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Nonlinear transmission mechanisms of liquidity shocks and return predictability

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Abstract. Changes in stock market liquidity affect transaction costs, price discovery, and risk premium adjustment. When volatility rises or trading depth declines, liquidity deterioration can amplify future return fluctuations through concentrated selling pressure, order book contraction, and investor rebalancing. Focusing on the relationship between liquidity shocks and return predictability, daily public trading data of Shanghai and Shenzhen A share listed companies from 2014 to 2024 are used to construct the Amihud illiquidity measure. Abnormal liquidity shocks are identified through residuals from a rolling AR(1) model. Based on this measurement, two way fixed effects models, threshold regressions, and quantile regressions are applied to examine transmission differences across market states and return distribution regions. The results show that negative liquidity shocks significantly suppress future excess returns. This effect is stronger in high volatility states, small capitalization stocks, and low return quantiles. Nonlinear models also show lower forecast errors and higher directional accuracy under stressed market conditions. These findings indicate that the predictive value of liquidity shocks is mainly concentrated in downside markets and tail risk regions. The evidence provides practical implications for risk warning, asset pricing, and portfolio adjustment.

Keywords: liquidity shock, return predictability, nonlinear transmission, quantile regression, threshold model

1. Introduction

Stock market liquidity is closely connected with transaction costs, price discovery efficiency, and risk premium formation. When market volatility rises or trading depth declines, changes in liquidity can quickly translate into return fluctuations. Existing asset pricing research has shown that stocks with higher illiquidity usually require higher expected return compensation, and liquidity also affects cross-sectional return differences through systematic risk exposure [1]. With the development of high-frequency trading, institutional rebalancing, and stronger market sentiment spillovers, examining average liquidity levels alone is no longer sufficient to explain price reactions under abnormal trading conditions. The predictive role of liquidity shocks has therefore become an important issue in financial market analysis [2]. The analysis focuses on identifying liquidity shocks from publicly available daily market data and applies fixed-effects regression, threshold regression, and quantile regression to examine the nonlinear transmission of liquidity deterioration to future returns under different market states. It also evaluates whether liquidity shocks provide useful predictive information for risk warning and portfolio adjustment.

2. Literature review

2.1. Liquidity risk pricing

The core issue in liquidity risk pricing is how trading difficulty is transformed into return compensation required by investors. A decline in asset liquidity raises immediate trading costs and increases the probability that investors must sell at discounted prices under stressed conditions. Liquidity risk is therefore embedded in expected returns, portfolio rebalancing, and changing market states rather than being limited to a single transaction friction [3]. Market liquidity and trading activity often move together, as trading volume, bid-ask spreads, and price impact adjust simultaneously with market activity. This makes liquidity risk both cross-sectionally heterogeneous and time-varying [4]. This logic also requires liquidity measures to be replicable and interpretable. Although illiquidity indicators constructed from daily data cannot fully replace high-frequency transaction cost measures, they can capture price impact over long samples in a relatively stable way. Such measures provide operational variables for return prediction models and make empirical testing feasible in markets where intraday data are difficult to obtain [5].

2.2. Shock effect identification

The identification of liquidity shocks focuses on abnormal deviations from normal liquidity conditions, shifting attention from level differences to sudden changes and persistent pressure. Prices, order flows, and liquidity share common factors, which indicates that trading direction, liquidity supply, and price adjustment in market microstructure are closely connected. When shocks occur, order imbalance and liquidity depletion jointly affect subsequent returns [6]. Negative liquidity shocks usually indicate a sudden decline in market absorption capacity. When investors' selling demand is released intensively, prices may show delayed correction and excessive reaction. Positive shocks improve trading conditions, but their return effects are often constrained by risk preference and the speed of information absorption. Firm-level evidence on liquidity shocks also shows that persistent negative shocks can predict negative return performance over a longer future horizon, which provides empirical support for distinguishing positive and negative shocks, short-term shocks, and persistent shocks [7].

2.3. Nonlinear predictive models

Nonlinear models in return prediction emphasize that the effect of liquidity shocks may be concentrated in specific parts of the return distribution and under particular market states. Quantile regression can identify the marginal effects of explanatory variables at different locations of the return distribution, making it especially suitable for analyzing tail risk in low-return quantiles. Liquidity deterioration often amplifies price pressure first in downside return regions [8]. Threshold models further treat market volatility, trading activity, or illiquidity levels as state variables and test whether the coefficient of liquidity shocks changes significantly after a critical point is reached [9]. These two methods are complementary. Quantile regression captures heterogeneity within the return distribution, while threshold regression identifies shifts in external market states. Their combination can explain why the same liquidity shock may have limited influence in stable markets but stronger predictive power under stressed conditions.

