Attention and Volatility in Renewable Energy Stocks

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Abstract: Under the Efficient Market Hypothesis stock prices should reflect only the fundamental information relevant to the company in question. If other, such as behavioural factors affect the stock price, then this discrepancy should be resolved by the means of arbitrage traders. In our study we look at the effect of retail trader attention on the volatility of renewable energy companies' stocks. We find that attention, measured by Google Trends, is a good in-sample predictor of next day volatility for a given company's stock. We later try to explore this anomaly in an out-of-sample study.

Keywords: Volatility, Behavioural finance, Volatility modelling, HAR

JEL classification: *G10, G14, G17*

1 Introduction

With the deepening of the sustainable development concept, the clean energy industry has proliferated in recent years. Given the rapid expansion of the renewable energy industry, the performance of the renewable energy companies in financial markets has attracted increased attention from policymakers and investors. With recent rise of retail investment activity and popularity of ESG topics among the wider public, renewable energy investment is likely to be the retail market's favourite play.

Investor sentiment affects the attitude toward financial assets and investment decisions, and it is widely used as a behaviour factor in financial research. Behavioural finance suggests that investors and markets are not fully rational, and that investors are influenced by their biases and cognitive errors. It is comprised of two main components: psychology, which explains the fallibilities in human behaviour, and limits to arbitrage, which argues that in an economy of rational and irrational traders, irrationality could have a sustained and significant impact.

In this paper, we model volatility of available stocks in the renewable energy sector of SP500 and investigate the relationship between investors' attention and stock price volatility. Given that markets are to a large degree efficient and any leftover mispricing is often quickly discovered and exploited, we would expect that investors' attention should not play a significant role if any. Although, many authors were able to find pricing anomalies, most do not persist much longer after they are published. What can be thus said is that markets are efficient in the long run and any departure from the optimal price of assets is eventually corrected. The time it takes to arbitrage away mispricing due to sentiment is largely driven by the relative strength of the opposing forces that drive stock price away and towards its intrinsic value. As arbitrageurs face limitations on the amount of capital and risk they can deploy, mispricing can persist for a surprisingly long time. As the adage says: "markets can remain irrational longer than you can remain solvent". Historical example of such situation is the GameStop episode where traders driven by somewhat arbitrary desire to gamble grouped fanatically around the Wallstreet bets forum and decided to bid up price of certain stocks to multiples of their rational value. Due to the market frictions such as limited ability to short GameStop, as well as lack of risk appetite to intervene by the informed traders, the stock of GameStop was significantly mispriced for longer than an efficient market should allow. This shows that although sentimental investors can not prevail over the whole stock market, they can still contribute to local inefficiencies by rising volatility and driving asset prices away from fundamentals.

Being cognisant of the localised effects that noise traders have on the markets, we focus our study on the burgeoning field of renewable energy which we believe have been and will continue to occupy retail investors' attention. If noisy traders are sufficiently present in this industry, they may be able to tilt the balance of arbitrager vs noise trader such that stock prices are considerably moved away from their intrinsic value. As a result of this we would expect to find excess volatility that could be to some extend related to the investors sentiment measured by their attention. A large amount of literature provides evidence that investor sentiment has an important impact on the financial market. However, only a few studies have discussed the influence of investor sentiment on clean energy stock so far.

3 Literature review

Early studies of stock returns established that economic and fundamental company information explain only a small part of their variance (Shiller (1981), Leroy and Porter (1981), and Roll (1988)). Several studies point to the role of noise traders and find that their impact is greater than information regarding company's cashflows or dividends. For example, Campbell and Kyle (1988) attributes the level of unexplained volatility to the interaction between informed and noise traders. Noise traders are able to drive prices due to the risk aversion of the informed investors. Foucault et al. (2011) uses the natural experiment provided by French stock market trading costs to show that retail investors have a positive effect on the volatility of stock returns. Given the contribution of noise traders on the stock market volatility, numerous researchers started to become interested in predicting noise traders' actions. Measures that approximate noise traders are for example past volatility and price moves, stock market news and related company information and particularly retail traders' activity such as reading and searching for news including posting on stock forums. Traders' attention to the changes in prices and news can by directly measured by looking at the number of times a certain website is searched for. Google lends itself to be an excellent source of information on such activity.

