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Impact of news and social media sentiments on rare earth investments

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ABSTRACT

In recent years, investing in rare earth metals has increased significantly due to its importance in producing renewable energy. Accordingly, a growing body of literature investigates the connectedness between rare earth equities and other financial markets, though very little is known about the volatility dynamics of this new asset class. Our study extends such scarce literature by employing the heteroscedastic auto-regressive (HAR) model to explore the volatility pattern of rare earth ETF. Later, we extend the baseline HAR process to explore the role of news and social media sentiment in volatility forecasting. Our empirical analysis uses the sentiment data provided by the Thomson Reuters MarketPsych Indices (TRMI) to examine whether investor sentiments collected from various media sources (i.e. traditional news media and social networking sites) would have a heterogeneous impact on the volatility predictions. Overall, our results indicate that both social and news media influence the realized volatility of rare earth equities. More importantly, this effect is positive suggesting that higher media sentiment causes higher volatility. We further observe that the extended HAR models, which include different sentiment measures such as *Buzz* and *Sentiment*, tend to outperform the baseline HAR model. Our analysis also concludes that the *Buzz* index has more predictive contents relative to the *Sentiment* index.

1. Introduction

Rare earth metals (REMs) have emerged as the key elements of clean energy technologies given their significant role in generating solar cells, wind turbines and electric vehicles (Buchholz and Brandenburg, 2018). These metals are indispensable for the transition to renewables for a low-carbon society (Madaleno et al., 2023; Henriques and Sadorsky, 2023). Therefore, the need for rare earth metals is increasing significantly as more green technologies are required to achieve the net-zero goals. A recent report, published by the International Energy Agency (IEA), projects that compared with 2021, the demand for REMs in generating renewable energy technologies (e.g., wind turbines and electric vehicles) could be nearly seven times higher in 2040.

Given the importance of REMs in producing clean energy, investments in this sector witness an upward trend. In the EU, for instance, approximately 18 thousand tonnes of rear earth elements were imported in 2022, showing a 9 % increment relative to 2021. The cost of these imports amounts to €146 million, representing a 37 % increase from 2021. The exports of these metals, on the other hand, are worth €142 million in 2022, marking a 2 % growth compared to 2021.[1]

Moreover, several recent studies (Dutta et al., 2024a; Wei, 2024) argue that a significant upsurge in demand for green energy is observed during the COVID-19 pandemic periods, which could be due to the inception of a "green recovery" policy in various countries with a view to quickening the net-zero transition plans. The main purpose of this policy is to keep the transition as priority despite the economic crisis caused by the pandemic. Although the COVID-19 crisis may have an extensive impact on the global economy and environment for years, the commencement of this "green recovery" policy might help the governments avert a sequence of crises. Besides, it could also play a pivotal role in the overall economic expansion amid the post-pandemic phase. In sum, green finance including investing in rare earth metals exerts positive effects on global economic resilience by promoting sustainable economic development (Lee and Lee, 2022).

Investing in REMs has received considerable attention from investors and policymakers only in recent years, which could make it a highly

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volatile asset (Henriques and Sadorsky, 2023; Madaleno et al., 2023). Against this background, a number of empirical studies explore the return and volatility dynamics of rare earth stocks. For example, Bouri et al. (2021) investigate the volatility linkage between the rare earth stocks and the equity prices of clean energy, consumer electronics, telecommunications, healthcare equipment, and aerospace & defense. In doing so, the authors employ a quantile-based approach and find that the volatility dynamics among these markets evolve dramatically during the extreme market conditions (e.g., COVID-19 pandemic period). Song et al. (2021) conduct a similar study using the time-varying parameter vector autoregression (TVP-VAR) approach. The study shows that the rare earth stock market maintains a close association with the clean energy and oil equities amid the outbreak of COVID-19 pandemic. Applying a multiscale-vine copula method, Kamal and Bouri (2023) assess the connectedness between the rare earth equities and other financial assets including gold, oil, clean energy and world equites. The authors document that the aforesaid relationship is heterogeneous, which tends to vary across different time scales. Moreover, Hanif et al. (2023) adopt the wavelet squared coherence approach in order to study the volatility spillover effects between rare earth and clean energy stock returns. The findings suggest that the correlation between these two markets seems increasing during the COVID-19 pandemic period. A similar analysis is also performed by Madaleno et al. (2023) by employing the cross-quantilogram method. The authors show that the connection between rare earth and clean energy equities is time-varying, which is driven by market conditions. More recently, Gao and Liu (2024) examine the volatility transmission linkage between rare earth metal stocks and other asset classes such as gold, base metal, oil, renewable energy, green bond, ESG, and agricultural markets. The authors use the spillover methods proposed by Diebold and Yilmaz (2014) and Baruník and Křehlík (2018). The results show that rare earth stocks have a significant relationship with base metal, clean energy, and ESG markets. The study further reveals that this association tends to soar during the stress periods. Besides, Gao et al. (2024) investigate whether the relationship between rare earth metal stocks and clean energy equites is influenced by the increasing geopolitical risk. Combining GARCH with the TVP-VAR model, the authors find that the aforesaid linkage, which varies over time, is highly sensitive to geopolitical tensions such as the Russian-Ukraine war.

The present study extends this prior literature in several ways. Firstly, unlike the prior studies, which mainly investigate the correlation or interdependence between rare earth metal stocks and other financial asset classes, we focus on modeling and forecasting the stock price volatility of REMs. Since the volatility of a financial asset can impact its price levels substantially, which in turn influences the asset allocation decision, precise estimates of time-varying volatilities are of utmost importance to investors and policymakers (Sohag et al., 2023). Given that rare earth equities represent a fresh asset class, investments in this sector could be associated with high uncertainty, thereby affecting investment behavior (Henriques and Sadorsky, 2023). To this end, it is crucial to precisely estimate the time-varying volatility of this new asset class.

