



# Empirical Study on the Impact of Liquidity Factor Turnover Rate on Stock Returns: Based on CAPM and Fama-French Models

Sijie Guo

School of Finance and Investment, Guangdong University of Finance, Guangzhou, 510000, China  
22151A203@m.gduf.edu.cn

**Abstract.** This study aims to investigate whether the inclusion of turnover rate (HSL) as a liquidity factor can enhance the explanatory power of the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model (FF3) in predicting stock returns. This issue is of critical importance in academic research, as it could reveal the impact of market microstructure on asset pricing and provide a new perspective for investment decisions. The author use regression analysis and stock data from six technology companies (Apple, Microsoft, Amazon, Alphabet, Tesla, Plug Power) between June 2016 and October 2020, including excess returns, market excess returns, company size, book-to-market ratio, and turnover rate. The results show that the inclusion of HSL significantly increases the R-squared value of the models, indicating that turnover rate is an important factor influencing stock returns. This finding has practical implications for investors considering liquidity indicators when evaluating stocks and provides a theoretical basis for regulatory authorities to monitor market manipulation behavior.

**Keywords:** Turnover rate, liquidity, CAPM, Fama-French model, asset pricing.

## 1 Introduction

Accurate prediction of expected asset returns is crucial for investors and financial institutions in financial market analysis. The CAPM and the FF3 are both pivotal frameworks for assessing the anticipated returns on investments. However, whether these models can fully capture all relevant market information, particularly liquidity factors, remains an open question. The motivation of this study is to explore whether introducing turnover rate (HSL) as a proxy for liquidity can improve the explanatory power of these models, which is significant for understanding market dynamics and optimizing investment strategies.

A considerable body of existing literature has consistently affirmed the efficacy of the CAPM and FF3 [1-6]. These models explain asset returns through market risk, company size, and book-to-market ratio. However, research on liquidity factors such as turnover rate is relatively scarce, despite the general consensus that liquidity has a

© The Author(s) 2025

M. M. Husin (ed.), *Proceedings of the 2025 International Conference on Financial Risk and Investment Management (ICFRIM 2025)*, Advances in Economics, Business and Management Research 333,  
[https://doi.org/10.2991/978-94-6463-748-9\\_47](https://doi.org/10.2991/978-94-6463-748-9_47)

significant impact on asset prices. This research seeks to address this void by carrying out an empirical examination of how HSL affects the predictive accuracy of these models.

In this study, the author selected stock data from six companies covering multiple industries, including technology, automotive, e-commerce, and new energy. The author uses historical stock data from these six technology companies and apply regression analysis to verify the effectiveness of the CAPM and FF3 before and after incorporating HSL. The main focus of the study is on evaluating the impact of HSL on the models' explanatory power, analyzing the sensitivity of stock returns to HSL across different companies, and exploring the statistical significance of HSL through multiple specifications tests to ensure robustness.

## 2 Methodology

In financial market analysis, the CAPM and the FF3 are the two core models for evaluating expected asset returns. The CAPM model predicts asset returns based on market risk (Beta), while the FF3 extends the CAPM by adding two additional factors: company size (SMB) and book-to-market ratio (HML). This study investigates whether the inclusion of turnover rate (HSL) as a liquidity factor can enhance the explanatory power of these models.

### 2.1 Data Collection and Processing

The author selected stock data for six companies: Google, Apple, Plug Power, Tesla, Microsoft, and Amazon. The data includes stock excess returns, market excess returns, company size, book-to-market ratio, and stock turnover rate. The author collected daily closing prices and monthly trading volume data from June 2016 to October 2020 via Yahoo Finance. Monthly returns were calculated as follow:

$$R_t = (P_t - P_{t-1}) / (P_{t-1}) \quad (1)$$

Monthly turnover rate data for the same period were collected from Wind Information. Market returns ( $R_m$ ), risk-free rate ( $R_f$ ), SMB, and HML were also obtained from Yahoo Finance, ensuring they were aligned with the time series of company returns.

