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Modelling Stock Market Volatility and Attention

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Abstract **–** This paper aims to model stock market volatility by incorporating attention as an input variable, addressing the inconclusive evidence on its impact on stock volatility. Given the varying importance of attention across studies and the absence of a standard definition, the paper seeks to advance volatility and attention modelling by reviewing and testing different approaches. The study employs a VAR model to examine the relationship between volatility and attention in the U.S. renewable energy sector from 2006 to 2020. Using realized volatility, VIX, trading volume, and Google search volume indices, the research investigates the influence of these variables on the following day's stock price volatility for twenty renewable energy companies. Initial results from the VAR model indicate the statistical significance of some variables, such as prior variance and actual variance, while volume changes appear to have limited significance, contrary to previous findings. The study aligns with existing research, suggesting that attention and trading volume generally increase stock price volatility, whereas attention to industry fundamentals may reduce volatility.

Keywords – finance, realized volatility, volatility models, forecasting, attention

I. INTRODUCTION

Stock market modeling is essential for understanding the complexities of financial markets and making informed investment choices. Traditional models, such as the Efficient Market Hypothesis (EMH) and the Capital Asset Pricing Model (CAPM), have been used to explain long-term trends and returns based on assumptions of rationality and efficient markets. However, recent studies have highlighted the significant impact of investor attention on stock market dynamics.

Investor attention, which pertains to the focus and awareness market participants direct towards specific stocks, sectors, or events, is now recognized as a crucial influence on stock market behavior. Unlike traditional models that emphasize fundamental factors alone, attention-based models suggest that stock prices and returns are affected by both fundamental factors and variations in investor attention.

To understand the dynamics of attention and its connection with stock market variables, several models have been developed, utilizing techniques such as sentiment analysis, natural language processing, and machine learning. These models aim to extract and analyze information from large-scale data sources, including social media platforms like Twitter and online communities such as Wallstreetbets on Reddit. Social media provides investors with real-time information, sentiment analysis, and discussions about specific stocks and market trends. However, investors should be cautious as information from social media can be susceptible to manipulation and pump-and-dump schemes.

In addition to gathering information and conducting sentiment analysis, social media platforms allow investors to share their trading experiences and strategies. Stock chats and forums create a collaborative environment where investors can exchange ideas and refine their trading strategies.

As stock prices become more influenced by non-economic factors like sentiment and attention, researchers and practitioners are encouraged to develop new approaches for modeling stock returns and volatility. This dissertation aims to investigate the impact of attention on stock market volatility by proposing new models that incorporate attention as a factor and testing their predictive capabilities.

By acknowledging new investor behaviors and integrating them into stock market models, we can gain a better understanding of stock market volatility dynamics and make more accurate predictions about future market movements. This research contributes to the ongoing development of stock market modeling and provides insights into the factors influencing stock market behavior in the digital age.

II. MATERIALS AND METHOD

In this model we extend VAR model with two sets of attention variables. The first measure is a direct measure of investor attention and is based on Google search query volume. The second measure of attention is daily trading volume for a given stock. Trading volume is more indirect proxy for measuring investor attention and complements Google search. As we describe in length, both these measures are established factors that capture attention, with volume being one of the oldest ways to approximate attention in financial modelling.

We estimate the dynamics between realised volatility, search queries, and trading volume, by estimating an extended vector auto regressive model. Let $\boldsymbol{x_t}$ be a vector of volatilities at time t. $\boldsymbol{c}$ is a vector of constants, $\boldsymbol{\varepsilon_t}$is a vctor of independent white noise variations. The lag-length is determined using the Schwarz Bayesian information criterion. In the base model of our analysis, investigates the dynamics between realised volatility and search queries, i.e $\boldsymbol{x_t} = (\log RV_t \; Log\ SQ_t)'$. In the extended mode is a joint model of realised volatility, search queries and trading volume such that $\boldsymbol{x_t} = (\log RV_t \; \boldsymbol{Log\ SQ_{ti}} \; logVO_t)'$