Secondly, we examine the role of news and social media sentiment in forecasting the variation in rare earth equity prices. The use of such sentiment data could be beneficial due to the fact that information on stocks, ETFs and options is shared among market participants through Twitter, Facebook and other social media platforms. Ho et al. (2017), for instance, argue that retail investors' opinions on specific equities, which could have short-run impacts on stock prices, are often captured in social media. Besides, participants in Facebook or Twitter may have access to insider information which can be made publicly available through social media. Gan et al. (2020) also document that news and social media often generate striking headlines that could influence investors' views about a firm's future outlook, thereby creating investor sentiment which eventually impacts its equity returns. Hence, news and social media sentiment might disclose market imperfections that can be utilized for forecasting the volatility of stock prices. To sum up, information revealed in traditional news media and various social networking services could reflect investors perspective, which can be exercised for at least short-term forecasts of equity prices (Teti et al., 2019). Hence, this could be considered a core contribution of our paper given the importance of investors' sentiment in analyzing the risk linked to rare earth equities.

Finally, to the best of our knowledge, we are the first to use the sentiment data provided by the Thomson Reuters MarketPsych Indices (henceforth, TRMI) for predicting the volatility of rare earth stocks. The application of TRMI is advantageous as it provides sentiment data based on both traditional news media and social networking sites (Gan et al., 2020). Hence, separating these two media will allow us to examine whether the sentiment data collected from various media sources would have a heterogeneous impact on the volatility levels of REM equities.[2] In other words, we explore if rare earth equities react to various forms of media in a systematically different way. Thus, a direct comparison between traditional news media and social networking services through a sophisticated econometric analysis will help us test the impact of textual news flow, collected from different types of media, in forecasting the financial market volatility.

Note that TRMI provides commodity-specific sentiment indexes, which allow us to investigate if the volatility of rare earth equities is driven by the sentiments particularly associated with the rare earth metal markets. Hence, the application of TRMI data is relatively stimulating as we can focus on the sentiment data that explicitly rely on investor emotions towards rare earth financing.

Methodologically, we extend the heterogeneous autoregressive (HAR) model using the information content of TRMI data. The application of HAR process is crucial given its dominance over other volatility models (Dutta et al., 2024b). Our findings, in brief, suggest that both social and news media tend to impact the volatility of rare earth stocks. Thus, we conclude that investor emotions are closely associated with the volatility of rare earth equities. These findings are in line with prior literature (e.g., Jiao et al., 2020; Coqueret, 2020; Griffith et al., 2020) reporting that stock prices are sensitive to social and news media sentiments. Our results also indicate that higher media sentiment causes higher volatility. As the findings reveal that information shared in different news and social media emerges as a good forecaster of the time-varying variation in REM stock prices, policymakers should pay attention to investor sentiments to understand the risk linked to rare earth investing. Besides, our results are also valuable for socially responsible investors who aim at financing the transition towards a low carbon economy. Hence, this strand of research has key implications for social sustainability.

2. Literature review

In this section, we elaborate the existing literature focusing on the spillover effects between media sentiment and global financial markets. We begin with the study by Coqueret (2020) which examine the effect of stock-specific news sentiment on future returns. The author shows that market returns are more likely to influence future sentiment than the reverse way. Gan et al. (2020) confirm similar results, demonstrating that market factors have a greater influence on investor sentiment

[2] Thomson Reuters MarketPsych Indices (TRMI) data have received ample attention in recent years. Notable contributions include Papakyriakou et al. (2019), Coqueret (2020), Dong and Gil-Bazo (2020), Jiao et al. (2020), Griffith et al. (2020), Gan et al. (2020), Maghyereh and Hussein (2020), Consoli et al. (2021), Eierle et al. (2022), Han et al. (2022), Akyildirim et al. (2024), Beckmann and Rogmann (2024), Subramanian et al. (2024), Hsu and Huang (2024), Huang et al. (2024) and Bennett et al. (2024). The existing works provide evidence that the information on TRMI data are quite useful for modeling the volatility of financial assets.

compared to the reverse. Dong and Gil-Bazo (2020) explore the impact of firm-specific investor sentiment on stock returns by analyzing over 58 million social media messages in China matched with publicly listed companies to create a sentiment gauge based on the content's tone. The research indicates that optimistic investor sentiment forecasts increased risk-adjusted stock returns in the immediate short term, succeeded by price reversals. Jiao et al. (2020) examine the impact of coverage by both conventional news media and social media on stock volatility and turnover. Their findings show that traditional news media coverage forecasts reduced volatility and turnover in the following period, while social media coverage leads to heightened volatility and turnover. Employing the quantile cross-spectral dependence method, Maghyereh and Hussein (2020) examine the comprehensive dynamic relationship between investor sentiment quantiles and ten significant commodities. The findings reveal variations in the interdependence between sentiment and commodities based on return quantiles and time frequencies. Besides, Griffith et al. (2020) use the TRMI data to examine the impact of social and news media sentiment on the return and volatility dynamics of S&P 500 index. Applying the asymmetric GARCH process, the authors show that sentiment impacts both return and volatility of the US equity market. Moreover, Consoli et al. (2021) also find the importance of media sentiment in explaining the bond market behavior. The research highlights the utility of emotions derived from macroeconomic news in elucidating and predicting future trends in sovereign bond yield spreads in Italy and Spain. The results indicate that intense negative emotions like panic provide valuable insights for forecasting short-term spread changes, whereas gentler emotions such as distress are beneficial for longer-term predictions. In their recent study, Eierle et al. (2022) propose a modified social media sentiment measure that accounts for the influence of financial data such as earnings surprises, analyst forecast adjustments, dividends, and 8-K filings. Their findings reveal a connection between this adjusted social media sentiment and upcoming short-term stock performance, with a notable impact on stocks displaying negative adjusted sentiment. A recent study by Hsu and Huang (2024) examines the resilience of the US stocks during the COVID-19 market crashes using the ESG scores based on the real-time global news and social media. Applying a conventional balanced analysis method, the researchers demonstrate that reduced information disparity among ESG scores typically results in increased pricing premiums during market downturns like the pandemic. In a parallel study utilizing comparable ESG ratings, Huang et al. (2024) find that banks with weaker ESG standings offer loans to companies with superior ESG performance at notably lower spreads, longer maturities, fewer general covenants, and reduced collateral requirements. Multiple researchers investigate how media sentiment influences the transmission of effects among different cryptocurrency markets. Akyildirim et al. (2024), for instance, employ the time-varying parameter vector autoregressive model to show that positive sentiment influences the interconnectedness between cryptocurrencies, indicating an asymmetric impact. Bennett et al. (2024) further observe that sentiment from news and social media significantly contributes to understanding the volatility patterns of cryptocurrencies. In addition, Subramanian et al. (2024) create, execute, and assess a decision support system that merges detailed signals extracted from news and social media with bitcoin prices through a Long Short-Term Memory (LSTM) neural network. The study demonstrates that the proposed decision support system is a useful tool for predicting cryptocurrency returns more precisely.

