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News-based sentiment and bitcoin volatility☆

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ABSTRACT

In this work, I studied whether news media sentiments have an impact on Bitcoin volatility. In doing so, I applied three different range-based volatility estimates along with two different sentiments, namely psychological sentiments and financial sentiments, incorporating four various sentiment dictionaries. By analyzing 17,490 news coverages by 91 major English-language newspapers listed in the LexisNexis database from around the globe from January 2012 until August 2021, I found news media sentiments to play a significant role in Bitcoin volatility. Following the heterogeneous autoregressive model for realized volatility (HAR-RV)—which uses the heterogeneous market idea to create a simple additive volatility model at different scales to learn which factor is influencing the time series—along with news sentiments as explanatory variables, showed a better fit and higher forecasting accuracy. Furthermore, I also found that psychological sentiments have medium-term and financial sentiments have long-term effects on Bitcoin volatility. Moreover, the National Research Council Emotion Lexicon showed the main emotional drivers of Bitcoin volatility to be anticipation and trust.

1. Introduction

Around 2.5 billion people in the world read newspapers regularly in hard copy, whereas more than 600 million read newspapers in digital form.[1] The growing audience of news media, social media, and blogging websites has widened the scope of textual analysis beyond linguistic studies. From high-frequency traders using real-time news sentiment for trading activities to predicting future volatility, news sentiment has also become an essential market factor in finance. Therefore, an accurate estimation of positive or negative sentiment from the news is crucial for investment decision-making and portfolio management (Mishev, Gjorgjevikj, Vodenska, Chitkushev, & Trajanov, 2020). News also provides the opportunity to see a context analytically from a wider perspective. As a consequence, the reader can assess the quality of a project, product, or service through understanding the general sentiment of the crowd. However, many readers often misjudge the true sentiment behind the news. Fürsich (2009) argued that media texts present a distinctive discursive moment between encoding and decoding that requires special scholarly engagement. News generally provides either negative or positive sentiment to its readers. People are less interested in reading news articles of neutral sentiment (Dos Rieis et al., 2015). In this regard, psychological literature has frequently confirmed the priority of processing words with negative or positive emotion against words with neutral emotion (for example, Chen, Lin, Chen, Lu, & Guo, 2015; Kissler, Herbert, Peyk, & Junghofer, 2007; Yap & Seow, 2014; Zhang et al., 2014).

In the past decade, Bitcoin (BTC) has made a lot of news in mainstream media. According to 99bitcoins.com, BTC has "died" 432 times in the news.[2] While many newspapers have covered BTC as a possible scam or a bubble, some newspapers have highlighted the opportunities it has created. BTC hackings, crypto exchange collapses, government bans, regulations, taxes, scams, etc. have made many headlines in global news media outlets. Nonetheless, there has also been positive news of BTC such as a legal tender, means of payment, futures, exchange-traded funds, etc. Furthermore, news like Tesla acquiring $1.5 billion worth of BTC has given this digital innovation a significant positive-sentiment

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[1] See more at: http://www.ifabc.org/news/More-People-Read-Newspapers-Worldwide-Than-Use-Web

[2] See the details at: https://99bitcoins.com/bitcoin-obituaries/

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hype. Unfortunately, there was a reversal of sentiment when Tesla Chief Executive Officer (CEO) Elon Musk removed it as a payment option on the Tesla website, stating the energy and environmental risk imposed by this financial technology innovation. Both the Tesla acceptance and rejection were sensational in the news and crypto world. The sentiment conveyed or imposed by the media has been easily noticeable by looking at the BTC price swing after a big news item either in favor of it or against it. However, a swing could be triggered by sentiment from a small news item as well. Even if we could see the direction of the sentiment after a big news item, we cannot exactly measure the degree or magnitude of this qualitative phenomenon. In this regard, Bonato, Gkillas, Gupta, and Pierdzioch (2020) stated that investor sentiment cannot be directly measured or observed.

Thankfully, machine-learning tools like natural language processing are becoming handy in quantifying qualitative transcripts. We can now easily quantify news and articles, and they can provide more accurate, more efficient proxies for investor sentiments (for example, Ho, Shi, & Zhang, 2020; Shen et al., 2018) in comparison to traditional approaches like that of Baker and Wurgler (2006, 2007), who used several market-based measures as proxies. Besides the market-based measure, the other most common approach applied in earlier research has been survey-based indices. More recently, building an investor-sentiment index employing daily news, internet search, and social media data has gained popularity because traditional approaches like market-based and survey-based methods seem to be less transparent. Furthermore, the advantage of internet-based sentiment is that it can be extracted in real time and at a lower frequency, like every second, minute, hour, or day, compared to traditional approaches that extract every month, quarter, or year (Bonato et al., 2020). One can extract sentiment scores following various sentiment dictionaries. Studies comparing various sentiment dictionaries have focused on those of Henry (2008) and Loughran and McDonald (2011). Using the Harvard-IV general dictionary, Loughran and McDonald (2011) found its word list to be largely inapplicable to financial contexts and created a finance-specific list. Henry (2008) captured the tone of earnings press releases in order to create a word list for financial texts. Both studies found finance-specific word lists to be more powerful than general word lists.

In recent years, cryptocurrency markets have attracted considerable attention in the academic literature. This is not surprising given that from an economic perspective, the sums of money involved are substantial (Fry & Cheah, 2016). The current market cap of cryptocurrency is 2.6 trillion dollars, whereas the dominance of BTC is 45%—slightly less than half of the total market cap.[3] However, the dominance of BTC tends to fluctuate heavily following good or bad news, making this digital currency highly volatile.[4]

Modeling volatility is an important step to precisely measure the risk associated with an asset or portfolio of assets. An accurate estimation of volatility is vital to investors to develop an adequate strategy to hedge potential risks associated with an investment. In this paper, I used the past realized volatilities (RVs) of BTC to predict its future RVs by following the popular volatility-forecasting model proposed by Corsi (2009). The heterogeneous autoregressive model for realized volatility (HAR-RV) utilizes three AR(1) volatility processes at daily, weekly, and monthly windows. A natural economic interpretation of this model according to the author is that each volatility component in the model corresponds to a market component that forms expectations for the next period's volatility based on the observation of the current RV and the expectation for the longer-term volatility. By decomposing volatility into short-term (daily), medium-term (weekly), and long-term (monthly) frequencies, this model captures the heterogeneity among short-term, medium-term, and long-term investors. One of the flexibilities of the HAR-RV is that one can easily include additional explanatory variables in the ordinary-least-squares (OLS) regression equation.

Furthermore, in this study, I sought to explore whether news media sentiments have an impact on BTC volatility by including different sentiments as additional explanatory variables. On top of that, I differentiated between financial sentiment and psychological sentiment cached in the news and analyzed their impact on BTC volatility in different time windows, similar to the RV estimation, as daily, weekly, and monthly. I addressed the issue of heterogeneity in news arrival time and investors' sentiment memory length by incorporating short-term, medium-term, and long-term sentiment windows. While I incorporated sentiments as additional explanatory variables, one could also include RVs over other time windows besides daily, weekly, and monthly. An example can be found in the work of Busch, Christensen, and Nielsen (2011), who used implied volatility as an additional explanatory variable on top of RVs.

In this study, a comparison between the baseline HAR-RV and the HAR-RV extended with news sentiment index (HAR-RV-SI) showed the HAR-RV-SI to be a better fit. The out-of-sample forecast also showed that sentiments as explanatory variables in the HAR-RV have a higher forecasting accuracy. Furthermore, I also found psychological sentiments to have short-term and financial sentiments to have long-term effects on BTC volatility. Moreover, the results showed that either a mixture of positive and negative sentiments or purely positive sentiment is more responsible for BTC volatility, as compared with purely negative sentiment. Implementing the National Research Council (NRC) Emotion Lexicon showed the main emotional drivers of BTC volatility to be anticipation and trust.

This article contributes towards the multiple aspects in financial research such as literature, data, methodologies, sentiment approach, and practical implications. Firstly (*i*), this article contributes to the recent stream of financial literature in numerous ways. While earlier research studies have mostly focused on news sentiments around events related to macroeconomic announcements (for example, Andersen, Bollerslev, & Diebold, 2007; Corbet, Larkin, Lucey, Meegan, & Yarovaya, 2020; Corsi, Pirino, & Reno, 2010; Entrop, Frijns, & Seruset, 2020), this analysis covered all the BTC-related news sentiments published in major English-language newspapers from around the globe. Secondly (*ii*), this article contributes towards unique data as previous studies on sentiment and BTC price movements have mostly relied on news blogs and search websites rather than on mainstream newspapers (for example, Garcia, Tessone, Mavrodiev, & Perony, 2014; Karalevicius, Degrande, & De Weerdt, 2018; Kristoufek, 2013). I chose to go with the major newspapers. The main concern with creating a corpus with news blogs is the possible repetition or inclusion of advertisement texts along with the main news story. If screening is not done properly, sentiments will tilt more towards one direction as advertisements mostly trigger either positive or negative emotions. In this regard, Mcduff and Berger (2020) stated that when it comes to engaging the audience, what matters is not just provoking positive emotions, but provoking activating emotions, and those can be positive or negative. Another major issue with news blogs is that they are mostly clickbait, so sentiments in the headline and the main body do not necessarily always match. Even though I used a different data source in this study, I addressed the possibility of this issue by extracting sentiments from the whole body of the news story, not just the headline. While including as many blogs as possible might sound good, the majority of small news blogs generally copy or share their content from well-known cryptocurrency websites like cointelegraph.com, coindesk.com, etc., creating redundancies in the data sample and resulting in inaccurate estimation of investor sentiment. Furthermore, to overcome the issue of redundancies in the newspaper articles, I also used the filter of "maximum similarity" while searching the LexisNexis news database.