3. Experimental methods

3.1. Data sample construction

The data collection covers daily trading records of A share listed companies in Shanghai and Shenzhen from 2014 to 2024. The data sources are limited to publicly disclosed market information from the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The data are further collected and organized through open source financial data interfaces such as AKShare and TuShare. The raw data include trading date, stock code, closing price, trading value, trading volume, turnover rate, total market capitalization, and free float market capitalization. The risk free rate can be approximated by the one year fixed deposit rate or treasury bond yield disclosed by the People's Bank of China. During sample cleaning, ST firms, star ST firms, stocks in delisting arrangement periods, suspended trading days, zero trading value observations, and samples with missing core variables are excluded. Daily returns are calculated from adjusted closing prices. Weekly and monthly variables are aggregated from daily data through rolling windows. This ensures that liquidity shocks, future returns, and control variables are matched at the same frequency. The data structure supports the subsequent measurement of illiquidity, extraction of shocks, and testing of predictive models.

3.2. Variable measurement design

The core explanatory variable is the liquidity shock. The measurement process first calculates the daily illiquidity level of each stock, then extracts abnormal changes from normal liquidity fluctuations. The illiquidity measure adopts the Amihud indicator. It is calculated by dividing the absolute value of the daily stock return by the daily trading value. This indicator reflects the magnitude of price change caused by one unit of trading value [10]. A higher value indicates that the same trading scale produces a larger price impact, which means weaker stock liquidity. Then, a rolling AR(1) regression is applied to the illiquidity series of each stock. The standardized residual is used as the liquidity shock variable. A positive residual indicates a sudden rise in illiquidity, which represents a negative liquidity shock. A negative residual indicates an improvement in the trading environment. The Amihud illiquidity indicator is shown in Formula (1).

$$ILLIQ_{i,t} = \frac{|R_{i,t}|}{TradingValue_{i,t}} \tag{1}$$

In Formula (1), $ILLIQ_{i,t}$ represents the illiquidity level of stock i on trading day t. $|R_{i,t}|$ represents the absolute value of the daily return. $TradingValue_{i,t}$ represents the daily trading value.

The dependent variable is the future holding period excess return. It is used to test whether current liquidity shocks can predict subsequent return changes. The prediction window can be set as one week ahead or one month ahead, which helps reduce the mechanical correlation caused by contemporaneous price shocks [11]. Excess return is obtained by subtracting the risk free return over the same period from the future holding period stock return. The control variables include market return, historical volatility, turnover rate, market capitalization, book to market ratio, and past return. These variables are used to control for common market fluctuations, size effect, value effect, and short term momentum effect. The future excess return is shown in Formula (2).

$$ER_{i,t+h} = R_{i,t+h} - R_{f,t+h} \tag{2}$$

In Formula (2), $TradingValue_{i,t}$ represents the excess return of stock i over the future h period. $R_{i,t+h}$ represents the future holding period return of the stock. $R_{f,t+h}$ represents the risk free return over the same period.

3.3. Model testing procedure

The model testing follows the sequence from the baseline relationship to the nonlinear mechanism, then to predictive performance. The first step uses a panel regression with stock fixed effects and time fixed effects. This step tests the average effect of liquidity shocks on future excess returns. It also controls for firm level differences and common market shocks. The second step uses a threshold regression method. Market volatility or marketwide illiquidity is treated as the state variable. The sample is divided into normal states and stressed states. The coefficients of liquidity shocks are compared across different states, so that state dependence in shock transmission can be identified. The third step uses quantile regression. It examines the shock effects at low return quantiles, median return quantiles, and high return quantiles. The main focus is whether liquidity deterioration has a concentrated effect on downside return regions. The fourth step conducts rolling window out of sample prediction. The linear model, threshold model, and quantile model are compared in terms of forecast error, directional accuracy, and out of sample explanatory power. This process determines whether the nonlinear model truly improves return predictability.