### 2.2 Model Setup

The study follows a four-step process: First use regression analysis to test the effectiveness of the CAPM model:

$$R_i - R_f = \alpha_i + \beta_1(R_m - R_f) + e \quad (2)$$

Second add turnover rate to the CAPM model:

$$R_i - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2 HSL + e \quad (3)$$

Third use regression analysis to test the effectiveness of the Fama-French model:

$$R_i - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2SMB + \beta_3HML + e \quad (4)$$

Fifth add turnover rate to the Fama-French model:

$$R_i - R_f = \alpha_i + \beta_1(R_m - R_f) + \beta_2SMB + \beta_3HML + \beta_4HSL + e \quad (5)$$

### 3 Empirical Results

In different models, the coefficient of HSL varies between positive and negative, indicating that the impact of turnover rate on stock returns may differ across companies. From the overall trend observed in Table 1, it can be seen that the HSL coefficients for different companies vary in both the CAPM and FF3. In the “CAPM+HSL”, Microsoft has the highest HSL coefficient at 0.4448901, while Amazon has the lowest at 0.0033359. In the “FF3+HSL”, Microsoft’s HSL coefficient is also the highest at 0.3207178, while Amazon’s HSL coefficient is the lowest at -0.0029761.

Comparative analysis between companies shows that, in the “CAPM+HSL”, Google’s HSL coefficient is 0.0994047, while in the “FF3+HSL”, it is -0.0246509. This suggests that in the CAPM model, Google’s stock performance has a certain positive correlation with the market portfolio, but in the Fama-French model, after considering the size and value factors, Google’s performance slightly worsens.

Apple’s HSL coefficient in the “CAPM+HSL” is 0.4064626, and in the “FF3+HSL”, it is 0.2413075. This indicates that Apple performs better in the CAPM model, but its performance declines slightly when other factors are considered in the Fama-French model, although it remains relatively high.

For Plug Power, the HSL coefficient in the “CAPM+HSL” is 0.3036445, and in the “FF3+HSL”, it is 0.2945752. This shows that Plug Power’s performance in both models is relatively close.

Tesla’s HSL coefficient in the “CAPM+HSL” is 0.1425163, and in the “FF3+HSL”, it is 0.144521. Tesla’s performance is also quite similar across both models.

Microsoft has the highest HSL coefficient in the “CAPM+HSL” at 0.4448901, and in the “FF3+HSL”, it is 0.3207178. This indicates that Microsoft performs exceptionally well in both models.

Amazon has the lowest HSL coefficient in the “CAPM+HSL” at 0.0033359, and in the “FF3+HSL”, it is -0.0029761. This suggests that Amazon performs relatively poorly in both models.

There are significant differences in the HSL coefficients for different companies in the CAPM and FF3. The evaluation of company stock performance in the CAPM and FF3 differs mainly because the Fama-French model incorporates additional risk factors. Microsoft performs very well in both models, while Amazon performs relatively poorly in both.

**Table 1.** The HSL Coefficients in the CAPM and FF3 for Each Company After Introducing HSL.

	CAPM	Fama French
Google	0.0994047	-0.0246509
Apple	0.4064626	0.2413075
Plug Power	0.3036445	0.2945752
Tesla	0.1425163	0.144521
Microsoft	0.4448901	0.3207178
Amazon	0.0033359	-0.0029761

The p-values of HSL vary significantly across different models, with some models showing p-values less than 0.05, indicating that the HSL factor is statistically significant in these models. According to the comparison analysis in Table 2, it can be observed that for Google, the p-value in the “CAPM+HSL” is 0.907, and in the “FF3+HSL”, it is 0.978. This suggests that in both models, Google's data is not statistically significant, meaning there is insufficient evidence to reject the null hypothesis.

For Apple, the p-value in the “CAPM+HSL” is 0.189, and in the “FF3+HSL”, it is 0.477. This indicates that Apple's data in the “CAPM+HSL” is close to the significance level, while in the “FF3+HSL” model, the data is not significant.

For Plug Power, the p-value is 0.000 in both the “CAPM+HSL” and “FF3+HSL”, indicating that the data is highly statistically significant, providing strong evidence to reject the null hypothesis.