Next (*iii*), this article contributes methodologically by extending HAR-RV towards a new direction. To the best of my knowledge, no

[3] www.coinmarketcap.com (as of 26.10.2021)

[4] See more at: https://www.goldmansachs.com/insights/pages/crypto-a-new-asset-class-f/report.pdf

article has yet explored newspaper-based sentiment as an additional explanatory variable in the HAR-RV environment in forecasting future volatilities of BTC or any other digital financial asset. Furthermore (*iv*), by further classifying sentiments into psychological- and finance-specific and extending them into three different horizons to capture heterogeneity in news arrival time among readers, this article contributes towards a better understanding of time-varying news sentiments, their memory length, and their effect on BTC volatility. On top of that, this work studied the role of different human emotions by applying Emotion Lexicon–based sentiments and their implications on digital financial innovations like BTC. Finally (*v*), from the practitioner point of view, this paper also sheds light on capturing different sentiments in the news because accurate estimation of volatility is vital to investors for developing an adequate strategy in hedging potential risks associated with their investments.

2. Literature review

Sentiment analysis in general investigates opinions expressed in texts and their polarity as positive, negative, or neutral (Muhammad, Wiratunga, & Lothian, 2016). The Emotion Lexicon can further categorize sentiments into different human emotions like fear, trust, etc. Sometimes, the tone of news is perhaps more influential than its substantive content in the body. There have been plenty of studies exploring the sentiment of news content, political speeches, blogs, advertisements, financial statements, earnings announcements, etc. Earlier research has shown how news sentiment affects individual decision-making, especially political judgment. In this regard, Young and Soroka (2012) highlighted that negative sentiment has more impact on human psychology and political interactions. Furthermore, Tetlock (2007) highlighted the advantage of applying sentiment analysis to predict or forecast the return of financial assets as being able to measure the impact of a wide range of events without the need to specify them.

Previous literature has covered sentiments in a wide range of asset classes. News and social media sentiments impact foreign exchange, stocks, bonds (for example, Busch et al., 2011), and commodities (for example, Qadan & Nama, 2018; Zhang & Li, 2019; Dutta, Bouri, & Saeed, 2021). Investigating the sentiment in the oil market, Bonato et al. (2020) used the HAR-RV to analyze whether a measure of investor happiness predicts the daily RV of oil-price returns. They used high-frequency intraday data to measure RV and found it to be significantly negatively linked to investor happiness in the short term. Furthermore, they also found that investor happiness significantly improves the accuracy of RV forecasts in the short term. Besides the conventional asset class, a new strand of literature is exploring sentiment in new blockchain-based digital financial markets (for example, Entrop et al., 2020; Hu, Kuo, & Härdle, 2019; Sapkota & Grobys, 2021).

Karalevicius et al. (2018) highlighted that only a small number of studies have considered the sentiment of publicly available textual information as an indicator for BTC price movements. However, a growing number of studies are stepping into the exploration of this relationship. Aalborg, Molnár, and de Vries (2019) studied how the return and trading volume of BTC depends on other variables such as trading volume, number of unique BTC addresses, and Google search trends on BTC. They found that the past RV of BTC predicts its future RV on the HAR-RV setup. In addition to that, they found that trading volume improves volatility prediction. They further identified a causal relationship between Google search trends to trading volume and trading volume to BTC volatility. Another BTC sentiment paper that applied HAR-RV is that of Bouri, Gkillas, Gupta, and Pierdzioch (2021), who analyzed the role of the United States–China trade war in predicting the daily RV of BTC returns. They extended the HAR-RV to include a metric of United States–China trade tensions. Their findings revealed that United States–China trade uncertainty improves forecast accuracy.

Baillie, Calonaci, Cho, and Rho (2019) stated that long memory in RV is a widespread stylized fact. Long memory in RV has been synonymized with jumps, structural breaks, and nonlinearities. They highlighted the forecasting power of the HAR model and its extensions. They assessed the separate roles of fractionally integrated, long memory models, extended HAR models, and time-varying-parameter HAR models and found the presence of the long memory parameter to be often important in addition to the HAR model. Andersen et al. (2007), from analyses of exchange rates, equity index returns, and bond yields, found that the volatility jump component is highly important and that separating the rough-jump moves from the smooth-jump moves results in significant improvement in volatility forecast. Furthermore, they also found many of the significant jumps to be associated with specific macroeconomic news announcements. In this regard, Corsi et al. (2010) showed that fragmenting volatility into jumps and continuous variation substantially improves volatility forecasting because of the significant positive impact of past jumps on future volatility. Corbet et al. (2020) also examined the link between macroeconomic news announcements and BTC returns. They constructed a sentiment index based on news stories following the announcements of four macroeconomic indicators. They found that an increase in positive news surrounding unemployment rates and durable goods results in a corresponding increase in equity returns and a decrease in BTC returns. Furthermore, they also observed that an increase in the percentage of negative news surrounding the announcement is linked with an increase in BTC returns. They concluded that the cryptocurrency market is further maturing through interactions with macroeconomic news. On the contrary, Entrop et al. (2020) found that attention and macroeconomic news have no impact on the price discovery of BTC. In addition to that, they also showed higher news-based BTC sentiment to increase the informational role of the futures market. Rognone, Hyde, and Zhang (2020) also contributed to the current debate on the nature of BTC implementing news sentiment. They explored whether the digital currency should be considered a financial asset or a medium of exchange. They investigated the intraday relationship between BTC and the major fiat currencies to assess whether there exists a similar reaction to high-frequency unscheduled news sentiment applying a vector autoregression (VAR) model.

The rest of the paper is organized as follows. Section 3 briefly discusses data, data sources, and sentiment data generation from the news corpus. Section 4 provides detailed descriptions of the methodologies. Section 5 presents the results, and Section 6 concludes.

3. Data

I retrieved daily open, high, low, and close (OHLC) prices for BTC from the website investing.com. The BTC OHLC data sample was from January 1, 2012, until August 31, 2021, accounting for 3530 daily observations. I also downloaded BTC-related news covered by major English-language newspapers from around the globe from the LexisNexis news database. LexisNexis has a list of 91 English news media in its "Major Newspapers" category, which is reported in Appendix A.1. During the sample period, from January 1, 2012, until August 31, 2021, there were a total of 17,490 news pieces covered on BTC by these major newspapers, which were extracted using the search term "Bitcoin". While searching the news database, one can limit LexisNexis search by Contents (for example, news, cases, etc.), Publication type (for example, newspapers, blogs, etc.), Language (for example, English, German, etc.), Industry (finance, media, technology) and many other criteria. However, there is no further filter within the "Newspaper" segment to see whether the news is a daily coverage or an article on that particular search topic. Therefore, the news items that I downloaded from LexisNexis includes not just the BTC-related news articles but also the news coverages on it. Furthermore, to reduce redundancies, I applied the filter of "maximum similarity" while searching this news database. The geographical representation of the newspapers included in the list of major newspapers can be considered global because it also covers big non-English–speaking countries around the world. The newspapers listed as major English language newspapers from around the globe

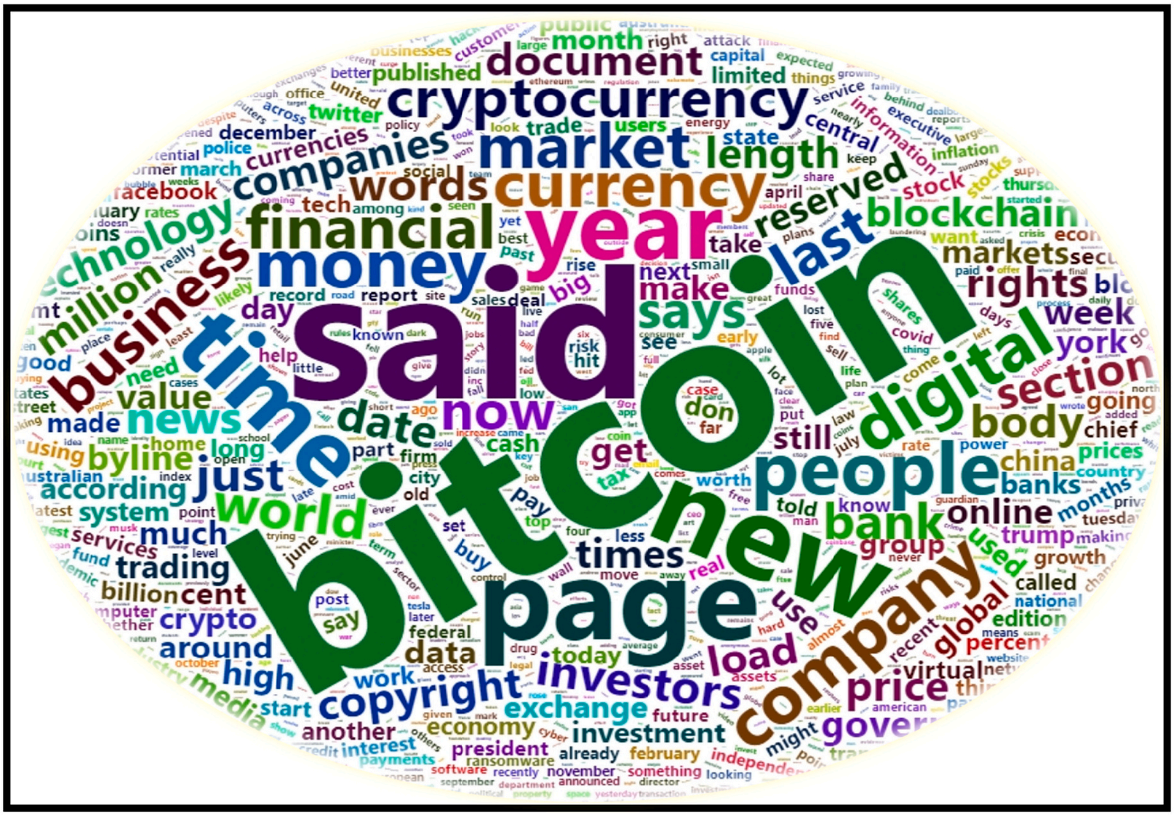

Fig. 1. Wordcloud of the most used words on BTC news by major English-language global newspapers (Jan 2012–Aug 2021). Note: This wordcloud was created using the wordcloud2 package in R.

includes newspapers from English speaking countries like the USA, UK, Australia, New Zealand, Canada, etc. as well as non-English speaking countries like China, Brazil, Singapore, Japan, Malaysia, Israel, etc.