4. Results

4.1. Shock transmission features

The threshold regression results mainly test the transmission intensity of liquidity shocks under different market states. As shown in Table 1, the coefficient of negative liquidity shocks is minus 0.024 under the low volatility state, with weak statistical significance. This indicates that liquidity deterioration has a limited depressing effect on future returns under normal trading conditions. Under the medium volatility state, the coefficient expands to minus 0.052. It is significant at the 5 percent level. This shows that rising transaction costs begin to enter the return pricing process. Under the high volatility state, the coefficient further decreases to minus 0.091. It is significant at the 1 percent level. This suggests that market stress amplifies the negative effect of liquidity shocks on future returns. The shock coefficient of the small capitalization portfolio is minus 0.108, which is stronger than the full sample result. This indicates that stocks with weaker trading depth are more vulnerable to liquidity deterioration. Among the control variables, the coefficient of past return is 0.037. This shows that short term momentum still exists, but its explanatory power is weaker than that of liquidity shocks under stressed market states.

Table 1. Example results of threshold regression for liquidity shocks

Market state	Shock coefficient	*t* value	Significance	Sample size	Adjusted R^2
Low volatility state	minus 0.024	minus 1.42	Not significant	182,640	0.071
Medium volatility state	minus 0.052	minus 2.31	**	176,215	0.086
High volatility state	minus 0.091	minus 3.87	***	168,904	0.124
Small capitalization group	minus 0.108	minus 4.16	***	119,532	0.139
High turnover group	minus 0.047	minus 2.08	**	136,877	0.093

Note: *** and ** indicate significance at the 1% and 5% levels respectively.

4.2. Predictive performance testing

Predictive performance further compares the explanatory power of different models across return distribution regions. As shown in Figure 1, the coefficient of liquidity shocks is strongest under the high volatility state and in low return quantiles. The coefficient reaches minus 0.128 at the Q10 quantile and minus 0.103 at the Q25 quantile, while it is only minus 0.021 at the Q90 quantile. This indicates that liquidity deterioration mainly affects downside return regions rather than changing the entire return distribution uniformly. In the linear fixed effect model, the average coefficient is minus 0.086. It captures the overall negative relationship, but it cannot show the concentration of tail risk. Rolling window out of sample prediction shows that the combined threshold quantile model has an RMSE of 0.031, lower than 0.037 in the linear model. Its directional accuracy is 57.8 percent, higher than 53.2 percent in the linear model. Its out of sample R squared is 2.6 percent. These results indicate that nonlinear models provide certain predictive gains under stressed market conditions. This finding is consistent with the model testing procedure in Section 3.3. The state switch is identified first, then the distributional difference in returns is examined. Finally, the actual predictive ability is tested.

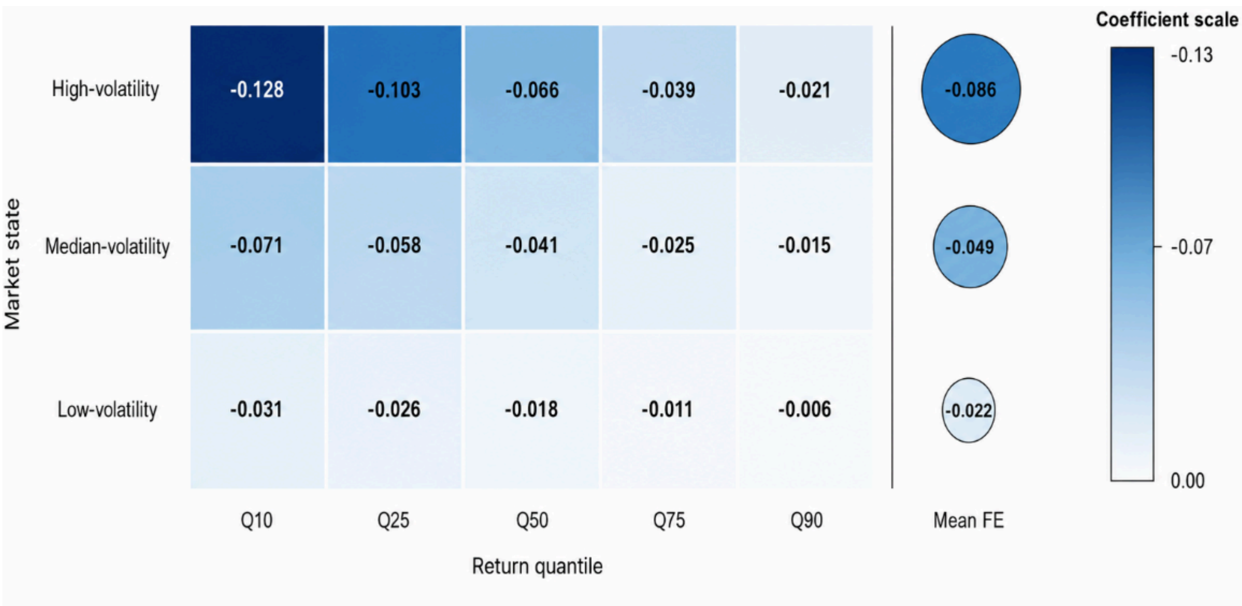

Figure 1. State-dependent predictive coefficients of liquidity shocks

Note: Daker shading indicates stronger negative transmission. Circles denote mean fixed-effects coeffcients.