For Tesla, the p-value in the “CAPM+HSL” is 0.006, and in the “FF3+HSL”, it is 0.015, which indicates that Tesla's data is statistically significant in both models, providing sufficient evidence to reject the null hypothesis.

For Microsoft, the p-value is 0.281 in the “CAPM+HSL” and 0.471 in the “FF3+HSL”, suggesting that Microsoft's data is not significant in either model.

For Amazon, the p-value is 0.989 in the “CAPM+HSL” and 0.990 in the “FF3+HSL”, indicating that Amazon's data is not significant in either model.

There are significant differences in the p-values across companies in the CAPM and Fama-French models. The data for Plug Power and Tesla is statistically significant in both models, while the data for Google, Apple, Microsoft, and Amazon is not significant in either model. The evaluation of company stock performance in the CAPM and Fama-French models differs, mainly because the Fama-French model considers more risk factors.

**Table 2.** P-values of HSL in the CAPM and FF3 for Each Company After Introducing HSL.

	CAPM	Fama French
Google	0.907	0.978
Apple	0.189	0.477
Plug Power	0.000	0.000
Tesla	0.006	0.015
Microsoft	0.281	0.471
Amazon	0.989	0.990

After introducing the HSL factor, the R-squared values increased, indicating an improvement in the model's explanatory power. According to the comparison analysis in Table 3, it can be observed that Google's R-squared value in the "CAPM+HSL" is 0.3553, and in the "FF3+HSL", it is 0.3624. This indicates that in both models, Google's goodness of fit is relatively low, and the proportion of variance explained by the model is small.

Apple's R-squared value in the "CAPM+HSL" is 0.3673, and in the "FF3+HSL", it is 0.3853. This suggests that Apple's goodness of fit in both models is slightly higher than Google's, but still at a moderate level.

For Plug Power, the R-squared values are 0.4614 in the "CAPM+HSL" and 0.4957 in the "FF3+HSL", indicating that Plug Power has relatively high goodness of fit in both models, with the model explaining a larger proportion of the variance.

Tesla's R-squared value in the "CAPM+HSL" is 0.3066, and in the "FF3+HSL", it is 0.3090, indicating that Tesla has the lowest goodness of fit in both models, with the model explaining a smaller proportion of the variance.

Microsoft's R-squared value in the "CAPM+HSL" is 0.3573, and in the "FF3+HSL", it is 0.3672. This indicates that Microsoft's goodness of fit is similar to that of Google's in both models.

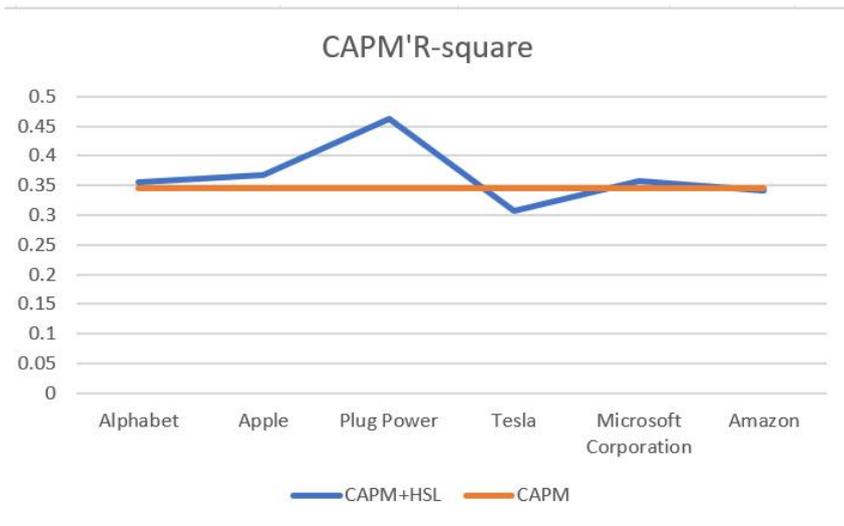
Amazon's R-squared value in the "CAPM+HSL" is 0.3412, and in the "FF3+HSL", it is 0.3948. This suggests that Amazon has lower goodness of fit in the "CAPM+HSL" but a higher goodness of fit in the "FF3+HSL".