Furthermore, earlier research has found that Google trends have a positive relationship with the future volatility of BTC. For example, Aalborg et al. (2019) found Google searches on BTC to predict trading volume and found trading volume to predict BTC volatility. As a control for the model, I also downloaded the daily Google search trends on BTC for the entire sample period of January 1, 2012, until August 31, 2021. Daily Google trends, by default, are not available through web interface or application programming interface (API). However, applying open-source code along with the gtrendsR package, I generated a daily time series of Google search trends on the term "Bitcoin" for the given sample period.[5]

3.1. Extracting sentiment scores of news on Bitcoin

From the LexisNexis database, one can either download all news files as a single file or by individual news article in PDF and other document formats.[6] I choose the latter, as the first option would make it complicated to convert the news into a time-series object. First of all, to create the corpus in a time-series format, I extracted the publication dates of all 17,490 news PDF files. Each news corpus starts with a header that includes the page number and the headline. The heading section is structured as follows:

1st line: Headline.

2nd line: Newspaper name (with/without location).

3rd line: Publication date.

By applying the "readLines" function, I extracted publication dates from most of the news files. To have the dates from the rest of the news articles, I used an alternative method for extracting the publication date by applying the "Key Word in Context" (KWIC) function. The PDF version of the downloaded news comes with the key word "load date" in the footer section of each file. The majority of the news files are uploaded in the LexisNexis database on the same day of publication; therefore, the "load date" can be used as the publication date.

Fig. 1 shows a "word cloud" of the most frequently used words by the 91 major English language–based newspapers during the sample period. Next, I extracted the BTC news sentiments by applying four different sentiment dictionaries. The Sentiment Analysis package in R statistical software supplies *positive*, *negative*, and *overall* sentiment scores for four different sentiment dictionaries applied to the corpus of news. I further grouped these four dictionaries into two subgroups, *psychological and discourse sentiment dictionaries* and *finance-specific sentiment dictionaries*. The "analyzeSentiment" function in this package gives sentiment scores for:

i. *Psychological and discourse sentiment dictionaries*
   a. Harvard-IV general-purpose psychological dictionary (GI)
   b. Quantitative Discourse Analysis Package (QDAP) dictionary

ii. *Finance-specific sentiment dictionaries*
   a. Henry's (2008) finance-specific dictionary (HE)
   b. Loughran and McDonald (2011) finance-specific dictionary (LM)

The Harvard-IV psychological dictionary is a general-purpose dictionary that maps a corpus with counts on positive, negative, and overall sentiments. Similarly, QDAP provides quantitative analysis of a

[5] R script for daily Google search trends can be found at http://alexdyachenko.com/all/how-to-get-daily-google-trends-data-for-any-period-with-r/

[6] A sample news file is attached as Appendix A.2.

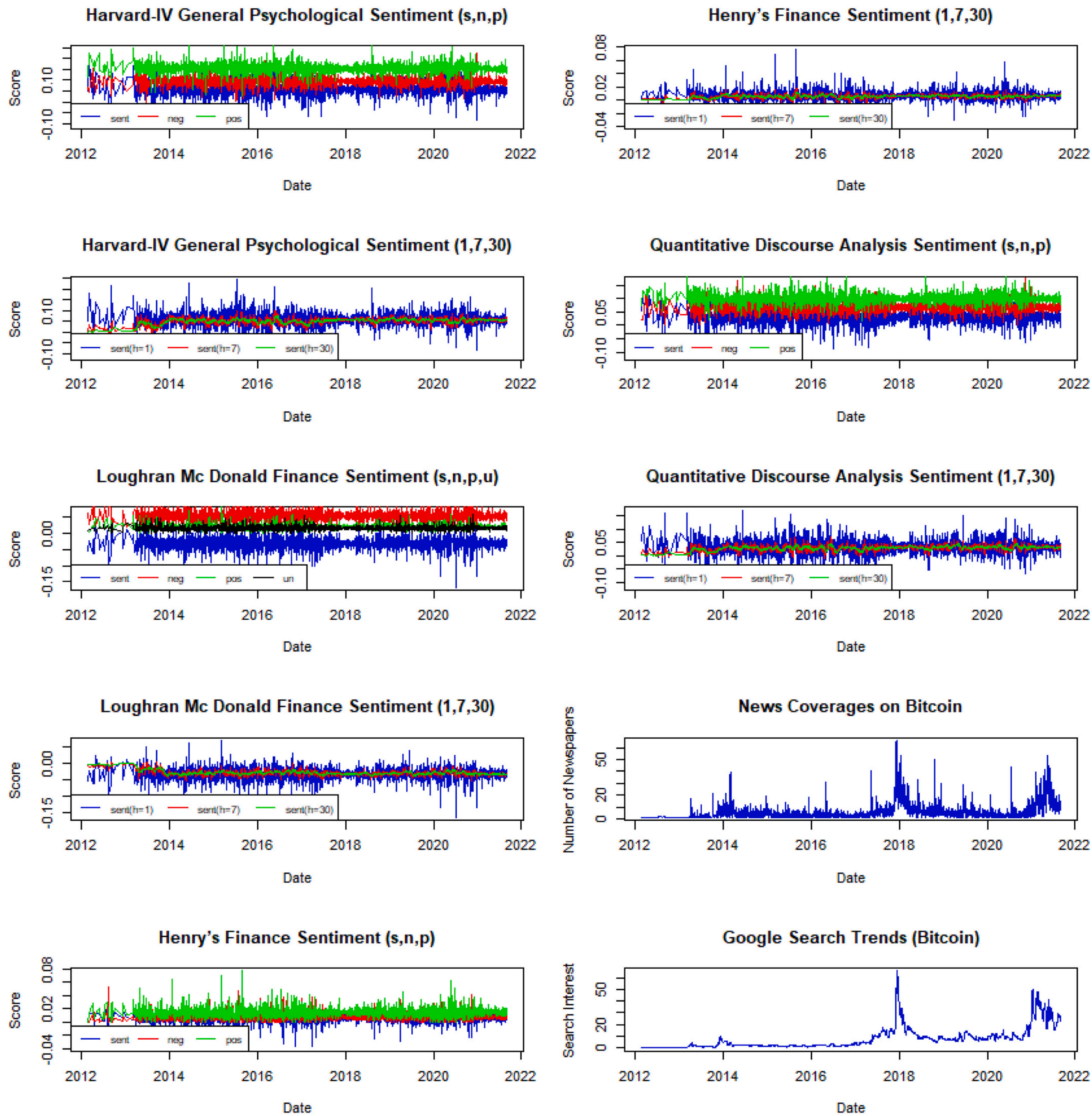

Fig. 2. BTC news coverage, sentiments, and daily worldwide Google search trends (Jan 2012–Aug 2021).
Note:
s = overall sentiment (p-n-u).
n = negative sentiment.
p = positive sentiment.
u = sentiment uncertainty.
1 = daily.
7 = weekly.
30 = monthly.

qualitative corpus. It also gives positive, negative, and overall sentiments of the news. For the finance-specific sentiments, Henry (2008) studied capital market data to assess the impact on investors of tone and other stylistic attributes. The dictionary categorizes sentiments as positive, negative, and overall. Another popular finance-specific dictionary is that of Loughran and McDonald (2011). This measure gives positive, negative, risk for sentiment uncertainty, and overall sentiment scores of the text. Fig. 2 shows the polarity and time-varying sentiments on BTC news coverage and daily worldwide Google search trends.

Table 1.a summarizes the statistics of the news coverage, Google

Table 1.a
Summary Statistics on Sentiments and BTC News Pieces (Jan 2012–Aug 2021).

