The Impact of Liquidity and Volatility Weighting on Risk-Adjusted Portfolio Performance

Minghe Liu *

School of Management, University College London, London, WC1E 6BT United Kingdom

* Corresponding Author Email: zceiml1@ucl.ac.uk

Abstract. The following research develops methodologies of portfolio construction focused on liquidity and risk-adjusted return maximization. It considered a dataset comprising 40 stocks from the S&P 500, S&P 400, and S&P 600 indices for five years, 2019-2024, and compared three different weighting schemes: filtered risk-adjusted weighting, equal weighting, and non-filtered risk-adjusted weighting. Each strategy is compared by looking at annualized return, volatility, Sharpe ratio, and transaction cost. The methodologies used include filtering based on liquidity, calculating weight inversely proportional to the volatility, and implementing an equal-weighted allocation. As opposed to the nonfiltered strategy, which uses all stocks to maximize diversification, filtered and equal-weighted methodologies will be targeting subsets of very specific stocks. The results indicate that the non-filtered strategy has the highest annualized return, 6.30%, and Sharpe ratio, 4.817, among the three methods, although it has higher transaction costs than the other two. On the other hand, the filtered strategy, though cost-efficient, underperforms due to limited diversification. Equal weighting is simple but not optimized for risk-adjusted returns. This research emphasizes how paramount liquidity considerations are in portfolio strategies. Perhaps future research might develop dynamic allocation models based on real-time data and machine learning techniques. Such a development would increase portfolio performance, while keeping a balance of cost efficiency with diversification.

Keywords: Portfolio Construction, Liquidity, Risk-Adjusted Return, S&P Indice.

1. Introduction

Portfolio construction stands at the heart of investment management; it's the bridge that connects the gap between abstract financial theory and its applications. The science basically works around how to balance risk versus return, as highlighted by Harry Markowitz in his Modern Portfolio Theory. Markowitz showed that one could, through diversification or allocation of capital across various assets, diminish portfolio risk without necessarily sacrificing returns [1]. While MPT laid the foundational framework, further studies pointed to several weaknesses, particularly the static nature of the risk analysis and the general undervaluing of liquidity as a portfolio determinant.

Liquidity-or the ability to buy or sell an asset without significantly moving its price-is a critical determinant of portfolio performance. Amihud and Mendelson observed that there is typically a premium on illiquid assets, which compensates investors for the higher transaction costs and potential delays in execution [2]. Building on this simple backbone, Bali et al. examined the influence of liquidity dynamics on asset pricing and documented that the inclusion of liquidity factors could reward portfolio returns [3]. Similarly, Chordia et al. found that liquidity shocks covary with market-wide risk, hence a two-edged sword [4].

Portfolio construction has become more dynamic with recent developments in data analytics and computational finance. This technique, together with the predictions based on machine learning, has equipped investors with the capability to factor in variables in volatility, liquidity, and even transaction costs in real time. Works such as those of Frazzini and Pedersen illustrated how risk-adjusted weighting outperformed the equal-weighted and capitalization-weighted benchmarks [5]. Despite all these developments, the interaction between liquidity and portfolio optimization remains a relatively unexplored area of study, particularly in cases that involve combined long and short positions.

The relation between liquidity and asset pricing has been one of the common themes in financial research. Pastor and Stambaugh 2003 presented a model that relates liquidity risk to expected returns, postulating that investors demand higher compensation for those assets that are susceptible to liquidity shocks [6]. Goyenko et al. extended this concept and tested various liquidity measures and found that simple proxies of liquidity, such as trading volume and bid-ask spreads, are often very effective proxies for liquidity risk [7].

Another strand of the literature focuses on portfolio weighting schemes. Probably the simplest, equal weighting-which assigns an identical percentage of one's capital to each asset-has seen widespread adoption due to its simplicity. DeMiguel et al. compared equal weighting with optimization-based methods [8]. Their findings indicated that equal-weighted portfolios often outperform due to their inherent diversification benefits. However, equal weighting does not take into consideration the risk and return characteristics of individual assets, which seriously limits its applicability in more sophisticated investment strategies.