Da, Engelberg and Gao (2011) were among the first to use Google search frequencies as a measure of investor attention. They find that Search Volume Index is similar but different to previously used attention proxies and that it is much more direct measure of attention that is likely attributed to retail investor. Their study finds that an increase in SVI predicts increase in stock prices in the next 2 weeks. Furthermore, Dimpfl and Jank (2011) find a strong relationship between realized volatility and the stock search queries for the stock name. The causality runs in both directions, both high volatility leads to increase in search queries and increase in queries leads to increases in subsequent volatility.

Vlastakis and Markellos (2012) relate information demand measured by Google trends and supply from Reuters, they conclude that variations in information demand appear to have a significant effect on the realised volatility of individual 30 NYSE stocks and the overall market. Andrei and Hasler (2015) find that volatility increases quadratically with attention and uncertainty.

Audrino et al. (2020) looks for the predictive ability of sentiment and attention in a realised volatility model. They find that in a regression where they control for a range of economic and financial predictors variables such as attention measured by search frequencies for 'stock market' and related keywords is correlated with increase in realised volatility. They also note that wider group of searched keywords had more statistically significant effect compared to the individual company keywords. Ballinari et al. (2022) look at the effects of investor attention with respect to the time of announcements and report that investors' attention impact on volatility is conditional on the timing and events surrounding it. This study shows that the effect of Google searches is not linear and is at times is much more impactful, particularly when the attention is coupled with market announcement.

4 Data

We investigate the relationship between investor/ trader behavioral features linked to attention and the stock market volatility. Attention has been historically indirectly measured by market volume, turnover and news and while volume might be the natural candidate to link investor attention and volatility, several studies, such as Brooks (1998) and Donaldson and Kamstra (2005) show that it does not improve the accuracy of volatility forecasts. Furthermore, news as an alternative measure is mostly irregular and may underly a considerable publication lag. Recent publications use internet message postings (Kim and Kim, 2014), Facebook users sentiment data (Siganos et al., 2014) or search frequencies (Vozlyublennaia, 2014) to assess the influence of retail investors attention on the stock market. Among these studies, Da et al. (2011), Vlastakis and Markellos (2012) and Andrei and Hasler (2013), suggest that Google search volume is a driver of future volatility. With respect to the aforementioned literature, we chose to use Google Trends as a proxy for investor attention.

Regarding our choice of data, we collected investor attention data from Google Trends website and volatility was estimated based on the daily hi, low and close stock prices. Google trends was used to collect time series of data points that tell us the number of searches for specific keywords that are related to the company's stock price. For example, we downloaded daily number of searches for the word "Enphase energy share price" in the US between the years 2018 and 2021. Google gave us the time series of relative daily number of times that people searched for this keyword. As Google provides only a limited number of daily searches, we had to deploy a linking procedure to obtain the time series of sufficient length. The volatility of individual stocks was downloaded as daily realized volatility during the trading days for the given stocks. The volatility data was then merged with the Google search data by date. Lagged variables for both Google Trends and volatilities were created in order to obtain the variables we need for the regression.

The companies that we tested were all renewable energy companies from the SP500 index. These companies were selected by being part of both SP500 and renewable energy indices such as S&P Global Clean Energy Index (SPGTCLEN), Wilderhill ECO (ECO), Wilderhill NEX (NEX). We chose to focus on renewable energy as we feel that it is a sector that is favored by the retail traders and thus may provide answers for solving behavioral biases in studying volatility.

5 Methodology

To find the relationship between volatility and investors' attention we use a simple OLS regression using a HAR model.

5.1 OLS

In statistics, ordinary least squares usually abbreviated as OLS is a type of linear least squares method for estimating the parameters in a linear regression model. OLS chooses the parameters of a linear function of a set of explanatory variables by the principle of least squares by minimizing the sum of the squares of the differences between the observed dependent variable (values of the variable being observed) in the given dataset and those predicted by the linear function of the independent variable.

5.2 HAR

A rapidly growing body of literature has documented improvements in forecasting financial return volatility measurement using various heterogeneous autoregression (HAR) type models. Most HAR-type models use a sum of components to mirror the daily, weekly, and monthly averages of the volatility process, but they ignore model specification uncertainty. Although there are more complex models such as stochastic jump diffusion volatility models, we chose to use the HAR due to its parsimony and generality. Furthermore, HAR model has become a standard in modelling high frequency realized volatility data and thus is a prime choice in our study.