Variable	Nobs	Min	Max	1st Qu	3rd Qu	Mean	Median	StDev	Skew	Kurt
Btc_G	3525	0.00	100.0000	1.7400	9.9000	7.6108	4.1300	9.4241	2.80	11.81
WordC	2802	31.00	13,780	375	606.00	574.35	476.50	638.62	12.33	208.62
NewsC	2802	1.00	66.0000	2.0000	7.0000	6.1934	4.0000	7.0613	3.08	12.67
S_GI_1	2802	−0.11	0.2427	0.0426	0.0739	0.0585	0.0583	0.0302	0.06	3.78
S_GI_7	2802	−0.02	0.0989	0.0464	0.0617	0.0536	0.0552	0.0136	−0.68	1.51
S_GI_30	2802	0.00	0.0742	0.0489	0.0585	0.0527	0.0551	0.0097	−1.94	5.98
N_GI_1	2802	0.00	0.2234	0.0837	0.1047	0.0942	0.0940	0.0200	0.24	3.44
N_GI_7	2802	0.00	0.1221	0.0809	0.0961	0.0865	0.0908	0.0154	−1.82	4.66
N_GI_30	2802	0.00	0.1052	0.0822	0.0936	0.0851	0.0887	0.0135	−2.86	11.07
P_GI_1	2802	0.03	0.2868	0.1412	0.1640	0.1528	0.1522	0.0221	0.11	4.00
P_GI_7	2802	0.02	0.1834	0.1322	0.1543	0.1401	0.1481	0.0236	−2.10	5.57
P_GI_30	2802	0.00	0.1591	0.1326	0.1510	0.1378	0.1445	0.0216	−2.96	11.62
S_HE_1	2802	−0.04	0.0769	0.0031	0.0101	0.0067	0.0065	0.0075	0.53	9.37
S_HE_7	2802	−0.01	0.0185	0.0045	0.0080	0.0062	0.0064	0.0030	−0.28	1.43
S_HE_30	2802	0.00	0.0116	0.0053	0.0071	0.0061	0.0063	0.0017	−0.67	1.36
N_HE_1	2802	0.00	0.0531	0.0048	0.0097	0.0079	0.0072	0.0051	2.10	9.21
N_HE_7	2802	0.00	0.0172	0.0060	0.0084	0.0072	0.0073	0.0021	0.00	1.26
N_HE_30	2802	0.00	0.0106	0.0064	0.0080	0.0071	0.0073	0.0014	−1.43	4.86
P_HE_1	2802	0.00	0.0769	0.0107	0.0176	0.0146	0.0140	0.0068	1.63	8.12
P_HE_7	2802	0.00	0.0257	0.0117	0.0154	0.0134	0.0138	0.0033	−0.47	1.36
P_HE_30	2802	0.00	0.0183	0.0123	0.0147	0.0132	0.0136	0.0024	−1.90	6.37
S_LM_1	2802	−0.17	0.0694	−0.0418	−0.0222	−0.0328	−0.0322	0.0183	−0.57	4.37
S_LM_7	2802	−0.05	0.0044	−0.0348	−0.0263	−0.0301	−0.0309	0.0076	0.73	1.50
S_LM_30	2802	−0.04	0.0002	−0.0329	−0.0274	−0.0296	−0.0308	0.0053	2.02	6.51
N_LM_1	2802	0.00	0.1696	0.0423	0.0589	0.0512	0.0504	0.0156	0.93	4.16
N_LM_7	2802	0.00	0.0717	0.0430	0.0524	0.0470	0.0488	0.0089	−1.44	3.61
N_LM_30	2802	0.00	0.0564	0.0439	0.0507	0.0462	0.0482	0.0074	−2.73	10.62
P_LM_1	2802	0.00	0.0833	0.0146	0.0217	0.0184	0.0178	0.0071	1.38	6.72
P_LM_7	2802	0.00	0.0284	0.0150	0.0190	0.0169	0.0174	0.0036	−0.74	1.82
P_LM_30	2802	0.00	0.0219	0.0155	0.0183	0.0166	0.0172	0.0028	−2.34	8.70
RU_LM_1	2802	0.00	0.0552	0.0108	0.0172	0.0144	0.0139	0.0061	1.14	4.51
RU_LM_7	2802	0.00	0.0220	0.0117	0.0150	0.0132	0.0136	0.0029	−0.93	1.93
RU_LM_30	2802	0.00	0.0165	0.0121	0.0143	0.0130	0.0134	0.0021	−2.49	10.20
S_QDAP_1	2802	−0.12	0.1705	0.0189	0.0475	0.0330	0.0327	0.0270	0.04	2.41
S_QDAP_7	2802	−0.01	0.0716	0.0243	0.0364	0.0301	0.0306	0.0106	−0.19	0.86
S_QDAP_30	2802	0.00	0.0475	0.0267	0.0336	0.0296	0.0308	0.0066	−1.09	2.38
N_QDAP_1	2802	0.00	0.1760	0.0559	0.0771	0.0668	0.0663	0.0187	0.38	1.96
N_QDAP_7	2802	0.00	0.0932	0.0562	0.0689	0.0613	0.0642	0.0117	−1.52	3.62
N_QDAP_30	2802	0.00	0.0737	0.0578	0.0667	0.0604	0.0625	0.0098	−2.68	10.15
P_QDAP_1	2802	0.02	0.2174	0.0899	0.1088	0.0998	0.0991	0.0181	0.52	3.31
P_QDAP_7	2802	0.01	0.1222	0.0862	0.1010	0.0915	0.0962	0.0158	−1.91	4.89
P_QDAP_30	2802	0.00	0.1061	0.0865	0.0986	0.0900	0.0944	0.0142	−2.89	11.17

Note: BTC_G (Google daily BTC search intensity), WordC (News word count), NewsC (Daily news count), GI (Harvard psychological sentiment), HE (Henry's finance sentiment), LM (Loughran's and McDonald's finance sentiment), S (overall sentiment), P (purely positive Sentiment), N (purely Negative Sentiment), 1 (daily), 7 (weekly), and 30 (monthly).

Table 1.b
Summary Statistics on Lexicon-Based Sentiments (2012−2021).

Variable	Nobs	Min	Max	1st Qu	3rd Qu	Mean	Median	StDev	Skew	Kurt
syuzhet_1	2802	−28.10	67.55	2.50	9.70	6.28	5.95	6.98	0.83	5.34
syuzhet_7	2802	−8.99	17.64	3.85	7.55	5.71	5.74	3.05	−0.07	1.01
syuzhet_30	2802	−2.67	12.43	4.51	6.91	5.62	5.82	2.03	−0.50	0.93
bing_1	2802	−71.00	42.00	−4.60	2.33	−1.15	−1.00	6.86	−0.56	8.14
bing_7	2802	−20.24	9.86	−2.67	0.65	−1.11	−1.00	2.96	−0.83	4.01
bing_30	2802	−11.63	4.04	−2.23	0.17	−1.08	−0.95	1.99	−0.82	2.90
afinn_1	2802	−95.00	96.00	−5.50	10.98	2.40	3.33	15.45	−0.26	3.64
afinn_7	2802	−30.29	22.86	−1.56	6.71	2.18	2.74	6.80	−0.72	1.66
afinn_30	2802	−17.07	14.39	−0.78	5.43	2.13	2.95	4.57	−0.84	1.21
nrc_1	2802	−15.00	86.00	6.50	15.60	11.72	10.83	8.71	1.55	6.92
nrc_7	2802	−1.14	27.36	8.16	12.94	10.69	10.56	3.82	0.33	0.65
nrc_30	2802	0.40	18.65	9.17	12.07	10.51	10.67	2.48	−0.55	1.44
anger	2802	1.00	102.00	5.00	12.00	9.66	8.00	7.44	3.19	20.07
anticipation	2802	0.00	146.00	8.00	18.00	14.48	12.00	10.63	3.17	19.78
disgust	2802	0.00	69.00	1.00	6.00	4.19	3.00	4.63	3.97	32.11
fear	2802	0.00	135.00	5.00	14.00	11.17	9.00	10.13	3.37	22.33
joy	2802	0.00	107.00	4.00	11.00	8.59	7.00	7.59	3.27	21.54
sadness	2802	0.00	102.00	3.00	11.00	8.19	6.00	7.88	3.91	27.99
surprise	2802	0.00	71.00	2.00	8.00	5.60	4.00	5.11	3.20	20.72
trust	2802	0.00	227.00	11.00	26.00	20.62	17.00	15.65	3.51	24.29
negative	2802	1.00	231.00	10.00	25.75	20.29	17.00	16.96	3.78	26.28
positive	2802	0.00	358.00	17.00	40.00	31.90	27.00	25.14	3.73	26.52

Note: 1 (daily), 7 (weekly), and 30 (monthly).

Table 1.c
Summary Statistics on BTC OHLC and Different RV Estimates (2012–2021).

Variable	Nobs	Min	Max	1st Qu	3rd Qu	Mean	Median	StDev	Skew	Kurt
Open	3525	4.70	63,544.2000	441.1250	8922.0250	7694.7779	3434.0000	12,472.3915	2.59	6.32
High	3525	4.80	64,778.0000	450.8250	9189.2500	7930.1425	3490.4000	12,867.4114	2.57	6.22
Low	3525	4.50	62,067.5000	428.8500	8723.6750	7433.9823	3380.9500	12,025.7293	2.60	6.42
Close	3525	4.60	63,540.9000	441.1250	8915.5000	7711.4243	3440.0000	12,495.0922	2.58	6.28
Volume	3525	0.00	13,328,655	90,898.5	1,469,082.50	961,943.36	487,111.00	1,285,228.79	2.35	8.45
PK_RV1	3525	0.00	0.4367	0.0002	0.0019	0.0034	0.0007	0.0174	15.75	296.66
PK_RV7	3525	0.00	0.1888	0.0005	0.0023	0.0033	0.0011	0.0121	10.38	125.08
PK_RV30	3525	0.00	0.0745	0.0007	0.0027	0.0032	0.0012	0.0080	6.37	45.41
GK_RV1	3525	0.00	0.8706	0.0004	0.0033	0.0061	0.0012	0.0348	17.54	366.45
GK_RV7	3525	0.00	0.4833	0.0008	0.0040	0.0059	0.0019	0.0239	11.95	170.21
GK_RV30	3525	0.00	0.1580	0.0013	0.0047	0.0059	0.0022	0.0159	7.16	57.65
RS_RV1	3525	0.00	0.6599	0.0003	0.0020	0.0038	0.0007	0.0234	18.71	430.50
RS_RV7	3525	0.00	0.2161	0.0005	0.0024	0.0037	0.0010	0.0140	9.42	101.26
RS_RV30	3525	0.00	0.0832	0.0007	0.0030	0.0037	0.0013	0.0094	6.05	39.93

Note: PK (Parkinson), GK (Garman-Klass), RS (Rogers-Satchel), RV (realized variance), 1 (daily), 7 (weekly), and 30 (monthly).