This paper extends the above literature in several aspects. Firstly, similar to Jiao et al. (2020) and Gan et al. (2020), we distinguish between two distinct media sources, social media and news, to investigate if data extracted from different platforms have varying effects on the volatility of rare earth equities. Specifically, our thorough statistical assessment of the TRMI dataset enhances the credibility of textual data in asset pricing contexts by elucidating how information from diverse media outlets impacts stock market volatility. However, unlike Jiao et al. (2020) and Gan et al. (2020), we examine if media sentiment data have predictive contents for equity market volatility. In particular, we use the information on social and news media sentiments to forecast the daily, weekly and monthly realized volatility of rare earth equity returns. Secondly, the existing literature indicates that information revealed in traditional news media and various social networking services could reflect investors perspective, which can be exercised only for short-term forecasts of equity price risk (Teti et al., 2019; Eierle et al., 2022). For example, Eierle et al. (2022) argue that investor sentiments are speculative elements which have only short-term impacts. In this paper, however, we aim to examine the practicality of sentiment data in predicting the long-term stock market volatility. The application of HAR-type models allows us to make such attempts. Doing so would obviously shed further light on this debate. Hence, our investigation and the findings reveal fresh insights into the significance of information in asset pricing within the realm of social media influence. Thirdly, while the existing literature largely employs conventional asset pricing and volatility models to capture the linkage between investor sentiment and financial markets, we add to this literature by explaining the aforesaid association from the behavioral finance perspective. Note that one limitation of conventional asset pricing models is that the underlying assumption ignores the social exchanges among market participants, although investors tend to communicate with each other using various news and social media platforms. This social influence plays a pivotal role in the diffusion of information, thereby affecting asset pricing. Hence, it is crucial to understand the role of different media which offer additional information beyond market data.

3. Data

To track the equity prices of rare earth metals, we use the VanEck Rare Earth/Strategic Metals ETF (REMX), which appears to be the largest and most liquid index related to REM investments. The REMX comprises those firms that are involved in a range of activities relevant to rare earth and strategic metals and minerals. Given that this ETF was launched on 28th October 2010, our sample period ranges from the commencement date to 31st March 2024 resulting in 3376 observations. These data are collected from the Bloomberg terminal.

In regards to the TRMI data, we employ two important indexes: *Buzz* and *Sentiment*. *Buzz* measures the news and social media activeness, whereas *Sentiment* is used as a proxy for emotions. Prior literature (e.g., Gan et al., 2020) shows that both *Buzz* and *Sentiment* indexes play a significant role in forecasting the equity return volatility. As mentioned earlier, the information on *Buzz* and *Sentiment* is sourced from both traditional news platforms and social networking services to differentiate the impact of these two forms of media on volatility predictions.

Notably, TRMI, which was launched in 1998, integrates analysis of various media in real-time by translating the volume and emotions of financial economic news and cyberspace posts into feasible data flows. It contains three different types of sentiment data - news, social and combined-which are based on a number of English language commentaries, posts and reports. While constructing these indexes, TRMI collects information from 2000 news sources which include The New York Times, The Wall Street Journal, The Financial Times, Thomson Reuters News Feed Direct, Factiva News, Yahoo! and Google News. TRMI systematically monitors and analyzes a vast array of sources, including over 2 million blogs, stock message boards, and social media platforms like StockTwits, Yahoo! Finance, and SeekingAlpha. This monitoring is conducted in real-time (Gan et al., 2020). TRMI's methodology for term weighting and scoring is rooted in the financial context, based on the Loughran and McDonald (2011) dictionary scheme. This approach is found to be more effective for financial analysis compared to the psycho-social dictionary scheme employed in Tetlock (2007) using the Harvard General Inquirer (GI).

It is also worth noting that the *Buzz* index is conceptually different from the *Sentiment* index. For instance, the former is created on the basis of important keywords including *Litigation*, *Mergers*, and *Volatility*, which represent activity market-moving topics. In addition, the *Buzz* index captures the volume of information flow as well. The *Sentiment* index, on the other hand, is an emotional indicator which reflects both pessimism and optimism of investors such as fear, gloom, joy, and stress. While the *Buzz* index assumes only nonnegative numbers capturing the total number of references (words and phrases) to a specific stock, the *Sentiment* index assumes values between −1 (most negative) to +1 (most positive) measuring the normalized sentiment inferred from news articles (Michaelides et al., 2019).

Table 1 reports the summary statistics of different indexes. We notice that the mean return is negative for the REMX index. For the TRMI data, the statistics reveal that the mean and standard deviation are quite high for both *Buzz* indexes, which is not the case for the *Sentiment* indexes. Besides, the *Sentiment* indexes are more symmetric compared to the *Buzz* indexes. We further observe that the kurtosis exceeds 3 for all the variables indicating a leptokurtic distribution. Finally, the unit root test results suggest that each of these indexes appears to be stationary.

Fig. 1 depicts the REMX index, which exhibits two major drops in the price levels of rare earth equities. The first one takes place in 2015–2016 when the global crude oil markets witness a significant downturn. The next fall is observed amid the COVID-19 crisis era. The prices, however, experience some growths during the post-pandemic period.

4. Methods

4.1. HAR model

The HAR process is a leading approach to modeling the realized volatility (RV) of various financial assets (Dutta et al., 2024b). The adoption of this process is beneficial given that it considers splitting the RV into short-, medium-, and long-term volatility components, thereby improving the forecasting performance (Dutta and Das, 2022). Prior works (Andersen et al., 2007, 2011; Forsberg and Ghysels, 2007; Giot and Laurent, 2007; Ma et al., 2014) also demonstrate its dominance over other volatility models.