Base model:

$$\boldsymbol{x_t} = \boldsymbol{c} + \sum_{j=1}^{a} \boldsymbol{\beta_j x_{t-j}} + \boldsymbol{\varepsilon_t}$$

$$(\log RV_t \; Log\ SQ_{ti})' = \boldsymbol{c} + \sum_{j=1}^{a} \boldsymbol{\beta_j} (\log RV_t \; Log\ SQ_{ti})'_{\boldsymbol{j}} + \boldsymbol{\varepsilon_t}$$

Extended model:

$$(\log RV_t \; \boldsymbol{Log\ SQ_{ti}} \; logVO_t)' = \boldsymbol{c} + \sum_{j=1}^{a} \boldsymbol{\beta_j} (\log RV_t \; \boldsymbol{Log\ SQ_{ti}} \; logVO_t)'_{\boldsymbol{j}} + \boldsymbol{\varepsilon_t}$$

III. RESULTS

Our analysis utilizes a VAR model to investigate the relationship between investor attention, as measured by Google Trends indices, and trading volume. We begin with a basic VAR model that includes only one explanatory variable: a lag of daily stock variance, measured using three range-based variance estimators. The dependent variable is the current stock variance. The extended VAR model builds on this base by incorporating additional covariates for attention and the VIX. Attention measures include variables capturing industry-specific attention across the renewable energy sector and a stock-specific measure focusing on investor attention. Alongside the Google search data-based attention measure, we include a volume-based measure that serves as an indirect proxy for attention. We also incorporate the VIX, a market-based volatility index known for predicting future volatility, as demonstrated in empirical research.

Our findings indicate significant estimates of the autoregressive parameters for realized volatility across the 20 companies studied. Search queries also show significant autoregressive terms at the first lag, as shown in Table 1, rows 2 to 6. Although not detailed here, there is a high contemporaneous correlation between volatility and search activity, suggesting that searches respond immediately to volatility shocks. Our primary interest is in how past search activity affects present volatility. We find that search queries significantly enter the RV-equation at lag 1, whereas higher-order lags are less significant for past realized volatility, volume, and VIX, and not significant for the attention indices.

When examining regressions with volatility as the dependent variable, past volatility emerges as the most significant predictor of future volatility. Similarly, VIX is significant across all 20 stocks, as expected. For attention-related coefficients, volume is significant for 15 out of 20 stocks, aligning with previous academic literature. Google search-based attention measures present a more varied picture. Attention based on stock-related news and prices (GT_stock_index) shows a positive effect on next-day volatility for 7 out of 20 stocks, indicating that investors search for stock news and prices before trading. This relationship is explored in detail in the thesis.

Renewable energy-specific attention indices show a more nuanced relationship. Higher attention to renewable energy generally correlates with lower next-day volatility. The Solar Index is significant in 7 out of 20 instances, all with a negative coefficient. The Wind Index is significant in 12 out of 20 instances, with mixed coefficient signs, suggesting varying impacts on volatility. The Bio Index is significant in 10 out of 20 instances, showing a positive impact on volatility. The EMO Index is significant in 9 out of 20 instances, with mixed impacts on volatility. The Gen Index is significant in 8 out of 20 instances, with a positive impact on volatility.

The causality between attention and volatility appears to be bidirectional, indicating that past searches provide valuable information about future volatility, and volatility influences search queries by drawing investor attention to the renewable energy sector. We reject the null hypothesis that past log search queries have no effect on current log (realized) volatility at all conventional significance levels. These results support the noise trader model of excess volatility proposed by De Long et al. (1990). Following an initial volatility shock, search intensity increases, which is subsequently followed by elevated volatility levels.