The model that we use has the following specifications:

$$V_t = \beta_0 + \beta_1 V_{t-1} + \beta_2 V_{t-5} + \beta_3 V_{t-22} + \beta_4 GT_{t-1} + \epsilon_t$$

As the distribution of the residuals was not Gaussian, we used log transformation to all our variables. After the transformation we run a number of tests to make sure the OLS conditions are satisfied:

Breusch-Pagan test
lmtest::bptest(regression)
White's test
Shapiro-Wilk normality test
sresid <- MASS::studres(regression)
shapiro.test(sample(sresid,5000))

To run the regression and estimate parameters we use the statistical language R.

```
regression <-
lm(log(ENPH_joint$VI.H1)~log(ENPH_joint$VI.L1)+log(ENPH_joint$VI.L5)+log(ENPH_joint$VI.L22)+log(ENPH_joint$est_hits.L1 + 1))
```

The regression analysis was run using the following stocks Enphase Energy Inc, SolarEdge Technologies Inc, Consolidated Edison Inc, Tesla and NextEra Energy Inc. The keywords that we used are "[company name] + stock price".

6 Results

In order to quantify the relationship between investors' behavioral biases and the stock market, we estimate the impact of investors' attention (measured by Google trends) on the next trading day volatility of company's stock price. In addition to the attention variable, we also use a number of lagged volatilities as regressors. We include the full set of results for all the control variables along with the residual statistics for the reader's content. We use individual company regression results to make a general argument about investors' attention in the renewable sector. Stocks were chosen based on their presence in renewable energy indices and SP500 index. This choice was motivated partly by the data availability, but mainly by design not to introduce selection or other bias in the regression. We are aware of potential limitations in our approach arising from the small sample size and we aim to improve on this in the future iteration of our study where we consider renewable energy companies from a wider index such as SP1500.

The results of the individual regressions are the following:

Enphase energy (Enphase energy stock price)

Coefficients:					
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.53215	0.30664	4.997	6.60E-07	***
log(ENPH_joint$VI.L1)	0.32078	0.02667	12.026	2.00E-16	***
log(ENPH_joint$VI.L5)	0.28080	0.03674	7.642	4.03E-14	***
log(ENPH_joint$VI.L22)	0.19724	0.04108	4.801	1.75E-06	***
log(ENPH_joint$est_hits.L1+1)	0.02967	0.01636	1.814	0.07	.

Residuals:				
Min	1Q	Median	3Q	Max
-3.4861	-0.5274	-0.0393	0.4758	3.4360

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.78 on 1351 degrees of freedom (Multiple R-squared: 0.3137, Adjusted R-squared: 0.3117 F-statistic: 154.4 on 4 and 1351 DF, p-value: < 2.2e-16

SolarEdge (SEDG stock price)

Coefficients:					
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.37191	0.25941	5.289	1.40E-07	***
log(SEDG_joint$VI.L1)	0.30941	0.02427	12.751	2.00E-16	***
log(SEDG_joint$VI.L5)	0.28685	0.03316	8.651	2.00E-16	***
log(SEDG_joint$VI.L22)	0.20593	0.03706	5.557	3.20E-08	***
log(SEDG_joint$est_hits.L1+1)	0.02733	0.01360	2.010	0.0446	*

Residuals:				
Min	1Q	Median	3Q	Max
-2.17664	-0.53613	-0.03266	0.47596	3.12643

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.7635 on 1639 degrees of freedom. Multiple R-squared: 0.3202, Adjusted R-squared: 0.3185, F-statistic: 193 on 4 and 1639 DF, p-value: < 2.2e-16

Consolidated Edison (ed stock price)

Coefficients:					
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.55703	0.14211	3.92	9.20E-05	***
log(ED_joint$VI.L1)	0.27570	0.02345	11.755	2.00E-16	***
log(ED_joint$VI.L5)	0.37422	0.03412	10.968	2.00E-16	***
log(ED_joint$VI.L22)	0.22046	0.03543	6.223	6.07E-10	***
log(ED_joint$est_hits.L1+1)	0.01962	0.01168	1.681	0.093	.
Residuals:					
Min	1Q	Median	3Q		Max
-2.04447	-0.44162	-0.01835	0.43094		2.21 640

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.6754 on 1796 degrees of freedom. Multiple R-squared: 0.4263, Adjusted R-squared: 0.425, F-statistic: 333.6 on 4 and 1796 DF, p-value: < 2.2e-16

NextEra Energy (NEE stock price)