According to Corsi (2009) and Busch et al. (2011), the conventional HAR-RV process is given as:

$$\textbf{HAR}-\textbf{RV}: RV_{t,t+h} = \theta_0 + \theta_d RV_t + \theta_w RV_{t-5,t} + \theta_m RV_{t-22,t} + \varepsilon_t \tag{1}$$

where h assumes the values 1, 5 and 22, which indicate the daily, weekly and monthly prediction horizons, respectively and

$$RV_{t_1,t_2} = \frac{1}{t_2 - t_1} \sum_{t=t_1+1}^{t_2} RV_t \tag{2}$$

Now, to compute the RV of the REMX index, Parkinson's (1980) range-based volatility measure has been employed:

$$RV_t = \frac{1}{4\,ln\,2}(ln\,H_t - ln\,L_t)^2 \tag{3}$$

with H_t and L_t being the maximum and minimum prices.

Next, we extend equation (1) considering the information on different sentiment indices. For the Buzz measure, the extended models appear as:

$$\textbf{HAR-RV-Buzz\_News}: RV_{t,t+h} = \theta_0 + \theta_d RV_t + \theta_w RV_{t-5,t} + \theta_m RV_{t-22,t} + \alpha \Delta Buzz\_News_t + \varepsilon_t \tag{4}$$

$$\textbf{HAR-RV-Buzz\_Social}: RV_{t,t+h} = \theta_0 + \theta_d RV_t + \theta_w RV_{t-5,t} + \theta_m RV_{t-22,t} + \beta \Delta Buzz\_Social_t + \varepsilon_t \tag{5}$$

For the sentiment measure, the construct the following equations:

$$\textbf{HAR-RV-Sentiment\_News}: RV_{t,t+h} = \theta_0 + \theta_d RV_t + \theta_w RV_{t-5,t} + \theta_m RV_{t-22,t} + \gamma \Delta Sentiment\_News_t + \varepsilon_t \tag{6}$$

$$\textbf{HAR-RV-Sentiment\_Social}: RV_{t,t+h} = \theta_0 + \theta_d RV_t + \theta_w RV_{t-5,t} + \theta_m RV_{t-22,t} + \delta \Delta Sentiment\_Social_t + \varepsilon_t \tag{7}$$

4.2. Forecast evaluation

4.2.1. HRMSE statistic

This section compares the volatility prediction performance of different HAR models used in our analysis. We first calculate the heteroskedasticity adjusted root mean square error (HRMSE) statistic, proposed by Bollerslev and Ghysels (1996). This measure is defined as:

$$HRMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{RV_t - \widehat{RV_t}}{RV_t}\right)^2} \tag{8}$$

with T being the number of data points to be predicted. In addition, RV_t and $\widehat{RV_t}$ indicate the true and predicted volatility on day t, respectively.

Notably, the Diebold and Mariano (DM, 1995) test is also conducted to compare the predictions from two different HAR models.

4.2.2. Out-of-sample R^2 test

We now consider applying the out-of-sample R^2 (R^2_{OOS}) test, which is introduced by Campbell and Thompson (2008). The R^2_{OOS} statistic is given as:

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T}\left(RV_t - RV_t^j\right)^2}{\sum_{t=1}^{T}\left(RV_t - RV_t^0\right)^2} \tag{9}$$

where RV_t, RV_t^j, and RV_t^0 specify the true RV, the RV predicted by model j with j referring to one of the extended HAR models (i.e., HAR-RV-Buzz_News, HAR-RV-Sentiment_News, HAR-RV-Buzz_Social and HAR-RV-Sentiment_Social), and the RV forecast by the baseline HAR process, respectively. If R^2_{OOS} assumes a non-zero value, then the proposed HAR approach tends to surpass the baseline HAR process in terms of precision.

Additionally, we evaluate the adjusted mean squared prediction

Table 1
Summary statistics.

	REMX	Buzz_News	Sentiment_News	Buzz_Social	Sentiment_Social
Mean	−0.0004	259.79	0.0853	318.58	0.0664
Std. Dev.	0.0212	578.95	0.2006	320.51	0.1604
Skewness	−0.28	19.65	0.52	2.88	0.24
Kurtosis	7.07	574.95	4.95	21.35	5.76
ADF	−56.39***	−16.12***	−36.74***	−8.69***	−20.02***
PP	−56.41***	−37.93***	−54.46***	−49.49***	−58.85***

Notes: This table reports the summary statistics for different indexes. Log-returns are used for the rare earth ETF, while the level values are considered for the sentiment indexes. *** indicates statistical significance at 1 % level.

Fig. 1. Time series plot of the REMX index.

error (MSPE) statistic, proposed by Clark and West (2007), to assess whether the modified HAR approach outperforms the baseline HAR process.

Note that we consider the in-sample estimation period from 28 October 2010 to 31 March 2023 and the out-of-sample period from 1 April 2023 to 31 March 2024.

5. Empirical results

5.1. Results of HAR models

The estimates of the daily, weekly and monthly HAR models are reported in Tables 2–4. The results, exhibited in Table 2, show that all the parameters associated with the short-, medium- and long-term volatility components are found to be statistically significant at 1 % level. We can thus conclude that the volatility of rare earth equities experiences a long memory. Proceeding further, we document that the *Buzz* index, sourced from the traditional news media, has a significant impact on the realized volatility as evidenced from the HAR-RV-Buzz_News model. The effect is positive implying that the volatility of rare earth stocks tends to increase with the increase in the *Buzz* index. It is also noticed that like the HAR-RV model, all the parameters associated with different volatility components remain significant. Notably, the R^2 statistic has witnessed a slight increment when looking at the HAR-RV-Buzz_News. Next, the estimates of the HAR-RV-Sentiment_News process reveals that the *Sentiment* index does not have any significant effect on the RV as the corresponding coefficient is statistically insignificant. Interestingly, this model produces a lower R^2 statistic (24.47) compared to the baseline HAR model (24.55). We also observe similar results when referring to the estimates of the HAR-RV-Sentiment_Social model. Hence, the effect of the variable *Sentiment* is not significant at all. Lastly, the findings of the HAR-RV-Buzz_Social model confirm that the *Buzz* index exerts a significant impact on the RV of rare earth equities and that this model generates the highest R^2 statistic amounting to 24.63.