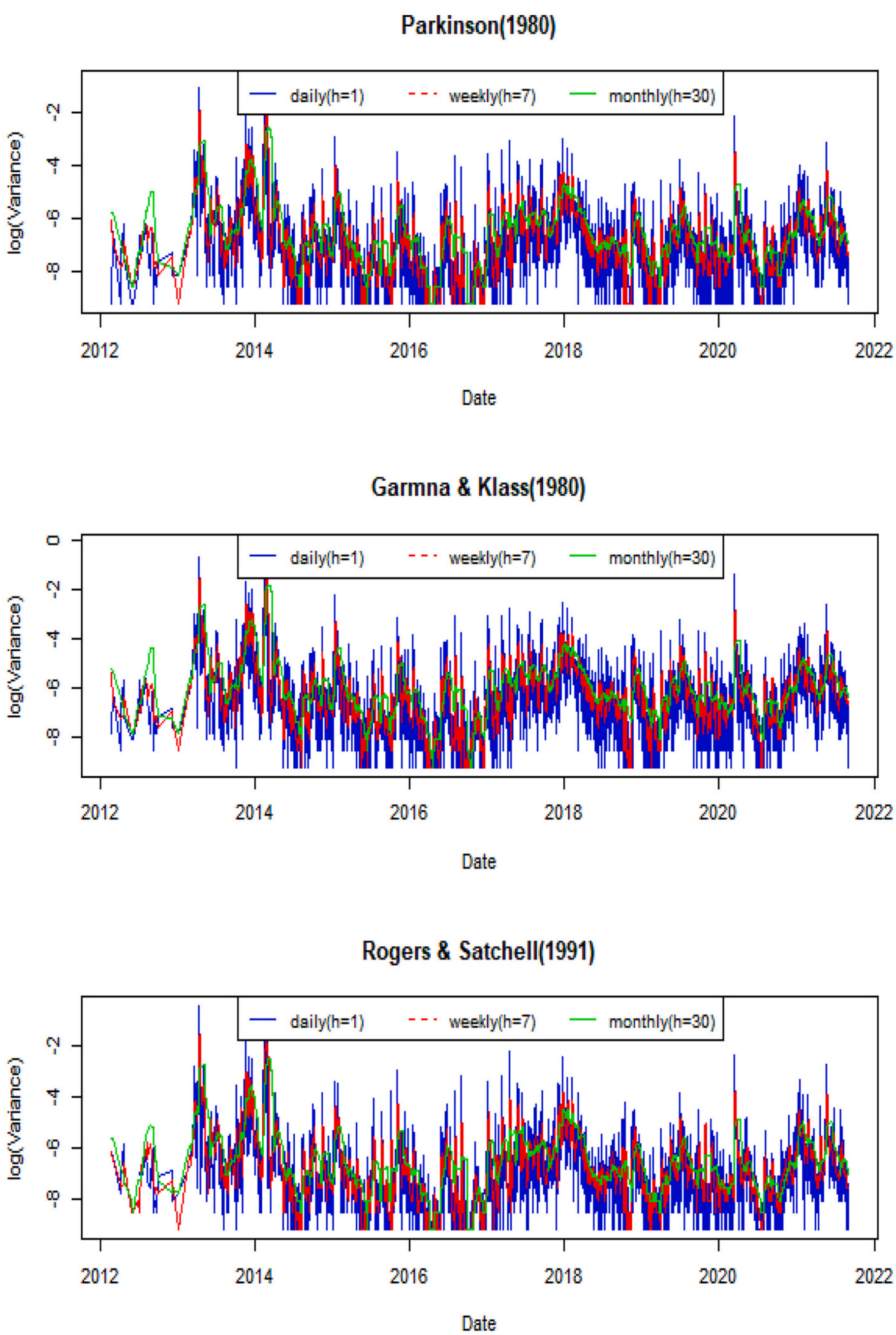

Fig. 3. Range-based volatility estimates, daily, weekly, and monthly (Jan 2012–Aug 2021).

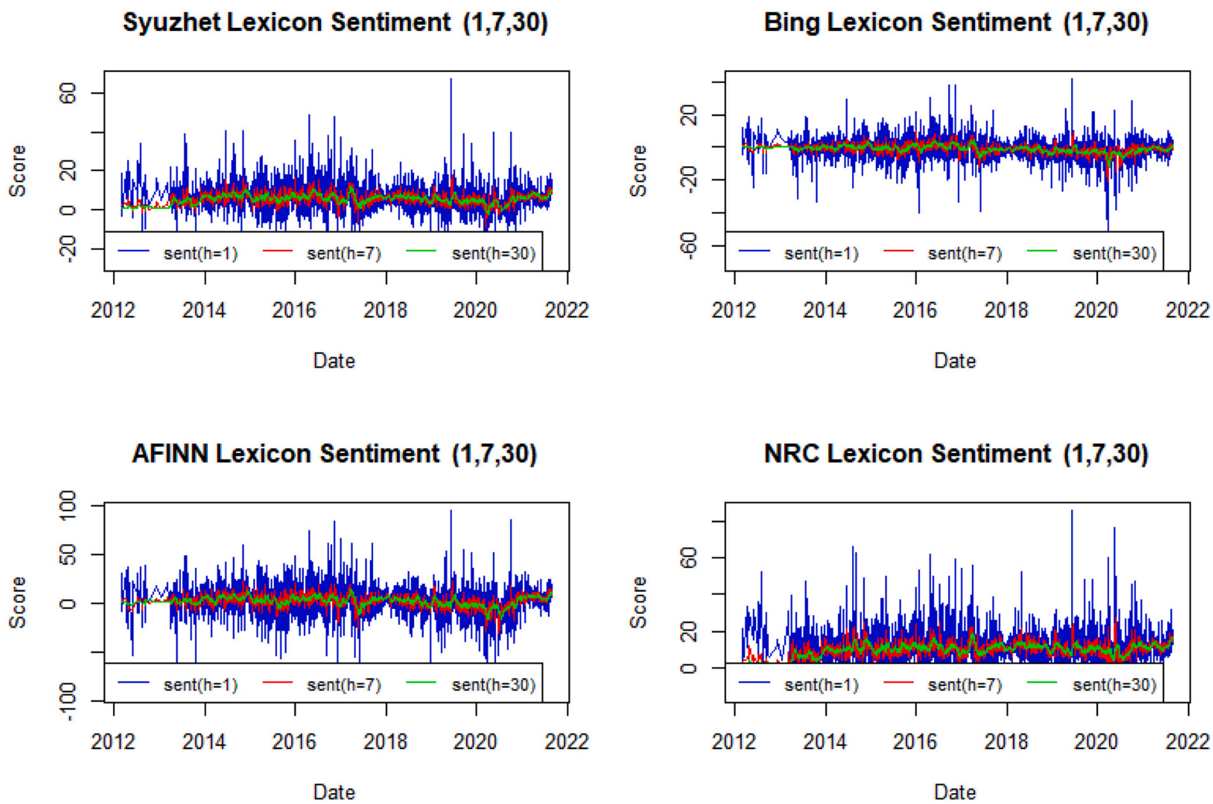

Fig. 4. Emotion Lexicon–based sentiments on BTC news, daily, weekly, and monthly (Jan 2012–Aug 2021).

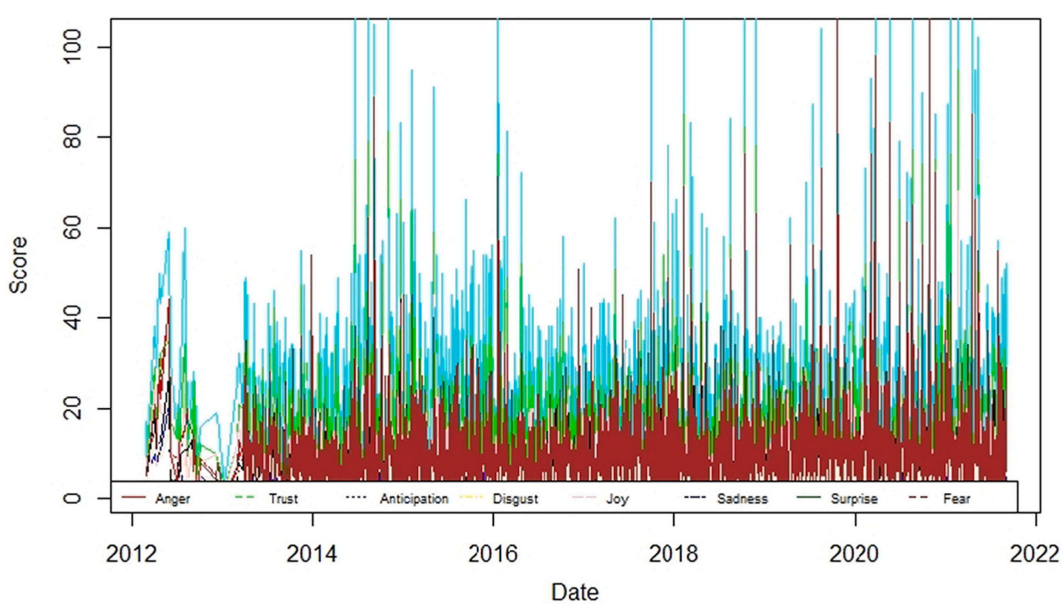

Fig. 5. NRC word-emotion association on global BTC news (Jan 2012–Aug 2021).

search trends, and various sentiments of different memory lengths, whereas Table 1.b includes the Emotion Lexicon–based summary statistics for 2802 days of news observations, totaling 17,490 news items. We can observe that there were on average 6 news pieces on BTC published daily within these 91 major newspapers, ranging from a minimum of 1 to a maximum of 66 daily news pieces. I aggregated the sentiment scores of a day if it had more than one news item.