Coefficients:					
	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	0.71159	0.15088	4.716	2.59E-06	***
log(NEE_joint$VI.L1)	0.35079	0.02313	15.165	2.00E-16	***
log(NEE_joint$VI.L5)	0.27645	0.03193	8.657	2.00E-16	***
log(NEE_joint$VI.L22)	0.21385	0.03424	6.246	5.26E-10	***
log(NEE_joint$est_hits.L1+	0.03703	0.01333	2.777	0.00555	**
Residuals:					
Min	1Q	Median	3Q	Max	
-2.03082	-0.48436	-0.01791	0.43063	2.78464	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1Residual standard error: 0.7053 on 1796 degrees of freedom. Multiple R-squared: 0.4345,Adjusted R-squared: 0.4332, F-statistic: 344.9 on 4 and 1796 DF, p-value: < 2.2e-1

Tesla (TSLA stock price)

Coefficients:							
			Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)			1.26163	0.21190	5.954	3.14E-09	***
log(TSLA_joint$VI.L1)			0.34887	0.02306	15.126	2.00E-16	***
log(TSLA_joint$VI.L5)			0.25974	0.03151	8.242	3.22E-16	***
log(TSLA_joint$VI.L22)			0.18191	0.03400	5.35	9.91E-08	***
log(TSLA_joint$est_hits.L1+1)			0.05845	0.01802	3.244	0.0012	**
Residuals:							
Min	1Q	Median		3Q		Max	
-2.04298	-0.51044	-0.04577		0.48033		3.03337	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.7423 on 1796 degrees of freedom. Multiple R-squared: 0.4074, Adjusted R-squared: 0.4061, F-statistic: 308.7 on 4 and 1796 DF, p-value: < 2.2e-16

The above regression results tell us about the relationship between estimated daily volatility of stock returns for a given stock and the amount of Google searches represented by the Google Trends index. The dependent variable is estimated daily realized volatility of stock price and explanatory variables are estimates of lagged daily, weekly and monthly realized volatilities of the stock price and the lagged daily Google trends index of the given stock-related search keyword. As the variables used in the regression are transformed to be logs, we can interpret the coefficients as elasticities: one percent increase in the Google Trends index for the search keyword "TSLA stock price", given the control variables, on average, is associated with 0.058 percent increase in the rise of volatility of Tesla stock on the following day. This result is statistically significant at 99 percent confidence level. Similarly, for Enphase Energy, Solar Edge, Consolidated Edison and NextEra Energy we find small positive relationship between Google trends and their next day volatilities that is significant but at lower confidence level.

6.1 Discussion

The topic of attention and stock volatility has been studied for over 20 years now. It is widely believed that volatility in stock prices is best modelled as an autoregressive function of past volatilities rather than fundamental information. Despite this there have been attempt to explain volatility using attention variables. Some of these studies claim to find little or no relationship, others are slightly more positive. For example, Audrino et. al 2021 finds that Google trends predict volatility however the size is somewhat insignificant. Our study corroborates Audrino's finding of significant effect. Similarly, the size of the effect is somewhat small and thus may not be exploitable by a volatility trader looking for an edge in modelling. This result is also described in a related study looking at the Google searches and stock returns, where Bijl et al. 2016 find a significant effect of attention on returns, yet a trading strategy based on this approach is deemed not to be profitable when transaction costs are takin into account.

7 Conclusion

Behavioural economics and finance is not yet a completely explored field of science. In this paper we wanted to shed some light on the role of attention of retail traders as well as test a more general hypothesis about the relationship between behavioural factors and volatility. We chose to use investors' attention and its effects on volatility as this is a non-fundamental variable that provides a relatively well-measured proxy for several biases such as recency bias, and others. The analysis was cantered around renewable-energy stocks which enables us to test secondary hypothesis regarding this sector of the stock market. We believe that both the choice of attention measure and renewable energy sector are correlated with retail investor interest and thus contain a higher percentage of sentiment-driven retail investors. As pointed out in the literature review, past studies point to retail investors being more prone to behavioural biases and thus a favourable sample for our study.

The regression analysis has shown that in most cases there is a statistically significant effect between the number of searches for the company stock price and the size of the company's price volatility the day after. On average we found that roughly 1% rise in the number of searches leads on average to 0.03 % rise in the volatility of the stock. This shows that a rise in the attention of retail investors leads on average to heightened volatility in the price of the stock the following day. Due to the sample size of our study, we can be fairly sure that this effect does not arise due to other events such as fundamental changes in the company performance. The coefficients on the Google trends variable were either 95% or 99% significant and we thus can also exclude the possibility of this effect arising purely by chance. Our finding has a number of applications in the risk management field by expanding the classic HAR model with daily data on attention. And last but not least, it also contributes to the volatility modelling literature.

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