**Table 3.** The R-squared values for each company in the CAPM and FF3 after introducing the HSL factor.

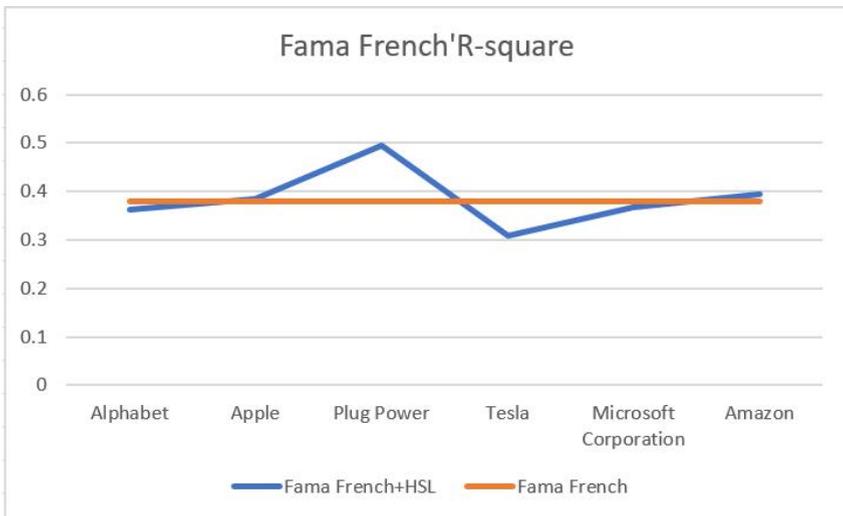
	CAPM	Fama French
Google	0.3553	0.3624
Apple	0.3673	0.3853
Plug Power	0.4614	0.4957
Tesla	0.3066	0.3090
Microsoft	0.3573	0.3672
Amazon	0.3412	0.3948

As can be seen from Figures 1-2, in most companies, the inclusion of HSL factors leads to an increase in the R-square value, especially in the case of Plug Power, where the R-square value significantly improves, approaching 0.5.

There are significant differences in the R-squared values across companies in the CAPM and FF3. Plug Power has the highest goodness of fit in both models, while Tesla has the lowest. In most cases, the FF3 has a better goodness of fit than the CAPM, indicating that the factors considered by the FF3 better explain the variance in stock returns.



**Fig. 1.** Comparison of R-squared values between the original CAPM model and the CAPM model with the HSL factor for each company (Photo credit: Original).



**Fig. 2.** Comparison of R-squared values between the original Fama-French model and the Fama-French model with the HSL factor for each company (Photo credit: Original).

A hypothesis test for the significance of turnover rate (HSL) was conducted, where the null hypothesis states that the HSL coefficient equals 0, implying that turnover rate has no impact on stock returns. The significance of HSL was assessed based on the p-value: if the p-value is less than 0.05, the null hypothesis is rejected, indicating that turnover rate has a significant effect on stock returns.

By comparing the R-squared values of the CAPM and Fama-French models before and after introducing HSL, the impact of turnover rate on the models' explanatory power was evaluated. The results show that for Apple, Plug Power, and Tesla, the explanatory power of the models significantly improved after introducing turnover rate.

For Plug Power and Tesla, the turnover rate coefficients were statistically significant, with p-values much smaller than 0.05, indicating that turnover rate has a significant effect on the stock returns of these companies. However, for Google, Microsoft, and Amazon, the turnover rate coefficients were not significant, suggesting that turnover rate may not be a significant predictor of stock returns for these companies.

## 4 Discussion

This study significantly enhances the explanatory power of the models by introducing turnover rate (HSL) as a liquidity factor. The changes in the HSL coefficient, p-value, and R-squared values clearly indicate that turnover rate is an important factor influencing stock returns and that its contribution to improving model explanatory power is statistically significant. As a proxy for liquidity, turnover rate reflects market interest and activity in a stock. A high turnover rate may signal greater market attention and liquidity, attracting more investors and thus affecting stock prices and returns. In certain companies, the turnover rate significantly improved the model's explanatory power, possibly because a high turnover rate indicates high market attention and liquidity demand for those stocks.