4. Methodologies

4.1. Estimating realized variance of Bitcoin

Parkinson (1980) introduced the high/low range–based volatility estimation technique. Thereafter, new range-based volatility estimation methods emerged including opening and closing prices. These new range-based estimators use OHLC prices in an intraday setting. By including different methods, we can gain a better understanding of the nature of ranges and their significance in forecasting future volatilities. Volatility plays a central role in many areas of finance, and price range provides an intuitive and efficient estimator of volatility (Chou, Chou, & Liu, 2010). Including various range-based estimation methods along with different sentiment dictionaries contributes to a comparative analysis for deciding the most suitable volatility estimation method with the right sentiment dictionary.

Utilizing the BTC intraday OHLC data from investing.com, I created three different, daily, range-based, BTC RV series applying the methods of Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991). Parkinson (1980) introduced a volatility measure that uses the high and low prices of the day instead of only a closing price, considering that large price movements could have happened during the day itself. Thus, Parkinson's volatility is considered to be more precise than the regular close-by-close volatility estimation.

$$\sigma_{PK}^2 = \frac{1}{4ln(2)n}\sum_{i=1}^{n} ln^2\left(\frac{H_i}{L_i}\right) \tag{1}$$

where σ_{PK}^2 is the Parkinson (1980) variance estimator, and H_i is the highest and L_i the lowest intraday price of asset i.

However, it does not consider price movements after market close, systematically undervaluing volatility. The Garman and Klass (1980) volatility estimator overcomes this drawback by incorporating OHLC prices of a security. Considering market swings during the opening and closing hours makes volatility estimation more accurate.

$$\sigma_{GK}^2 = \frac{1}{n}\left(\sum_{i=1}^{n}\frac{1}{2}ln^2\left(\frac{H_i}{L_i}\right) + (2ln(2)-1)ln^2\left(\frac{C_i}{O_i}\right)\right) \tag{2}$$

where σ_{GK}^2 is the Garman and Klass (1980) variance estimator, H_i is the highest and L_i the lowest intraday price, O_i is the opening and C_i the closing price of asset i.

One criticism of the Garman-Klass method is that it is not robust for opening jumps in price and trend movements. Nevertheless, it is still more effective than the regular close-by-close volatility estimation because it considers not only the opening and closing prices but also intraday price extrema. Rogers and Satchell (1991) proposed a more efficient method for assessing historical volatility that takes into account price trends.

$$\sigma_{RS}^2 = \frac{1}{n}\sum_{i=1}^{n}(u_i(u_i-c_i)+d_i(d_i-c_i)) \tag{3}$$

where σ_{RS}^2 is the Rogers and Satchell (1991) variance estimator, u_i is the normalized high and d_i the normalized low, and c_i is the normalized closing price of asset i.

The Rogers-Satchell method incorporates the drift term; as a result, it provides a better volatility estimation when the underlying is trending. These three range-based estimation methods were applied to the BTC data sample from January 2012 until August 2021, revealing a close-by-close volatility of 3.37%, Parkinson (1980) volatility of 5.56%, Garman and Klass (1980) volatility of 7.44%, and Rogers and Satchell (1991) volatility of 5.59%. All three range-based estimation methods showed higher volatilities than the regular close-by-close technique. Table 1.c presents the summary statistics of the BTC OHLC data, as well as a summary of the variance series of the three different range-based variance estimators with three different memory lengths.

4.2. HAR-RV for forecasting Bitcoin volatility

The HAR-RV proposed by Corsi (2009) is one of the most popular models for forecasting volatility. Recently, HAR-type models have received considerable attention in academic research. The HAR approach separates RVs into short-term, medium-term, and long-term volatility components. Previous studies (for example, Andersen et al., 2007; Ma, Wei, Huang, & Chen, 2014) have found that the HAR-RV process outperforms other approaches when forecasting future RV. Considering its outperformance in forecasting future RV, the basic HAR-RV has been extended in several other dimensions. First, the definition of RV for day t is:

Table 2
Estimation of Baseline HAR-RV with Range-Based RVs.

	Dependent variable: $\log(RV_{t+1})$		
	Parkinson (PK)	Garman-Klass (GK)	Rogers-Satchel (RS)
$\log(PK\_RV_1)$	0.343***		
	(15.729)		
$\log(PK\_RV_7)$	0.384***		
	(11.795)		
$\log(PK\_RV_{30})$	0.146***		
	(4.862)		
$\log(GK\_RV_1)$		0.299***	
		(13.632)	
$\log(GK\_RV_7)$		0.416***	
		(12.408)	
$\log(GK\_RV_{30})$		0.158***	
		(5.043)	
$\log(RS\_RV_1)$			0.285***
			(18.626)
$\log(RS\_RV_7)$			0.306***
			(9.945)
$\log(RS\_RV_{30})$			0.145***
			(4.997)
Constant	−0.512***	−0.506***	−0.611***
	(−9.159)	(−9.304)	(−10.998)
Observations	2802	2802	2802
Adjusted R^2	0.464	0.464	0.469
F Statistic (df = 3; 2798)	808.729***	809.825***	825.827***

Notes: This table reports the estimates for the daily HAR-RV models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs are considered in this empirical analysis. The basic HAR-RV is presented in Eq. (8). T-stats are reported in the parenthesis.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2;\ t = 1,2,\ldots,T \tag{4}$$

where $r_{t,\,j}$ is the logarithmic return for period j of day t, M indicates the number of intraday observations at time t, and T refers to the number of periods in the sample.

$$RV_t^{(d)} = RV_t^{(X)} \tag{5}$$

where $RV_t^{(X)}$ can refer to any measure of volatility.

The original HAR model was proposed to model daily RV with 5 days in a week and 22 days in a month. However, the BTC market is 24 h a day and 7 days a week. Therefore, the weekly and monthly RVs are aggregated as:

$$RV_t^{(w)} = \frac{1}{7}\sum_{h=0}^{6} RV_{t-h}^{(d)} \tag{6}$$

where $RV_t^{(w)}$ is weekly RV.

$$RV_t^{(m)} = \frac{1}{30}\sum_{h=0}^{29} RV_{t-h}^{(d)} \tag{7}$$

where $RV_t^{(m)}$ is monthly RV.

Therefore, the HAR-RV for BTC can be written as:

$$HAR\_RV_{t,t+1} = \beta_0 + \beta^d RV_t^{(d)} + \beta^w RV_t^{(w)} + \beta^m RV_t^{(m)} + \varepsilon_t \tag{8}$$

Table 3
Estimation of HAR-RV with Range-Based Volatilities and Overall Psychological & Discourse Sentiment.

	Dependent variable: $log(RV_{t+1})$					
	PK (1980)		GK (1980)		RS (1991)	
	(GI)	(QDAP)	(GI)	(QDAP)	(GI)	(QDAP)
logPK_RV1	0.326***	0.325***				
	(14.861)	(14.782)				
logPK_RV7	0.371***	0.373***				
	(11.404)	(11.488)				
logPK_RV30	0.148***	0.147***				
	(4.920)	(4.880)				
logGK_RV1			0.300***	0.299***		
			(14.427)	(14.355)		
logGK_RV7			0.385***	0.387***		
			(12.219)	(12.299)		
logGK_RV30			0.155***	0.155***		
			(5.256)	(5.221)		
logRS_RV1					0.278***	0.275***
					(13.161)	(13.009)
logRS_RV7					0.368***	0.371***
					(11.790)	(11.883)
logRS_RV30					0.154***	0.154***
					(5.201)	(5.171)
S_GI_1	−0.099		−0.090		0.011	
	(−0.312)		(−0.267)		(0.035)	
S_GI_7	2.371***		2.381**		2.307**	
	(2.653)		(2.510)		(2.519)	
S_GI_30	−0.943		−1.216		−1.534	
	(−0.785)		(−0.954)		(−1.245)	
S_QDAP_1		−0.064		−0.046		0.003
		(−0.176)		(−0.119)		(0.008)
S_QDAP_7		2.851***		2.854**		2.930***
		(2.590)		(2.442)		(2.597)
S_QDAP_30		−1.902		−2.251		−2.560
		(−1.151)		(−1.283)		(−1.508)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.644***	−0.619***	−0.845***	−0.823***	−0.894***	−0.844***
	(−8.258)	(−8.600)	(−11.329)	(−12.085)	(−11.414)	(−11.683)
Observations	2802	2802	2802	2802	2802	2802
Adjusted R^2	0.498	0.498	0.499	0.499	0.456	0.456
F Statistic (df = 8; 2793)	348.569***	348.740***	349.406***	349.675***	295.042***	294.731***

Notes: This table reports the estimates for the HAR-RV-SI models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs along with two overall psychological sentiments are considered in this empirical analysis. The extended HAR-RV-SI is presented in Eq. (9). T-stats are reported in the parenthesis.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

where d is the daily, w is the weekly, and m is the monthly horizon.

4.3. HAR-RV-SI: Adding news sentiment in Bitcoin volatility modeling

In this study, I extended the baseline HAR-RV model by adding news sentiments and other control variables, called HAR-RV-SI. I used the logarithm of the RV for getting the time series of daily volatilities. Furthermore, weekly and monthly variances were also calculated in a rolling window fashion, and to get the respective volatilities, I also log-transformed the weekly and monthly series. The time-series plot of RVs of BTC separated into short-term, medium-term, and long-term volatility components following different estimation methods is presented in Fig. 3. Similarly, to capture the effect of sentiment variables at each frequency, in addition to the daily sentiment indices, I also derived the weekly and monthly sentiment indices of BTC-related news for all four dictionaries, which can be observed in Fig. 2.

Moreover, to test the order of integration, I followed the common literature and employed the well-known augmented Dickey-Fuller (ADF) unit root test (Dickey & Fuller, 1979). All the right-hand and left-hand variables including log-transformed variance and sentiments at different time scales, including control variables, showed stationarity.