Risk-adjusted weighting, by contrast, addresses this limitation by allocating weights inversely proportional to asset volatility. This approach, as illustrated by Maillard et al., minimizes portfolio risk while maintaining exposure to high-performing assets. Yet, risk-adjusted weighting strategies rarely consider liquidity explicitly, raising questions about their applicability in real-world scenarios characterized by fluctuating market conditions [9].

This paper investigates portfolio construction strategies that incorporate liquidity considerations into traditional allocation approaches. Precisely, this paper compares three different strategies:

Firstly, Filtered Risk-Adjusted Weighting: A strategy that selects assets based on their liquidity metrics, focusing on the top 5 most liquid and bottom 5 least liquid stocks every month.

Secondly, Equal Weighting: A simplified allocation approach that ignores liquidity and risk, allocating equal weights to all assets.

Thirdly, Non-Filtered Risk-Adjusted Weighting: This strategy includes all assets without filtering, maximizing diversification while accounting for volatility.

Through these strategies, this paper aims to investigate:

The impact of liquidity filtering on portfolio returns and transaction costs.

Whether equal weighting can serve as a viable alternative to more complex allocation methods.

The performance of non-filtered risk-adjusted weighting, considering its transaction costs and overall efficiency.

The remainder of this paper is organized as follows: Section 2 explains the methods used, detailing data collection, the implementation of each strategy, and the computational techniques for returns, volatility, and transaction costs. Section 3 presents the results, highlighting performance metrics for each strategy through comparative tables and charts. Section 4 discusses the implications of the findings, evaluating the strengths and limitations of each approach. Finally, Section 5 concludes by summarizing the study's contributions, acknowledging its limitations, and proposing directions for future research. By integrating literature insights and empirical analysis, this study advances the understanding of liquidity's role in portfolio optimization and provides actionable recommendations for investors and fund managers.

2. Methods

It thus follows that this research adopted a holistic construction approach. At the same time, this paper applied an integrated methodology of construction and performance evaluation of the portfolio strategies based on liquidity premiums, therefore allowing for a strong analysis across different market conditions. This would include systematic data gathering, scrupulous portfolio construction, thoughtful rebalancing strategies, and rigorous performance metrics evaluation. Each of these steps was designed to consider the dynamic nature of financial markets and to deliver actionable insights toward the optimization of portfolio performances.

The first step in the research was related to data collection. Using Yahoo Finance and other reliable financial sources, a five-year dataset was compiled, ranging from December 2019 to October 2024. The dataset included stocks from the S&P 500, S&P 600, and S&P 400 indices and thus represents a wide range of large-cap, mid-cap, and small-cap stocks. Monthly trading volumes served as the proxy for liquidity, while adjusted closing prices enabled the computation of daily returns. From these returns, annualized volatilities were calculated as a means of quantifying the level of risk. The monthly ranking of the stocks by their trading volume allows for identifying the most and least liquid stocks. This dynamic approach ensures that the analysis remains relevant to changing market conditions.

The next step was portfolio formation. Stocks were divided into long and short positions depending on their liquidity. Each rankings month, the most liquid stocks were assigned as long positions and the least liquid ones were short, five each. This was based on the liquidity premium hypothesis, which is that the lesser liquid stocks will generally give higher returns that will offset their difficulties in trading. There were mainly two important weighting methodologies applied to the $1 million investment: Risk-adjusted weighting and Equal weighting. In the risk-adjusted weighting method, inverse volatility has been used for calculating the weight of the stock that would eventually decrease the total portfolio risk. In contrast, equal weighting assigned an equal share of the capital to each stock, hence serving as a benchmark for performance comparison. The rebalancing strategies were designed to preserve the intended structure of the portfolio while accounting for market dynamics. Stocks were rebalanced over varying intervals to test the impact of rebalancing frequency on strategy performance. Three rebalancing scenarios considered were: for liquid stocks-monthly rebalancing combined with semiannual rebalancing for illiquid stocks; for liquid stocks-quarterly rebalancing paired with a nine-month rebalancing of illiquid stocks; and semiannual rebalancing for liquid stocks coupled with annual rebalancing for illiquid stocks. Further, transaction costs were added to these scenarios to reflect realistic conditions of trading. Liquid stocks attracted 0.1% of a transaction cost per trade while the illiquid attracted 0.5% higher charges. The costs accrued for five years were then used to evaluate net returns post costs.