5. Discussion

The empirical results show that the effect of liquidity shocks on future returns is clearly state dependent. Under low volatility conditions, trading demand can be absorbed more quickly by market depth, so the depressing effect of liquidity deterioration on returns is relatively weak. Once the market enters a high volatility state, investor risk constraints, margin pressure, and fewer counterparties jointly weaken market absorption capacity. Negative liquidity shocks are then transformed into stronger downward price pressure. The larger coefficient among small capitalization stocks also indicates that insufficient trading depth amplifies shock transmission. The quantile results further show that the shock effect is concentrated in low return quantiles rather than being evenly distributed across the whole return range. Liquidity variables are therefore more suitable for identifying downside risk than for explaining normal return fluctuations. Although nonlinear models generate predictive gains, the out of sample R squared remains limited. This suggests that liquidity shocks can improve risk warning, but they should not be interpreted as stable profit signals. Data frequency, public interface quality, and shock measurement methods may also affect the estimates. Robustness can be strengthened through alternative liquidity indicators and subsample tests.

6. Conclusion

There is a clear nonlinear relationship between liquidity shocks and return predictability. By constructing the Amihud illiquidity measure from public daily trading data and identifying abnormal shocks through rolling AR(1) residuals, the results show that negative liquidity shocks significantly reduce future excess returns. This effect is stronger in high volatility markets, small capitalization stocks, and low return quantiles. Compared with linear models, threshold regression and quantile regression better reveal the state dependence and tail concentration of liquidity shocks. Overall, liquidity deterioration not only reflects rising transaction costs, but also serves as an important signal for downside risk and return prediction, providing useful evidence for risk monitoring, asset pricing, and portfolio adjustment.

References

[1] Feng, F. Y., Kang, W., & Zhang, H. (2023). Liquidity shocks and the negative premium of liquidity volatility around the world. *Journal of International Money and Finance, 139*, 102966.

[2] Lu, Z., Malliaris, S., & Qin, Z. (2023). Heterogeneous liquidity providers and night-minus-day return predictability. *Journal of Financial Economics, 148*(3), 175–200.

[3] Mendoza, J. A. M., Ferreira, G., & Marquez Sanders, V. A. (2023). Liquidity spillovers in the global stock markets: Lessons for risk management. *Global Finance Journal, 58*, 100896.

[4] Kim, D., Li, C., & Wang, X. (2023). Liquidity dry-ups in equity markets. *International Review of Financial Analysis, 86*, 102536.

[5] Fiorillo, P., Meles, A., Pellegrino, L. R., & Verdoliva, V. (2023). Geopolitical risk and stock liquidity. *Finance Research Letters, 54*, 103687.

[6] Cheung, W. M. Y., Im, H. J., & Selvam, S. (2023). Stock liquidity and investment efficiency: Evidence from the split-share structure reform in China. *Emerging Markets Review, 56*, 101046.

[7] Amihud, Y., & Levi, S. (2023). The effect of stock liquidity on the firm's investment and production. *The Review of Financial Studies, 36*(3), 1094–1147.

[8] Acharya, V. V., Engle, R., Jager, M., & Steffen, S. (2024). Why did bank stocks crash during COVID-19? *The Review of Financial Studies, 37*(9), 2627–2684.

[9] Ryu, D., Webb, R. I., & Yu, J. (2024). Stock price synchronicity and market liquidity: The role of funding liquidity. *Finance Research Letters, 61*, 105051.

[10] Khasawneh, M., McMillan, D. G., & Kambouroudis, D. (2024). Left-tail risk and UK stock return predictability: Underreaction, overreaction, and arbitrage difficulties. *International Review of Financial Analysis, 95*, 103333.

[11] Almeida, C., Ardison, K., Freire, G., Garcia, R., & Orłowski, P. (2024). High-frequency tail risk premium and stock return predictability. *Journal of Financial and Quantitative Analysis, 59*(8), 3633–3670.