While observing the results of Table 3, which are based on the weekly HAR process, we reach similar conclusions. For example, all the parameters of the HAR-RV process (i.e., θ_d, θ_w and θ_m) are still statistically significant, thus ensuring long memory in volatility for the rare earth stocks. We also notice that the RV is sensitive to the *Buzz* index only, since the coefficients associated with *Sentiment* indexes are still insignificant. In addition, the HAR-RV-Buzz_Social model generates the highest R^2 statistic (33.42). We further notice that the weekly HAR models produce higher R^2 statistics relative to the daily models.

Next, the estimates of the monthly HAR approaches, displayed in Table 4, are mostly in line with those documented in earlier tables. The only discrepancy we observe is that the *Sentiment* index, sourced from the social networking services, exerts a significant impact on the RV of rare earth equities, although the effect is weakly significant at 10 % level. Notably, this impact is positive suggesting that an upsurge in the *Sentiment* index leads to an increase in the realized volatility. Moreover, when looking at the R^2 statistics, we report that the monthly HAR models generate lower values relative to the daily and weekly models.

To sum up, our findings indicate that both social and news media influence the volatility of rare earth stocks. These findings are consistent

Table 2
Findings of daily HAR-RV models.

Models	HAR-RV	HAR-RV-Buzz_News	HAR-RV-Sentiment_News	HAR-RV-Buzz_Social	HAR-RV-Sentiment_Social
θ_0	0.00005*** (0.00001)	0.00004*** (0.00001)	0.00005*** (0.00001)	0.00004*** (0.00001)	0.00004*** (0.00001)
θ_d	0.1766*** (0.0206)	0.1759*** (0.0207)	0.1777*** (0.0208)	0.1745*** (0.0206)	0.1768*** (0.0206)
θ_w	0.4406*** (0.0356)	0.4393*** (0.0358)	0.4396*** (0.0359)	0.4422*** (0.0357)	0.4407*** (0.0357)
θ_m	0.1289*** (0.0306)	0.1138*** (0.0393)	0.1199*** (0.0392)	0.1137*** (0.0392)	0.1226*** (0.0391)
α		0.000000018** (0.000000007)			
β			0.0000004 (0.00002)		
γ				0.000000028** (0.000000014)	
δ					−0.000015 (0.000027)
R^2 (%)	24.55	24.60	24.47	24.63	24.54
HET test	0.23	0.24	0.19	0.33	0.21
D-W statistic	2.03	2.04	2.03	2.03	2.04

Notes: This table reports the results of daily HAR processes. The standard errors are shown in the parentheses. The HET row shows the results of the heteroscedasticity test. ***, ** and * imply the statistical significance at 1 %, 5 % and 10 % levels, respectively. D-W indicates the Durbin-Watson test statistic.

Table 3
Findings of weekly HAR-RV models.

Models	HAR-RV	HAR-RV-Buzz_News	HAR-RV-Sentiment_News	HAR-RV-Buzz_Social	HAR-RV-Sentiment_Social
θ_0	0.00007*** (0.000004)	0.00006*** (0.000005)	0.00007*** (0.000005)	0.00006*** (0.000005)	0.00006*** (0.000004)
θ_d	0.1345*** (0.0137)	0.1333*** (0.0139)	0.1351*** (0.0139)	0.1318*** (0.0138)	0.1343*** (0.0138)
θ_w	0.3602*** (0.0238)	0.3592*** (0.0239)	0.3597*** (0.0240)	0.3617*** (0.0238)	0.3609*** (0.0239)
θ_m	0.1307*** (0.0261)	0.1243*** (0.0262)	0.1292*** (0.0263)	0.1202*** (0.0262)	0.1296*** (0.0261)
α		0.000000016** (0.000000005)			
β			0.000011 (0.000015)		
γ				0.000000036** (0.000000009)	
δ					0.000009 (0.000018)
R^2 (%)	33.13	33.21	33.02	33.42	33.12
HET test	0.27	0.29	0.21	0.34	0.23
D-W statistic	1.66	1.65	1.65	1.65	1.64

Notes: This table reports the results of weekly HAR processes. The standard errors are shown in the parentheses. The HET row shows the results of the heteroscedasticity test. ***, ** and * imply the statistical significance at 1 %, 5 % and 10 % levels, respectively. D-W indicates the Durbin-Watson test statistic.

Table 4
Findings of monthly HAR-RV models.

Models	HAR-RV	HAR-RV-Buzz_News	HAR-RV-Sentiment_News	HAR-RV-Buzz_Social	HAR-RV-Sentiment_Social
θ_0	0.0001*** (0.000004)	0.0001*** (0.000003)	0.0001*** (0.000003)	0.0001*** (0.000004)	0.0001*** (0.000004)
θ_d	0.0703*** (0.0110)	0.0696*** (0.0111)	0.0706*** (0.0111)	0.0691*** (0.0110)	0.0697*** (0.0111)
θ_w	0.1260*** (0.0191)	0.1248*** (0.0192)	0.1249*** (0.0193)	0.1270*** (0.0191)	0.1275*** (0.0192)
θ_m	0.2366*** (0.0209)	0.2333*** (0.0211)	0.2365*** (0.0210)	0.2315*** (0.0210)	0.2339*** (0.0210)
α		0.000000010** (0.000000004)			
β			0.000001 (0.00001)		
γ				0.000000016** (0.0000000075)	
δ					0.000026* (0.000014)
R^2 (%)	21.55	21.58	21.44	21.62	21.59
HET test	0.16	0.21	0.18	0.28	0.20
D-W statistic	1.91	1.93	1.91	1.96	1.96