The log-transformed realized variance (log-RV), log-HAR-RV, then, according to Corsi (2009), can be specified as:

$$\begin{aligned} logHAR\_RV\_SI_{t,t+1} = & \alpha + \beta^d logRV_t^{(d)} + \beta^w logRV_t^{(w)} + \beta^m logRV_t^{(m)} \\ & + \delta^d SI_t^{(d)} \\ & + \delta^w SI_t^{(w)} + \delta^m SI_t^{(m)} + \gamma^d X_t^{(d)} + \varepsilon_t \end{aligned} \tag{9}$$

where $SI_t^{(w)}$ is the weekly sentiment index for each sentiment measure.

$$SI_t^{(w)} = \frac{1}{7}\sum_{h=0}^{6} SI_{t-h}^{(d)} \tag{9.a}$$

where $SI_t^{(m)}$ is the monthly sentiment index for each sentiment measure.

$$SI_t^{(m)} = \frac{1}{30}\sum_{h=0}^{29} SI_{t-h}^{(d)} \tag{9.b}$$

where $\boldsymbol{X}_t^{(d)}$ are the control variables, daily Google search intensity, and daily news count.

4.4. HAR-RV-PS/NS: Decomposing sentiment into purely positive and purely negative sentiments

I also extended the benchmark HAR-RV in several other dimensions. Specifically, I extended the benchmark HAR-RV to feature a measure of

Table 4
Estimation of HAR-RV with Range-Based Volatilities and Overall Financial Sentiment.

	Dependent variable: $log(RV_{t+1})$					
	PK (1980)		GK (1980)		RS (1991)	
	(HE)	(LM)	(HE)	(LM)	(HE)	(LM)
logPK_RV1	0.328***	0.326***				
	(14.923)	(14.799)				
logPK_RV7	0.375***	0.378***				
	(11.527)	(11.602)				
logPK_RV30	0.142***	0.143***				
	(4.732)	(4.759)				
logGK_RV1			0.302***	0.299***		
			(14.498)	(14.373)		
logGK_RV7			0.389***	0.392***		
			(12.337)	(12.406)		
logGK_RV30			0.150***	0.151***		
			(5.076)	(5.111)		
logRS_RV1					0.278***	0.277***
					(13.163)	(13.053)
logRS_RV7					0.373***	0.377***
					(11.930)	(12.058)
logRS_RV30					0.147***	0.146***
					(4.951)	(4.943)
S_HE_1	1.112		1.135		0.812	
	(0.844)		(0.862)		(0.592)	
S_HE_7	1.672		1.881		1.633	
	(0.432)		(0.487)		(0.406)	
S_HE_30	−1.155		−2.105		5.580	
	(−0.180)		(−0.328)		(0.834)	
S_LM_1		0.242		0.154		0.299
		(0.457)		(0.292)		(0.544)
S_LM_7		2.894*		2.962*		2.987*
		(1.821)		(1.872)		(1.811)
S_LM_30		−4.315**		−1.151		−4.571*
		(−1.999)		(−0.516)		(−1.959)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.648***	−0.588***	−0.858***	−0.791***	−0.860***	−0.835***
	(−9.177)	(−7.336)	(−12.949)	(−10.328)	(−12.108)	(−10.301)
Observations	2802	2802	2802	2802	2802	2802
Adjusted R^2	0.497	0.498	0.498	0.498	0.455	0.455
F Statistic (df = 8; 2793)	347.028***	347.863***	347.823***	348.711***	293.061***	293.784***

Notes: This table reports the estimates for the HAR-RV-SI models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs along with two overall financial sentiments are considered in this empirical analysis. The extended HAR-RV-SI is presented in Eq. (9). T-stats are reported in the parenthesis.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

positive and negative sentiments, called HAR-RV-PS/NS. To capture the heterogeneity between the optimistic and pessimistic investors, I decomposed sentiment into purely positive and purely negative. The general idea of this decomposition is that optimistic investors are mainly guided by positive sentiments in the news, whereas pessimistic investors are mainly guided by negative sentiments.

4.4.1. Positive sentiment

$$logHAR\_RV\_PS_{t,t+1} = \alpha + \beta^d logRV_t^{(d)} + \beta^w logRV_t^{(w)} + \beta^m logRV_t^{(m)} + \delta^d PS_t^{(d)} + \delta^w PS_t^{(w)} + \delta^m PS_t^{(m)} + \gamma^d X_t^{(d)} + \varepsilon_t \tag{10}$$

where $PS_t^{(d)}$ is the daily positive sentiment, and weekly (w) and monthly (m) positive sentiments are captured via the following equations:

$$PS_t^{(w)} = \frac{1}{7}\sum_{h=0}^{6} PS_{t-h}^{(d)} \tag{10.a}$$

$$PS_t^{(m)} = \frac{1}{30}\sum_{h=0}^{29} PS_{t-h}^{(d)} \tag{10.b}$$

4.4.2. Negative sentiment

$$logHAR\_RV\_NS_{t,t+1} = \alpha + \beta^d logRV_t^{(d)} + \beta^w logRV_t^{(w)} + \beta^m logRV_t^{(m)} + \delta^d NS_t^{(d)} + \delta^w NS_t^{(w)} + \delta^m NS_t^{(m)} + \gamma^d X_t^{(d)} + \varepsilon_t \tag{11}$$

where $NS_t^{(d)}$ is the daily negative sentiment, and weekly (w) and monthly (m) negative sentiments are captured via the following equations:

$$NS_t^{(w)} = \frac{1}{7}\sum_{h=0}^{6} NS_{t-h}^{(d)} \tag{11.a}$$

$$NS_t^{(m)} = \frac{1}{30}\sum_{h=0}^{29} NS_{t-h}^{(d)} \tag{11.b}$$

4.5. Emotion lexicon sentiment of the news and Bitcoin volatility: Robustness check

The NRC Emotion Lexicon is a list of 5636 English words and their associations, with 8 basic emotions—anger, fear, anticipation, trust, surprise, sadness, joy, and disgust—and 2 sentiments—negative and positive (Mohammad & Turney, 2013). To further explore the sentiments of different human emotions, I followed the NRC Emotion Lexicon. Fig. 4 shows the polarity and time-varying sentiments of BTC news items with different emotions. Fig. 5 shows a histogram of the

Table 5
Estimation of HAR-RV with Range-Based Volatilities and Positive Psychological Sentiments.

	Dependent variable: log(RV_{t+1})					
	PK (1980)		GK (1980)		RS (1991)	
	(GI)	(QDAP)	(GI)	(QDAP)	(GI)	(QDAP)
logPK_RV1	0.328***	0.327***				
	(14.911)	(14.892)				
logPK_RV7	0.371***	0.371***				
	(11.353)	(11.367)				
logPK_RV30	0.145***	0.145***				
	(4.811)	(4.789)				
logGK_RV1			0.285***	0.285***		
			(12.903)	(12.891)		
logGK_RV7			0.401***	0.402***		
			(11.928)	(11.941)		
logGK_RV30			0.157***	0.156***		
			(4.976)	(4.953)		
logRS_RV1					0.366***	0.365***
					(17.526)	(17.472)
logRS_RV7					0.292***	0.293***
					(9.458)	(9.480)
logRS_RV30					0.146***	0.146***
					(4.996)	(4.983)
P_GI_1	−0.050		−0.115		0.318	
	(−0.121)		(−0.260)		(0.746)	
P_GI_7	0.629		0.632		0.636	
	(1.065		(1.008		(1.052	
P_GI_30	−0.796		−0.938		−1.442**	
	(−1.206)		(−1.339)		(−2.125)	
P_QDAP_1		−0.064		−0.100		0.362
		(−0.125)		(−0.184)		(0.692)
P_QDAP_7		0.746		0.755		0.804
		(0.848)		(0.809)		(0.894)
P_QDAP_30		−1.176		−1.380		−2.221**
		(−1.178)		(−1.303)		(−2.166)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.614***	−0.600***	−0.576***	−0.570***	−0.697***	−0.670***
	(−5.952)	(−6.303)	(−5.379)	(−5.794)	(−6.748)	(−7.036)
Observations	2802	2802	2802	2802	2802	2802
Adjusted R^2	0.497	0.497	0.467	0.467	0.474	0.474
F Statistic (df = 8; 2793)	347.062***	347.026***	308.321***	308.305***	316.986***	317.082***

Notes: This table reports the estimates for the HAR-RV-PS models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs along with two positive psychological sentiments are considered. The extended HAR-RV-PS is presented in Eq. (10). T-stats are reported in the parenthesis.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

corresponding eight basic human emotions in the news data sample. We can observe from the graph that trust and fear were the two emotions most triggered by BTC-related news in the time period.

Next, I extended the benchmark HAR-RV model to feature different human emotions from the lexicon index beyond positive and negative sentiments. This extended HAR-RV-LI with all eight daily normalized emotions, along with Google search trends and news counts as controls, is calculated as follows:

$$\begin{aligned} logHAR\_RV\_LI_{t,t+1} = & \alpha + \beta^{d} logRV_{t}^{(d)} + \beta^{w} logRV_{t}^{(w)} + \beta^{m} logRV_{t}^{(m)} \\ & + \delta^{d1} nAng_{t}^{(d)} + \delta^{d2} nAnt_{t}^{(d)} + \delta^{d3} nDis_{t}^{(d)} + \delta^{d4} nFear_{t}^{(d)} \\ & + \delta^{d5} nJoy_{t}^{(d)} + \delta^{d6} nSad_{t}^{(d)} + \delta^{d7} nSur_{t}^{(d)} + \delta^{d8} nTru_{t}^{(d)} \\ & + \gamma^{d} X_{t}^{(d)} + \varepsilon_{t} \end{aligned} \tag{12}$$

where δ^{d1} to δ^{d8} are the eight different normalized emotions extracted implementing the NRC Emotion Lexicon. The eight emotions are anger, anticipation, disgust, fear, joy, sadness, surprise, and trust, as mentioned above.

