Liquidity Measures for Cryptocurrency Markets: Traditional Estimators and Machine Learning Approaches

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Abstract

This study aims to provide an analysis of liquidity across a wide range of cryptocurrencies, going beyond well-known assets like Bitcoin and Ethereum to include smaller capitalization and less liquid cryptocurrencies. We examine and compare different methods for estimating liquidity and spread. Traditional liquidity measures, such as those proposed by Corwin & Schultz (2012) and Abdi & Ranaldo (2017), are evaluated alongside machine learning techniques. We use highfrequency data to compute benchmark liquidity measures, which serve as the basis for assessing the accuracy of both traditional and machine learning estimators. In addition, we examine the robustness of these measures during periods of higher market volatility.

Keywords: cryptocurrency markets, machine learning, liquidity, spread estimation *JEL codes:* G11, G12, G17

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The cryptocurrency market presents unique challenges in measuring liquidity due to the lack of standardized metrics and the fragmented nature of trading across multiple exchanges. Cryptocurrencies are traded on hundreds of platforms[1], each with its own order book and liquidity profile. Furthermore, cryptocurrencies can be traded 24 hours a day, seven days a week against fiat currencies and other cryptocurrencies (Brauneis et al., 2021). This fragmentation requires empirical verification of models originally proposed for equity markets to assess their applicability and accuracy in the cryptocurrency context.

Many studies highlight the potential for higher returns from illiquid cryptocurrencies. Zhang and Li (2023) show a negative relationship between liquidity and expected returns in the cryptocurrency market. Specifically, cryptocurrencies with higher liquidity in a given week tend to have lower returns in the following week. Han (2023) argue that cryptocurrencies with high liquidity risk (beta) earned a risk-adjusted return that was 4.4% higher per week than those with low liquidity risk, after controlling for market, size, and reversal factors. Zaremba et al. (2021) show a daily reversal effect, but the pattern is cross-sectional by liquidity, and the handful of largest and most tradable coins show daily momentum rather than reversal. If alphas are concentrated in hard-to-trade assets and critically dependent on harvesting extreme returns on small, illiquid, and volatile coins (see also Cakici et al., 2024), an important consideration is whether these returns remain attractive after accounting for the higher transaction costs prevalent in this market.

Assessing liquidity is critical to developing robust investment strategies, as liquidity directly affects transaction costs and the ability to enter or exit positions without significant price impact. From a market efficiency perspective, understanding liquidity dynamics helps assess the extent to which cryptocurrency markets are efficient and where inefficiencies may lie. In addition, exploring whether machine learning methods can outperform traditional liquidity estimation techniques offers a promising avenue of research. Machine learning models, with their ability to uncover complex patterns, may provide more accurate and timely liquidity forecasts, thereby enhancing understanding and practical applications in trading and risk management.

[1] As of June 2024, the website https://coinmarketcap.com/rankings/exchanges/ listed 252 spot exchanges, 101 derivatives exchanges, and 492 decentralized exchanges.

References

Abdi, F., & Ranaldo, A. (2017). A Simple Estimation of Bid-Ask Spreads from Daily Close, High, and Low Prices. *The Review of Financial Studies*, *30*(12), 4437–4480. https://doi.org/10.1093/rfs/hhx084

Brauneis, A., Mestel, R., Riordan, R., & Theissen, E. (2021). How to measure the liquidity of cryptocurrency markets? *Journal of Banking & Finance*, *124*, 106041. https://doi.org/10.1016/j.jbankfin.2020.106041

Cakici, N., Shahzad, S. J. H., Będowska-Sójka, B., & Zaremba, A. (2024). Machine learning and the crosssection of cryptocurrency returns. *International Review of Financial Analysis*, *94*, 103244. https://doi.org/10.1016/j.irfa.2024.103244

Corwin, S. A., & Schultz, P. (2012). A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. *The Journal of Finance*, *67*(2), 719–760. https://doi.org/10.1111/j.1540-6261.2012.01729.x

Han, S. (2023). Is liquidity risk priced in cryptocurrency markets? *Applied Economics Letters*, *30*(17), 2481–2487. https://doi.org/10.1080/13504851.2022.2098235

Zaremba, A., Bilgin, M. H., Long, H., Mercik, A., & Szczygielski, J. J. (2021). Up or down? Short-term reversal, momentum, and liquidity effects in cryptocurrency markets. *International Review of Financial Analysis*, *78*, 101908. https://doi.org/10.1016/j.irfa.2021.101908

Zhang, W., & Li, Y. (2023). Liquidity risk and expected cryptocurrency returns. *International Journal of Finance & Economics*, *28*(1), 472–492. https://doi.org/10.1002/ijfe.2431