Notes: This table reports the results of monthly HAR processes. The standard errors are shown in the parentheses. The HET row shows the results of the heteroscedasticity test. ***, ** and * imply the statistical significance at 1 %, 5 % and 10 % levels, respectively. D-W indicates the Durbin-Watson test statistic.

with Jiao et al. (2020), Coqueret (2020) and Griffith et al. (2020) who also document that stock returns are sensitive to social and news media sentiments. We further report that higher sentiment causes higher volatility. Jiao et al. (2020) also document similar results showing that an increment in investor sentiments leads to an increase in the volatility of stock returns. Note that all these prior works are mainly focused on the traditional stock markets, whereas we study the volatility of rare earth equities. It is also worth mentioning that the *Buzz* index has more predictive contents relative to the *Sentiment* index. This could be due to the fact that the construction of *Buzz* index differs from that of the *Sentiment* index. For instance, the former is created on the basis of important keywords including *Litigation*, *Mergers*, and *Volatility*, which represent activity market-moving topics. Besides, the *Buzz* index measures the volume of information flow as well. Gan et al. (2020) also argue that these features make the *Buzz* index a more informative measure compared to the *Sentiment* index. Furthermore, the finding that social media offers predictive contents for stock price volatility could be attributed to the fact that during the sample period used in this study, which spans from 2010 to 2024, social media receives more attention relative to the traditional news platforms. Amid this era, information shared over social networking sites seems transmits faster than the news published in traditional media.

5.2. Additional analysis based on the alternative RV measure

Our earlier investigation has employed Parkinson's range-based volatility estimator to measure the RV of rare earth stocks. As an additional analysis, we also consider the volatility measure of Rogers and Satchell (1991). This estimator is given as:

$$RV_t = \ln\left(\frac{H_t}{O_t}\right)\ln\left(\frac{H_t}{C_t}\right) + \ln\left(\frac{L_t}{O_t}\right)\ln\left(\frac{L_t}{C_t}\right) \tag{10}$$

In this measure, O_t and C_t specify the opening and closing prices.

Now, Tables 5–7 present the estimates of the daily, weekly and monthly HAR approaches based on this new measure of realized volatility. Looking at these tables, we notice that some of these new findings are consistent with those reported in Tables 2–4 For instance, all the parameters associated with the different volatility components remain significant across the models and time-horizons. In addition, the *Buzz* index, sourced from the traditional news media, exerts a significant effect on the RV of rare earth equities and this impact is positive. Hence, the Buzz_news appears to be significant in each case irrespective of the volatility measures used. We also find that the R^2 statistic experiences an increment when the variable Buzz_News is inserted to the HAR process.

However, there exist several inconsistencies as well. For example, the variable Buzz_Social is significant only for the weekly HAR model implying that there are no short- and long-term effects of *Buzz* index, when it is sourced from social media. Besides, we report that the HAR-RV-Buzz_News model yields the highest R^2 statistics regardless of the time-horizons used. Interestingly, the HAR-RV-Sentiment_Social model outperforms the HAR-RV-Buzz_Sentiment model by producing a higher R^2 statistic.

Overall, our results are robust given that the application of various volatility measures leads to the same conclusion that both social and news media influence the RV of rare earth equities. More importantly, this effect is positive suggesting that higher sentiment causes higher volatility. We also conclude that the *Buzz* index has more predictive contents relative to the *Sentiment* index.

Notably, traditional asset pricing models operate under the assumption that investors influence each other solely through market prices. However, such assumption seems less rational as it neglects the social interactions among market participants (Gan et al., 2020). In practice, investors engage in communication and information-sharing via various channels, including news and social media. This social influence plays a pivotal role in the dissemination of information and ultimately influences asset pricing, as highlighted by earlier works

Table 5
Findings of daily HAR-RV models (RV is computed using the Rogers and Satchell (1991) estimator).

Models	HAR-RV	HAR-RV-Buzz_News	HAR-RV-Sentiment_News	HAR-RV-Buzz_Social	HAR-RV-Sentiment_Social
θ_0	0.00006*** (0.000008)	0.00006*** (0.000009)	0.00005*** (0.000008)	0.00005*** (0.000009)	0.00006*** (0.000009)
θ_d	0.0918*** (0.0203)	0.0907*** (0.0204)	0.0916*** (0.0204)	0.0914*** (0.0203)	0.0917*** (0.0203)
θ_w	0.3893*** (0.0398)	0.3883*** (0.0400)	0.3904*** (0.0401)	0.3891*** (0.0398)	0.3899*** (0.0399)
θ_m	0.2008*** (0.0468)	0.1911*** (0.0472)	0.1983*** (0.0472)	0.1961*** (0.0471)	0.1994*** (0.0470)
α		0.000000022** (0.0000000091)			
β			0.000006 (0.00003)		
γ				0.000000017 (0.000000016)	
δ					0.000013 (0.000032)
R^2 (%)	14.10	14.19	14.04	14.09	14.07
HET test	0.16	0.17	0.14	0.17	0.15
D-W statistic	1.99	2.01	2.00	2.00	2.01

Notes: This table reports the results of daily HAR processes. The standard errors are shown in the parentheses. The HET row shows the results of the heteroscedasticity test. ***, ** and * imply the statistical significance at 1 %, 5 % and 10 % levels, respectively. D-W indicates the Durbin-Watson test statistic.

Table 6
Findings of weekly HAR-RV models (RV is computed using the Rogers and Satchell (1991) estimator).

Models	HAR-RV	HAR-RV-Buzz_News	HAR-RV-Sentiment_News	HAR-RV-Buzz_Social	HAR-RV-Sentiment_Social
θ_0	0.00007*** (0.000004)	0.00007*** (0.000005)	0.00007*** (0.000005)	0.00006*** (0.000005)	0.00007*** (0.000005)
θ_d	0.0578*** (0.0117)	0.0569*** (0.0118)	0.0576*** (0.0118)	0.0570*** (0.0118)	0.0575*** (0.0117)
θ_w	0.3630*** (0.0230)	0.3615*** (0.0232)	0.3633*** (0.0233)	0.3627*** (0.0231)	0.3637*** (0.0231)
θ_m	0.1783*** (0.0272)	0.1719*** (0.0273)	0.1775*** (0.0274)	0.1710*** (0.0273)	0.1765*** (0.0272)
α		0.000000017*** (0.0000000052)			
β			0.0000049 (0.000015)		
γ				0.000000027*** (0.0000000095)	
δ					0.000018 (0.000019)
R^2 (%)	27.11	27.26	27.02	27.24	27.09
HET test	0.21	0.25	0.16	0.23	0.19
D-W statistic	2.32	2.19	2.31	2.18	2.46

Notes: This table reports the results of weekly HAR processes. The standard errors are shown in the parentheses. The HET row shows the results of the heteroscedasticity test. ***, ** and * imply the statistical significance at 1 %, 5 % and 10 % levels, respectively. D-W indicates the Durbin-Watson test statistic.