Based on these findings, the author proposes the following recommendations. Investors should consider turnover rate as a liquidity indicator when evaluating stocks. Stocks with high turnover rates may have higher market attention, but they may also exhibit higher volatility. Furthermore, high turnover rates may signal increased market volatility, so investors should diversify their portfolios to mitigate the risks associated with stocks that exhibit high turnover. Additionally, regulatory authorities should monitor the trading behavior of high-turnover stocks to prevent market manipulation and excessive speculation, ensuring market stability.

## 5 Conclusion

This study demonstrates through empirical analysis that the introduction of HSL as a liquidity factor significantly improves the explanatory power of the CAPM and Fama-French models. The results support HSL as an important factor influencing stock returns, with varying effects across different companies. This finding has practical implications for investors, suggesting that liquidity indicators should be considered when evaluating stocks, and provides a theoretical basis for regulatory authorities to monitor market manipulation activities.

The study employs empirical analysis and quantitative research methods, specifically using multiple linear regression to estimate model parameters. This

approach is widely accepted in the finance field, because it provides statistical significance tests and quantifies the impact of various factors on stock returns [7-10]. Its advantages include the ability to handle large datasets and produce easily interpretable results. However, the method also has limitations, such as the potential influence of multicollinearity and the assumption that the error terms follow a normal distribution.

Although this study offers valuable insights, it also has some limitations. The sample is limited to six technology companies, which may restrict the generalizability of the results. Future research could expand the sample size to include more industries and companies, thus enhancing the generalizability of the conclusions. Additionally, future studies could explore the interactions between HSL and other market factors, as well as the impact of HSL on stock returns under different market conditions, providing a deeper understanding of asset pricing models.

## References

1. Wu, Z. S.: An Empirical Study on the Applicability of the CAPM Model to China's A-Shares, Rental and Sales Information **2**, 71-74 (2023)
2. Asthana, A.; Ahmed, S. S.; Tiwari, A.: Empirical Evidence on the Validity of the Conditional Higher Moment CAPM in the Bombay Stock Exchange, Journal of Economics, Management and Trade **30** (4), 37-45 (2024)
3. Zhang, L. S.: An Empirical Study on the Constituent Stocks of China's SSE 50 Index - Based on the CAPM Model and the Fama-French Three-Factor Model, Economic Research Guide **26**, 78-80 (2022).
4. Kostin, K. B.; Philippe, R.; Mamedova, L. E.: Validity of the Fama-French Three- and Five-Factor Models in Crisis Settings at the Example of Select Energy-Sector Companies during the COVID-19 Pandemic, Mathematics and Financial Economics **11**(1), 49 (2023)
5. Liu, Y. W.; Deng, N.; Ding, P.: An Empirical Study on the Efficiency of the Shanghai Stock Market Based on the Bayesian CAPM Model, Financial Economics **4**, 15-28 (2022).
6. Mitalee, A. P.: Testing the validity of Fama-French Three Factor Model on Indian Stock Market, International Journal of Management, IT and Engineering **6** (3), 30-41 (2016)
7. Tang, Y. W.; He Y. T.; Li, J. Y.: Research on the Pricing and Influencing Factors of Lessee's Credit Risk — An Empirical Analysis Based on Credit Risk Models and Threshold Regression Models, Financial World **7**, 50-52 (2024).
8. Guo, Y. L.; Shi, L.; Li Z. M.: An Empirical Analysis of Agricultural Product Logistics Demand Forecasting in Chengdu Based on Multiple Linear Regression, China Storage and Transport **7**, 127-128 (2024)
9. Mohanty, S. K. et al.: Risk factors in stock returns of U.S. oil and gas companies: evidence from quantile regression analysis, Review of Quantitative Finance and Accounting **60**(2), 715-746 (2022)
10. Ananthi, M.; Vijayakumar, K.: Stock market analysis using candlestick regression and market trend prediction (CKRM), Journal of Ambient Intelligence and Humanized Computing **12**(5), 1-8 (2020)

**Open Access** This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