Table 1. In sample VAR model coefficients for Vol significance marked by (*)

Panel B: Coefficients (y = Vol)	WOLF	OLED	TSLA	THRM	PWR	WWD	AEIS	ACA	ESE	ITRI
Vol_l	0.323***	0.324***	0.392***	0.325***	0.339***	0.238***	0.266***	0.277***	0.291***	0.302***
GT_stock_index_l	0.034**	0.021	0.081***	0.011	0.058***	0.066***	0.013	-0.007	0.022	-0.004
SolarIndex_l	0.013	-0.245***	-0.160	-0.27***	-0.060	-0.039	-0.201**	-0.102	-0.246***	0.109
WindIndex_l	-0.111*	0.218***	0.078	0.531***	0.3***	0.212***	0.207***	0.5***	0.256***	0.008
BioIndex_l	0.301***	-0.087	-0.022	0.257***	0.355***	0.271***	0.237***	-0.136	0.306***	0.312***
EMOIndex_l	0.063	0.001	-0.072	-0.204***	-0.153***	-0.245***	-0.126**	-0.312*	-0.086*	-0.057
GenIndex_l	0.094	0.37***	0.319**	0.038	-0.129	-0.013	0.203**	0.030	0.023	-0.143
VIX_l	0.886***	0.676***	0.753***	0.909***	1.002***	1.324***	0.892***	1.012***	0.974***	1.017***
Volume_l	0.333	1.863***	1.44***	0.803***	-0.112	0.214	1.25***	2.414***	0.591**	0.485*

Panel B: Coefficients (y = Vol)	MYRG	ENPH	SEDG	RUN	FSLR	REGI	SPWR	ED	ALB	LTHM
Vol_l	0.286***	0.382***	0.343***	0.333***	0.447***	0.682***	0.422***	0.39***	0.305***	0.292***
GT_stock_index_l	0.005	-0.105**	-0.016	0.052	0.078***	0.014	0.059***	0.010	0.006	0.016
SolarIndex_l	0.052	-0.152	0.089	0.272*	-0.245***	-0.104	-0.074	0.126*	0.207***	0.044
WindIndex_l	0.099	0.084	-0.332**	-0.214*	-0.021	-0.180	-0.157**	-0.246***	-0.234***	-0.072
BioIndex_l	0.013	-0.091	0.173	0.009	0.126*	0.010	0.237***	0.238***	0.264***	0.014
EMOIndex_l	0.037	0.087	-0.277***	-0.078	-0.021	-0.071	0.216***	0.053	0.149***	-0.157
GenIndex_l	0.112	0.631***	0.524***	0.251	0.451***	0.336**	0.241***	-0.028	-0.046	0.293
VIX_l	0.821***	0.507***	0.71***	0.87***	0.554***	0.337***	0.67***	0.849***	1.224***	0.753***
Volume_l	0.93***	1.426***	2.227***	1.269**	1.03***	1.462***	0.175	-0.120	-1.015***	2.88***

Notes: Uncertainty of the estimated coefficients is based on the stationary-bootstrap procedure of Politis (1994) with 2000 bootstrapped samples. The 10%, 5% and 1% significant coefficients are denoted as *, **, and *** respectively

IV. DISCUSSION

Our VAR model to examine the relationship between investors' attention proxied by Google trends indices, trading volume and one day realised variance. Our analysis starts with a bare-bones VAR model, which includes a lag of daily stock variance and a dependent variable, stock variance at time t. The extended VAR model includes extra covariates for attention and the Vix, focusing on individual industry attention across different parts of renewable energy space. The model also includes a volume-based measure that proxies attention indirectly. We focused on how past search activity influences present volatility in stocks. Results show that search queries enter the RV-equation significantly at lag 1, while higher order lags are less significant for past realized volatility, volume, and Vix. Past volatility is the biggest determinant of future volatility, and Vix is significant across all 20 stocks. Volume is significant at 15 out of 20 stocks. Google search-based measures of attention show mixed results, with 7 out of 20 stocks showing a positive effect on next day’s volatility. Renewable attention-specific indices show a negative impact on volatility and are only significant for half of the stocks in our sample.

V. CONCLUSION

In conclusion, the results of our study support the findings of existing published research. We found that strength and significance of attention coefficients changes across the three models, but generally suggest that volume and attention to stock prices leads to volatility increases. However, attention to industry topics related to the sector of our stocks is often only weakly related to next day’s volatility and is often associated with volatility decreases. We postulate that such a negative effect is caused by investors making more consensus driven and data-based investments that marginally decrease volatility when their attention is focused on industry fundamentals rather than stock prices.

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