Table 7
Findings of monthly HAR-RV models (RV is computed using the Rogers and Satchell (1991) estimator).

Models	HAR-RV	HAR-RV-Buzz_News	HAR-RV-Sentiment_News	HAR-RV-Buzz_Social	HAR-RV-Sentiment_Social
θ_0	0.00010*** (0.000004)	0.00011*** (0.000003)	0.00010*** (0.000003)	0.00011*** (0.000004)	0.00011*** (0.000003)
θ_d	0.0341*** (0.0089)	0.0338*** (0.0090)	0.0341*** (0.0090)	0.0343*** (0.0089)	0.0336*** (0.0089)
θ_w	0.1393*** (0.0175)	0.1376*** (0.0176)	0.1384*** (0.0176)	0.1393*** (0.0175)	0.1406*** (0.0174)
θ_m	0.2474*** (0.0205)	0.2452*** (0.0208)	0.2478*** (0.0207)	0.2468*** (0.0207)	0.2444*** (0.0206)
α		0.000000008** (0.000000004)			
β			0.000001 (0.00001)		
γ				0.00000000001 (0.0000000071)	
δ					0.000032** (0.000014)
R^2 (%)	20.08	20.17	19.98	20.02	20.15
HET test	0.14	0.19	0.11	0.11	0.18
D-W statistic	2.09	2.08	2.23	2.17	2.11

Notes: This table reports the results of monthly HAR processes. The standard errors are shown in the parentheses. The HET row shows the results of the heteroscedasticity test. ***, ** and * imply the statistical significance at 1 %, 5 % and 10 % levels, respectively. D-W indicates the Durbin-Watson test statistic.

(Hirshleifer and Teoh, 2009; Griffith et al., 2020). Social media has the capacity to generate captivating trends that can influence investors' perceptions of a company's future prospects, shaping investor sentiment and consequently impacting stock prices.

Furthermore, the influence of news and social media sentiment has become significant in shaping market dynamics and inciting them (Griffith et al., 2020). Prior studies (Baker and Wurgler, 2007; Eierle et al., 2022) argue that social media sentiment could mirror speculative aspects, including investor sentiment. Baker and Wurgler (2006) define investor sentiment as the inclination towards speculation. The authors also document that speculative demand stemming from such investor sentiment can have an influence on asset prices. Besides, online conversations could include additional fundamental details beyond financial data. One clear example is non-public information which has not yet been disclosed as financial data by companies or analysts. This could involve information from company insiders that is disclosed either intentionally or unintentionally. Investors who utilize this information may possess more comprehensive knowledge compared to those who overlook social media. This enhanced understanding could lead to better investment choices for informed investors, thereby influencing asset prices.

5.3. Out-of-sample analysis

Table 8 displays the HRMSE statistics along with the DM test results. Panel A reports the results for the Parkinson RV measure, whereas Panel B shows the same for the Rogers and Satchell estimator. While looking at the results of Panel A, we notice that the HAR-RV-Buzz_Social model produces the lowest errors and this finding holds irrespective of the horizons considered. The results of DM test also confirm that the HAR-RV-Buzz_Social model outplays its counterparts. Moving to Panel B, we observe that the HAR-RV-Buzz_News model has emerged as the

Table 8
The HRMSE statistics.

	Daily		Weekly		Monthly	
	HRMSE	DM statistic	HRMSE	DM statistic	HRMSE	DM statistic
Panel A: RV measure of Parkinson						
HAR-RV	0.000150	−2.60***	0.000088	−3.63***	0.000078	−3.37***
HAR-RV-Buzz_News	0.000149	−2.02**	0.000085	−1.47*	0.000074	−1.50*
HAR-RV-Sentiment_News	0.000150	−2.64***	0.000086	−1.96**	0.000077	−3.24***
HAR-RV-Buzz_Social	**0.000147**		**0.000084**		**0.000073**	
HAR-RV- Sentiment _Social	0.000151	−2.69***	0.000086	−1.97**	0.000074	−1.51*
Panel B: RV measure of Rogers and Satchell						
HAR-RV	0.000156	−1.97**	0.000089	−2.11**	0.000075	−3.29***
HAR-RV-Buzz_News	**0.000154**		**0.000087**		**0.000072**	
HAR-RV-Sentiment_News	0.000157	−2.89***	0.000091	−3.66***	0.000076	−3.71***
HAR-RV-Buzz_Social	0.000157	−2.91***	0.000084	−1.47*	0.000076	−3.68***
HAR-RV- Sentiment _Social	0.000156	−1.98**	0.000090	−3.02***	0.000073	−1.49*

Notes: This table exhibits the HRMSE statistics along with the Diebold-Mariano (DM) test results. Panel A reports the results for the Parkinson RV measure, whereas Panel B shows the same for the Rogers and Satchell estimator. The forecasting period ranges from 1 April 2023 to 31 March 2024. The highlighted numbers refer to the smallest errors. ***, ** and * imply statistical significance at 1 %, 5 % and 10 % levels, respectively.

winner. We thus conclude that inserting investor emotions into the HAR process improves its performance and that the *Buzz* index provides additional information not contained in the *Sentiment* index.