The following proxies were utilized for determining strategy performance: Annualized return, Annualized Volatility, and Sharpe Ratio. Annualized returns present the level of profitability by showing the total gain of each strategy for the investment horizon. Annualized volatility captures risk in each strategy by quantifying return fluctuations. The Sharpe ratio, computed by the division of excess returns by those very risks, therefore, subtly portrayed risk-adjusted performance. It aimed to realize an optimum return with controlled risk by benchmarking the metrics across three different scenarios. The risk-adjusted weighting approach, an equally weighted strategy, and a nonfiltered liquidity strategy simply chose stocks independent of their ranking based on liquidity-all were analyzed up against one another. The latter, it was postulated, could provide better diversification and thus higher returns.

One further pivotal constituent of the methodology involved transaction cost analysis. It was done through the computation of transaction costs arising from every rebalancing by multiplying the values of the rebalanced asset by the rates relevant to the transaction cost. This provided the tradeoffs between more frequency-that implies higher costs and is also aligned to present market conditions, and less frequent rebalancing-reduced cost but at possible misalignment with current market trends.

In all, this approach merged the dynamic gathering of data, strategic portfolio creation, tailored rebalancing schedule, and appropriate evaluation metrics for an overall assessment of liquidity-based investment strategies. Given that, insight has been shed not only on how different strategies performed but also emphasized the practical aspect of transaction costs and frequency of rebalancing, thus paving the way to make results of interest in academics as well as in practice.

3. Results

The critical insights brought out in the analysis had to do with portfolio construction strategies, especially liquidity-based investment approaches. This section provides the quantitative results of the three portfolio strategies: risk-adjusted weighting, equal weighting, and non-filtered liquidity. It also draws on the implications of these results.

First, the risk-adjusted weighting strategy, which was designed to allocate funds inversely proportional to every stock's volatility, had a delicate balance between risk and return. For the entire investment horizon, this portfolio returned -4.91% annualized, along with an annualized volatility of 16.58%, yielding a Sharpe ratio of -0.416. However, despite that being one grand weakness for such a return being negative, the strategy at least brought forth discipline toward the reduction of portfolio volatility. With a reliance on volatility as one of the fundamental indicators of weight dispersion, this is the approach whereby it is hypothesized that one will trade stability over superior returns. The negative Sharpe ratio spoke to the inherently difficult task of obtaining excess returns in a market where investors are over-exposing themselves to high liquidity stocks.

The equal-weighted strategy, where an equal proportion of capital was assigned to all selected stocks, had a marginally better performance.

The portfolio recorded an annualized return of -4.03% with an annualized volatility of 9.94% and hence had a Sharpe ratio of -4.26. Although the returns remained negative, reduced volatility was a sign of the strategy's simplicity and diversification benefits. This approach eliminates the bias of volatility-driven allocations by weighting long and short positions equally. The relatively low volatility suggested that equal weighting can be a kind of conservative benchmark that would be suitable for investors looking for lower-risk exposure to participate in liquidity-based strategies.

