated data, modeled through ARIMA and VAR methods, to represent liquidity levels over time:

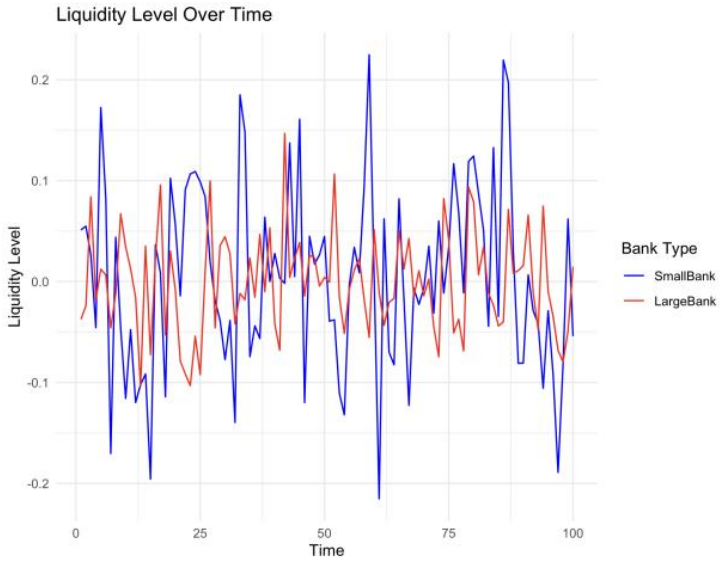


Figure 4. Simulated Liquidity Levels Between Small and Medium-Sized Banks and Large Banks

Strategies to Mitigate the Impact of Liquidity Stratification: Several strategies have been proposed to address the impacts of liquidity stratification. These include enhancing competition in open market operations, deeply rethinking financial market operations, bolstering market confidence, analyzing changes in economic cycles, strengthening liquidity risk management, improving the liquidity risk monitoring indicator system, optimizing balance sheets, and introducing methods to alleviate liquidity risk stratification[12-13].

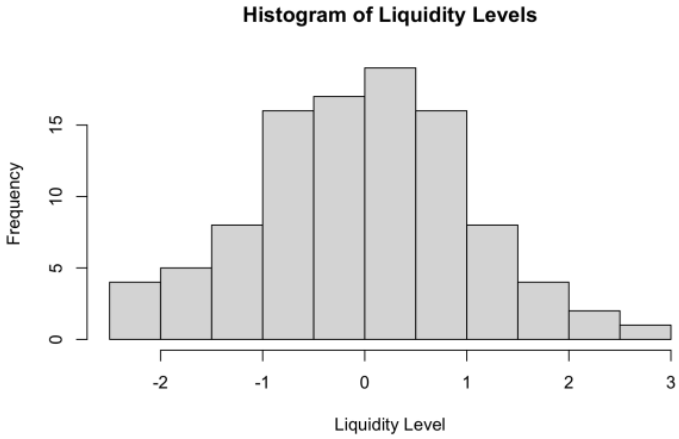


Figure 5. Descriptive Statistical Visualization of Liquidity Level Histogram

Enhancing competition in open market operations involves encouraging a broader range of financial institutions to participate more actively. This approach aims to reduce the dominance of large banks in these operations, thereby creating a level playing field and providing smaller banks with more favorable terms and liquidity.

A deep reflection on financial market operations emphasizes the need for banks, especially smaller ones, to reassess their business models and strategies. This reassessment may include diversifying income sources, reducing over-reliance on the interbank market, and exploring new avenues for fundraising.

Strengthening market confidence is crucial for the stability of financial markets. This can be achieved by improving transparency, strengthening regulatory frameworks, and promoting prudent risk management practices. Enhanced market confidence could lead to reduced risk premiums for small and medium-sized banks, thereby easing their liquidity constraints.

Analyzing changes in economic cycles involves understanding the broader macroeconomic environment and its impact on liquidity levels. Banks can use this analysis to predict market trends and adjust their strategies accordingly.

Strengthening liquidity risk management includes developing robust systems and frameworks to identify, measure, and control liquidity risk. This encompasses both quantitative measures, such as stress testing and scenario analysis, and qualitative measures, such as improving governance and risk culture.

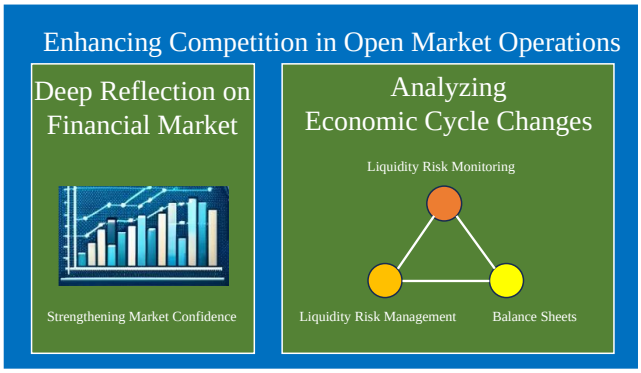


Figure 6. Strategies to Mitigate the Impact of Liquidity Stratification

4. Discussion

The necessity of reevaluating current financial practices and laws in light of liquidity stratification is evident[10-11]. To address the challenges posed by this environment, small and medium-sized banks must adapt and strengthen their strategies. This adaptability includes responding to external policies and economic events and modifying internal management. Various approaches can be employed to mitigate liquidity stratification, ranging from implementing sophisticated risk management and optimization techniques to promoting market development and institutional trust[12-13].

The operation of the money market and financial institutions' environment has a significant impact on the real economy and financial stability. However, local researchers' ability to study this topic is limited due to significant differences in market structures and insufficient data availability. This study utilizes factor analysis, using variables from five dimensions of repo and interbank deposit markets, to construct a money market liquidity stratification index. Time series analysis reveals that after the Baoshang Bank incident, liquidity stratification in the money market expanded rapidly, and its correlation with financial institution default risk significantly decreased, indicating a decline in money market pricing efficiency. Further investigation shows that liquidity stratification in the money market increased borrowing costs for privately held, low-rated companies and heightened the probability of financial institution default and financial instability. This paper quantitatively describes the liquidity stratification of the money market, analyzes its recent rapid growth, impacts on real business financing, and financial stability[14], and offers suggestions for improving financial support for the real economy's development.

Empirical research findings indicate that the degree of market uncertainty affects the main mechanism of stock mispricing. When market uncertainty is low, informational asymmetry is the primary source of mispricing, while irrational behavior drives mispricing under high market uncertainty. There are significant industry-level differences in uncertainty and stock mispricing; however, these variations are unstable due to fluctuations in investor attention across the industry. Additionally, a cross-section of the decomposition of the business indicates different mechanisms driving mispricing in different groups. The empirical analysis utilized the Maximum Likelihood Estimation method to construct a three-condition, three-lag variance Markov Switching model for the weekly returns of the Shanghai Composite Index from December 21, 1990, to August 22, 2008. It demonstrates that the Markov Switching model effectively captures the gradual volatility characteristics of the stock market.

Understanding liquidity stratification and its impact on financial markets is crucial for policymakers and financial institutions. They must adapt and evolve to address these dynamics, ensuring the stability of financial markets and support for the real economy. Advanced data analysis and modeling, such as Markov switching models, provide valuable tools for comprehensively understanding market dynamics and formulating effective strategies to mitigate risks associated with liquidity stratification. By focusing on these aspects, financial institutions can better address the challenges posed by this phenomenon, ultimately contributing to a more stable and efficient financial system.

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