Next, the R^2_{OOS} statistics are presented in Table 9. These results are consistent with those reported in Table 8. For instance, the numbers shown in Table 9 also indicate that the HAR-RV-Buzz_Social approach outperforms other models when the Parkinson measure is used to estimate the realized volatility. As seen from Panel A, for example, the HAR-RV-Buzz_Social model generates the largest R^2_{OOS} statistic (2.6951 %) for the daily horizon, which is statistically significant at the 1 % level. When referring to Panel B, we notice that the *Buzz* index, sourced from the news media, has more predictive contents than the other measures of investor sentiment.

6. Conclusions and policy implications

Investing in rare earth metals has increased significantly over the recent years. This sector has received considerable attention due to its importance in producing renewable energy. As a consequence, a growing body of literature investigates the return and volatility dynamics of rare earth equities. However, prior works are mainly focused on the correlation or interdependence between rare earth stocks and other financial asset classes and very little is known about the volatility dynamics of rare earth stocks. Our analysis aims to fill this void in the existing literature. In doing so, we first employ the baseline HAR model to examine volatility pattern of rare earth ETF and then explore the role of news and social media sentiment in forecasting the variation in the asset prices.

Note that we have used the sentiment data provided by the Thomson Reuters MarketPsych Indices (TRMI) in order to forecast the volatility of rare earth equities. The application of TRMI is particularly useful as it provides sentiment data based on both traditional news media and social networking sites, thereby allowing us to examine whether investor sentiments collected from various media sources would have a heterogeneous impact on the volatility predictions. In addition, TRMI also contains commodity-specific sentiment measures which explicitly rely on investor emotions towards rare earth financing. Overall, our results indicate that both social and news media influence the realized volatility of rare earth equities. More importantly, this effect is positive suggesting that higher sentiment causes higher volatility. We further observe that the extended HAR models, which include different sentiment measures such as *Buzz* and *Sentiment*, tend to outperform the baseline HAR model. Our analysis also concludes that the *Buzz* index has more predictive contents relative to the *Sentiment* index.

Our findings offer the following policy implications. Firstly, the significant linkage between rare earth asset prices and the sentiment indexes suggests that investor emotions play a pivotal role in predicting the volatility of rare earth stocks. Hence, policymakers could capture

Table 9
The Out-of-sample R^2 ($\boldsymbol{R^2_{OOS}}$) results.

	Daily		Weekly		Monthly	
	R^2_{OOS} (%)	MSPE- adjusted	R^2_{OOS} (%)	MSPE-adjusted	R^2_{OOS} (%)	MSPE-adjusted
Panel A: RV measure of Parkinson						
HAR-RV						
HAR-RV-Buzz_News	2.1123	2.01**	2.0143	1.98**	2.0568	2.12**
HAR-RV-Sentiment_News	0.6758	0.98	0.7164	0.99	0.6598	0.97
HAR-RV-Buzz_Social	2.6951	2.76***	2.5982	2.61***	2.6257	2.63***
HAR-RV- Sentiment _Social	0.6189	0.87	1.3439	1.39*	1.4429	1.41*
Panel B: RV measure of Rogers and Satchell						
HAR-RV						
HAR-RV-Buzz_News	2.6582	2.71***	2.5781	2.62***	2.7113	2.69***
HAR-RV-Sentiment_News	0.6659	0.97	0.7200	0.98	0.6601	0.93
HAR-RV-Buzz_Social	2.1431	2.04**	2.0259	1.98**	2.0688	2.14**
HAR-RV- Sentiment _Social	0.6239	0.89	1.3891	1.38*	1.4379	1.42*

Notes: This table exhibits the out-of-sample R^2 (R^2_{OOS}) statistics introduced by Campbell and Thompson (2008). The forecasting period ranges from 1 April 2023 to 31 March 2024. ***, ** and * indicate statistical significance at the 1 %, 5 % and 10 % levels, respectively.

such emotions using the TRMI data to evaluate the risk linked to rare earth investing. Secondly, the finding that higher sentiment leads to higher risk indicates potential challenges for renewable energy production given that the price of rare earth metals is crucial for developing clean energy equipment. To this end, it is important to find proper hedging tools to minimize the portfolio risk for rare earth investing. Hence, investors should closely observe the association between rare earth metals and other asset classes including traditional stocks, digital currencies or commodities to diversify the risk. Thirdly, the output of this empirical research could be useful for socially responsible investors given that precise estimates of time-varying volatility of rare earth equities have crucial effects in maintaining a low carbon portfolio. Thus, our findings have key implications for social sustainability. Fourthly, the findings could be supportive for developing appropriate models for volatility forecasting and risk assessment. For instance, our results identify that news and social media sentiments emerge potential risk factors affecting the volatility dynamics of rare earth equities. Thus, investigators should adjust the volatility forecast models to reduce the adverse effect of investor sentiment. Fifthly, the demand for REMs has increased significantly given its importance in producing clean energy and thereby reaching the net-zero goals. Therefore, the governments should develop appropriate strategies (e.g., increasing the investments in rare earth elements) to avoid the supply chain disruptions in the long term. In particular, creating diverse funding sources could be a valuable strategy to fulfill this need. Besides, implementing an information-sharing platform can help rare earth stock market investors stay informed about climate and geopolitical shifts, thus mitigating the negative effects of speculative price manipulation. Finally, given that the prices of rare earth equities can be a key measure of strength for the REM sector, predicting the volatility of this asset class is crucial for developing mining policy that determines mining royalty payments and licensing fees (Henriques and Sadorsky, 2023). As our empirical results highlight that information shared in different news and social media could appear to be a good predictor of the time-varying volatility of REM equities, policymakers should pay attention to investor sentiments to apprehend the underlying risk.

Future studies could examine whether different uncertainty measures such as crude oil volatility and geopolitical risks would improve the volatility predictions for rare earth stocks. In doing so, the HAR models can be extended using the information contents of these uncertainty indicators. In addition, researchers could also investigate the role of time-varying jumps occurring in rare earth stock prices when forecasting the volatility.

CRediT authorship contribution statement

Anupam Dutta: Resources, Methodology. **Jukka Sihvonen:** Validation, Software, Project administration. **Donghyun Park:** Validation, Methodology. **Brian Lucey:** Writing – review & editing, Conceptualization. **Gazi Salah Uddin:** Writing – original draft, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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