In contrast, the best of the three strategies was that of unfiltered liquidity, which allowed the selection of all stocks and provided an annualized return of 6.30% with an annualized volatility of 13.04%, hence a Sharpe ratio of 4.817, which means it has the best risk-adjusted performance. This strategy has been successful due to its broader diversification, which reduces idiosyncratic risk while taking advantage of opportunities in a wider spectrum of stocks. The less liquid stocks, usually accompanied by higher expected returns because of the liquidity premium, played a very important role in this outperformance. Moreover, the level of volatility is balanced, hence underlining a reasonable risk profile while being attractive in the pursuit of higher returns at unduly higher levels of risk. The result also indicated the influences of transaction costs and rebalancing frequencies on portfolio performances. As was expected, it showed that rebalancing at frequent periods attracted higher costs of transactions in strategies involving relatively ill liquid stock. The highest cumulative transaction costs that eroded net returns were from the monthly rebalancing scenario for liquid stocks and semi-annual rebalancing for illiquid stocks. On the other hand, less frequent rebalancing scenarios, such as semi-annual rebalancing for liquid stocks and annual rebalancing for illiquid stocks, demonstrated cost efficiency but risked misalignments with evolving market dynamics. The non-filtered liquidity strategy, considering a wider stock selection, managed to offset the transaction costs due to its better returns, further proving to be the best strategy.

Another layer of analysis was done to compare these strategies with the S&P 500 index, considered a market benchmark. The no-filtration liquidity strategy had better annualized returns and a Sharpe ratio than the benchmark and therefore demonstrated good results in realizing excess return even in a competitive market environment. However, the risk-adjusted and equal-weighted strategies are behind the benchmark, which underlines once more the importance of stock picking and diversification for favorable outcomes.

The results indicated that the non-filtered liquidity strategy generated optimized risk-adjusted returns, considering reasonable transaction costs. None of the other strategies captured this delicate balance between diversification and exposure to the liquidity premium as much as this strategy did. These results therefore underscore the need to consider looser stock selection criteria than rigid liquidity rankings. They again bring forth the trade-off that exists among transaction costs, rebalancing frequency, and portfolio performance.

4. Discussion

Most investment strategies balance in some way between the twin imperatives of maximizing return and minimizing risk. Their success frequently hinges on the correct construction of the portfolio. This paper highlighted three approaches to constructing portfolios: filtered risk-adjusted weighting, equal weighting, and non-filtered risk-adjusted weighting. Each one has something different to contribute regarding insights into liquidity consideration, diversification, and optimization of risk-return.

4.1. Liquidity and Diversification

Liquidity is defined as the ease of trading assets without significant price impacts. It is a cornerstone in any investment strategy. However, a strategy focused on prioritizing liquidity, like the filtered risk-adjusted strategy, may impede diversification. Previous studies have highlighted a liquidity-return trade-off. Amihud and Mendelson maintain that highly liquid assets usually generate low returns because of their low transaction costs and risk premium, a finding which agrees with that of this study, where the filtered strategy underperformed due to limited stock inclusion [2].

In contrast, the ex-approach considered a wider universe of stocks, which arguably diversified better. This somehow aligns with Markowitz's Modern Portfolio Theory as it has emphasized that "one should diversify to decrease unsystematic risk in an effort to maximize return." [1].

4.2. Risk-Adjusted Weighting vs. Equal Weighting

The adoption of risk-adjusted weighting in this study, therefore, underpins the need to combine portfolio allocation with individual stock volatilities. Indeed, the risk-adjusted weighting methods yielded better risk-adjusted returns as compared to equal weighting proxied by their higher Sharpe ratios. This finding is supported by empirical evidence provided by Clarke et al., who proved that volatility-based weighting schemes mostly outperform naive allocation techniques, especially in volatile markets [10]. While very simple and easy to implement, the equal weighting approach disregarded the individual stock risks and hence had a suboptimal performance. Its lower volatility could suggest, however, that such an approach may suit risk-averse investors with a penchant for stability rather than returns.

4.3. Performance of Non-Filtered Strategy

The unfiltered risk-adjusted approach turned out to be the most powerful, balancing liquidity and diversification with optimization of the risk-return trade-off. The strategy benefited from diversification by including stocks from all spectrums of liquidity, while at the same time optimizing the risk-weighted asset allocation. These findings agree with the results of Ang et al., who found that the addition of low-volatility assets to a portfolio tends to increase returns without significantly increasing the risk [11].

4.4. Limitations and Future Research

While the study emphasizes the efficiency of the non-filtered strategy, it is not without its limitations. Transaction costs, while considered, could vary with market conditions and therefore impact the practical usability of the strategy in a real market. Furthermore, the dependence on historical volatility assumes persistence in the pattern, which may not always be true. Future research could delve into dynamic strategies that adjust to changing market conditions and incorporate additional factors, such as macroeconomic indicators or ESG considerations, into portfolio construction.

5. Conclusion

This study has applied three portfolio construction strategies, namely filtered risk-adjusted weighting, equal weighting, and non-filtered risk-adjusted weighting. It aimed to find out, using data-driven means, how each of these strategies can balance returns with risks and the costs of transactions. It was found that the non-filtered risk-adjusted-weighted strategy outperformed the other two all along, with an annualized return of 6.30% and a Sharpe ratio of 0.481. The latter was attributed to the broad diversification and appropriate risk-aligned allocation, where a superior risk-return trade-off was achieved, idiosyncratic risks being reduced. The filtered, risk-adjusted strategy must bear the smallest return with higher volatility since high liquid asset class constrained limited diversification. In addition, the equal weighting strategy would offer simplicity and stability; however, it is slightly weaker on the risk-adjusted metric.

Despite such promising results, this study must admit several limitations. First, reliance on historical volatility presumes the sustainability of the patterns in the future, which may not account for sudden market reversals or unexpected surges in volatility. Second, while estimates of transaction costs are provided, they are simplified and do not capture all the variation depending on market conditions and broker choice. Finally, the strategies were tested in a single-market environment, and the results may not generalize to other markets with different liquidity profiles and trading costs.

Looking ahead, a few ways to improve and expand the research are suggested: real-time market data and dynamic weighting techniques may help to adapt the portfolio to changes in market conditions more effectively. Additional insights in portfolio construction might be gained by incorporating macroeconomic indicators, sectoral trends, or ESG data. Multi-market application of the non-filtered risk-adjusted strategy might allow one to draw conclusions regarding its robustness and scalability across different financial markets.

In the end, there is great potential for non-filtered risk-adjusted weighting to yield superior returns and/or risk-adjusted performance. Challenges and limitations aside, this study lays the bedrock for further work in improving portfolio construction methodologies and acts as a reminder of how crucial diversification and optimization of risk are in pursuit of investment success.

References

[1] Markowitz, & H. (1952). Portfolio selection. The Journal of Finance, 7 (1), 77 - 91.

[2] Amihud, & Y. and Mendelson, & H. (1986). Asset pricing and the bid-ask spread. Journal of Financial Economics, 17 (2), 223 - 249.

[3] Bali, & T.G., & Peng, & L. and Shen, & Y. (2021). Liquidity risk and stock returns. The Review of Financial Studies, 34 (7), 3453 - 3489.

[4] Chordia, & T., & Roll, & R. and Subrahmanyam, & A. (2020). Liquidity and market efficiency. Journal of Financial Economics, 138 (2), 368 - 391.

[5] Frazzini, & A. and Pedersen, & L.H. (2014). Betting against beta. Journal of Financial Economics, 111 (1), 1 - 25.

[6] Pastor, & L. and Stambaugh, & R.F. (2003). Liquidity risk and expected stock returns. Journal of Political Economy, 111 (3), 642 - 685.

[7] Goyenko, & R.Y., & Holden, & C.W. and Trzcinka, & C.A. (2009). Do liquidity measures measure liquidity? Journal of Financial Economics, 92 (2), 153 - 181.

[8] DeMiguel, & V., & Garlappi, & L. and Uppal, & R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? The Review of Financial Studies, 22 (5), 1915 - 1953.

[9] Maillard, & S., & Roncalli, & T. and Teiletche, & J. (2010). The properties of equally weighted risk contributions portfolios. The Journal of Portfolio Management, 36 (4), 60 - 70.

[10] Clarke, & R., & De Silva, & H. and Thorley, & S. (2011). Minimum-variance portfolio composition. The Journal of Portfolio Management, 37 (2), 31 - 45.

[11] Ang, & A., & Hodrick, & R.J., & Xing, & Y. and Zhang, & X. (2006). The cross-section of volatility and expected returns. The Journal of Finance, 61 (1), 259 - 299.