5. Results

5.1. Summary statistics

In the summary statistics in Table 1.a, the Google search trends show a minimum value of 0 and a maximum value of 100. The lowest search intensity days during the whole sample period of January 1, 2012, to August 31, 2021, score 0, and the highest search intensity days score 100. Because the result is normalized between 0 and 100, the search data series shows stationarity at the given level. The mean Google search score of 7.61 shows that BTC was not intensively searched on Google daily during the time period. During the sample period, there were a total of 17,490 news items which also includes the news articles on BTC published by the major English language newspapers from around the globe. The total days within the sample period was 3525; however, there was at least one news item on BTC by at least one of the major English-language newspapers for only 2802 days.

I downloaded the BTC Google search intensity and OHLC data for the full sample period and matched to the respective sentiment days. On average, there were 6 news pieces on BTC daily, ranging from a minimum of 1 news piece to a maximum of 66 news pieces in a day. One newspaper might have had more than one news item on BTC on a particular day. In other words, all 66 news items were not published by

Table 6
Estimation of HAR-RV with Range-Based Volatilities and Negative Psychological Sentiments.

	Dependent variable: log(RV_{t+1})					
	PK (1980)		GK (1980)		RS (1991)	
	(GI)	(QDAP)	(GI)	(QDAP)	(GI)	(QDAP)
logPK_RV1	0.326***	0.326***				
	(14.815)	(14.798)				
logPK_RV7	0.378***	0.380***				
	(11.567)	(11.630)				
logPK_RV30	0.141***	0.140***				
	(4.667)	(4.644)				
logGK_RV1			0.284***	0.284***		
			(12.819)	(12.814)		
logGK_RV7			0.408***	0.410***		
			(12.131)	(12.182)		
logGK_RV30			0.152***	0.152***		
			(4.841)	(4.825)		
logRS_RV1					0.364***	0.363***
					(17.368)	(17.356)
logRS_RV7					0.298***	0.299***
					(9.641)	(9.694)
logRS_RV30					0.143***	0.143***
					(4.904)	(4.915)
N_GI_1	−0.299		−0.381		−0.024	
	(−0.640)		(−0.768)		(−0.050)	
N_GI_7	−0.890		−0.885		−0.834	
	(−1.014)		(−0.950)		(−0.928)	
N_GI_30	0.122		−0.070		−1.099	
	(0.120)		(−0.065)		(−1.052)	
N_QDAP_1		−0.331		−0.378		0.005
		(−0.656)		(−0.706)		(0.009)
N_QDAP_7		−1.790		−1.771		−1.821
		(−1.581)		(−1.474)		(−1.570)
N_QDAP_30		0.859		0.617		−0.754
		(0.631)		(0.427)		(−0.540)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.547***	−0.558***	−0.514***	−0.532***	−0.593***	−0.597***
	(−5.934)	(−6.375)	(−5.420)	(−5.939)	(−6.432)	(−6.829)
Observations	2802	2802	2802	2802	2802	2802
Adjusted R^2	0.497	0.498	0.468	0.468	0.474	0.475
F Statistic (df = 8; 2793)	347.315***	347.723***	308.607***	308.877***	317.145***	317.354***

Notes: This table reports the estimates for the HAR-RV-NS models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs along with two negative psychological sentiments are considered. The extended HAR-RV-NS is presented in Eq. (11). T-stats are reported in the parenthesis.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

66 unique newspapers in a single day. Another interesting summary statistic is that the Harvard-IV psychological dictionary, QDAP discourse dictionary, and Henry's finance-specific dictionary showed similar patterns, whereas Loughran's and McDonald's finance-specific dictionary was overall negative on daily, weekly, and monthly aggregates. If we remove Henry's finance-specific dictionary, one can observe that the psychological and discourse sentiments from the BTC-related news were overall positive and that the finance sentiments were overall negative during the full sample period.

Similarly, in the summary statistics shown in Table 1.b, we can observe the basic statistics of four different lexicon sentiments. The Syuzhet R package with the "get_sentiment" function gives scores for *Syuzhet, Bing, Afinn*, and *NRC* sentiments. In this study, the NRC Emotion Lexicon had a higher mean score for positive sentiments than negative sentiments. Dividing the sentiments into eight different human emotions showed that the news articles during the sample period, on average, triggered mostly trust, anticipation and fear in its readers. Furthermore, on average, news during the sample period equally conveyed the emotions of joy and sadness to the public.

Table 1.c includes statistics summarizing BTC OHLC and three range-based variances on daily, weekly, and monthly averages calculated by a rolling window method. BTC closing price ranged from a minimum of 4.6 dollars to a maximum of 63,540.90 dollars, which is 13,813 times higher than its minimum value. The daily, average, range-based variance following Parkinson (1980) was 0.0034, Garman and Klass (1980) was 0.0061, and Rogers and Satchell (1991) was 0.0038. The weekly and monthly averages following each range-based method showed no vast differences in the average variance.

5.2. *Basic fitting of the HAR-RV*

The first step in the analysis was to fit the basic HAR(3) to compare if sentiments, as additional explanatory variables, improve the model fitting or not. The HAR(3) model utilizes three AR(1) volatility processes at daily, weekly, and monthly windows. As a natural economic interpretation of this model according to Corsi (2009), each component in the model corresponds to a short-term, medium-term and long-term volatilities. The baseline model–fitting results presented in Table 2 show

Table 7
Estimation of HAR-RV with Range-Based Volatilities and Positive Financial Sentiments.

	Dependent variable: log(RV_{t+1})					
	PK (1980)		GK (1980)		RS (1991)	
	(HE)	(LM)	(HE)	(LM)	(HE)	(LM)
logPK_RV1	0.327***	0.327***				
	(14.877)	(14.876)				
logPK_RV7	0.373***	0.370***				
	(11.459)	(11.348)				
logPK_RV30	0.144***	0.148***				
	(4.764)	(4.888)				
logGK_RV1			0.285***	0.285***		
			(12.882)	(12.873)		
logGK_RV7			0.403***	0.400***		
			(12.031)	(11.929)		
logGK_RV30			0.155***	0.159***		
			(4.934)	(5.054)		
logRS_RV1					0.365***	0.366***
					(17.486)	(17.532)
logRS_RV7					0.293***	0.291***
					(9.510)	(9.425)
logRS_RV30					0.145***	0.148***
					(4.987)	(5.082)
P_HE_1	1.168		1.317		1.316	
	(0.821)		(0.872)		(0.904)	
P_HE_7	0.921		0.788		2.099	
	(0.246)		(0.199)		(0.548)	
P_HE_30	−5.361		−6.300		−11.589**	
	(−1.038)		(−1.150)		(−2.181)	
P_LM_1		−0.515		−0.710		0.619
		(−0.380)		(−0.493)		(0.446)
P_LM_7		6.389*		6.718*		6.280*
		(1.838)		(1.821)		(1.764)
P_LM_30		−8.030*		−9.343*		−12.020***
		(−1.776)		(−1.947)		(−2.584)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.604***	−0.607***	−0.582***	−0.577***	−0.656***	−0.673***
	(−7.642)	(−7.197)	(−7.258)	(−6.694)	(−8.366)	(−8.047)
Observations	2802	2802	2802	2802	2802	2802
Adjusted R^2	0.497	0.498	0.468	0.468	0.475	0.475
F Statistic (df = 8; 2793)	347.187***	347.686***	308.478***	308.926***	317.146***	317.398***

Notes: This table reports the estimates for the HAR-RV models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs along with two positive financial sentiments are considered. The extended HAR-RV-PS is presented in Eq. (10). T-stats are reported in the parenthesis.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

similar results to those of Corsi (2009, page 187).

Table 2 reports the results of the estimation of the basic HAR-RV for three range-based volatility series. T-statistics confirmed all three RVs aggregated over the three different horizons to be highly significant. This result is in line with the results of Aalborg et al. (2019) where they found that the past RV of BTC predicts its future RV on the HAR-RV setup. One surprising finding in the current study is that RV aggregated weekly seemed to be less noisy and received more weight compared with RV aggregated daily and monthly, as in the cases of Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991). According to Corsi (2009), weekly and monthly RVs averaged over longer periods contain less noise and more information on the volatility process and, hence, receive higher weight from the model. However, in the table, the range-based volatilities seem to lose information or memory over a longer time period.

5.3. Extension of the HAR-RV with overall psychological and financial sentiments

While the daily, weekly, and monthly volatilities remained equally significant, as shown in the baseline HAR model presented in Table 2, we can observe an R-squared in Table 3 showing that after adding psychological sentiment, the quality of the extended HAR-RV was improved. A similar weight pattern on different scalings of sentiment can be observed. The weekly aggregates had more weight compared to daily and monthly averages. Another interesting finding is that only weekly aggregated psychological and discourse sentiments extracted from the news had a statistically significant impact on BTC volatility. For all the range-based estimators, neither daily nor monthly sentiments were significant. One possible reason behind this result might be the arrival of news to potential investors or readers. Not all audiences read newspapers on the same day they are published. Furthermore, general readers easily tend to forget the news over the long run, resulting in the decay of sentiment generated from the news within the month. Moreover, the extended model also accounted for Google search intensity and news counts as controls.

Similarly, in Table 4, results on the two separate financial sentiment dictionaries, along with three different range-based volatilities, are reported. Two dictionaries, those of Henry and Loughran and McDonald, are specifically targeted to the domain of finance. Loughran and McDonald (2011) used Harvard-IV and Henry (2008) used earnings press releases to capture tone. Both found finance-specific word lists to be more powerful than general word lists. However, in this study, Henry's finance-specific dictionary did not seem to show any significance in any time length for any of the range-based volatility estimators. As opposed to psychological and discourse sentiments, Loughran's and

Table 8
Estimation of HAR-RV with Range-Based Volatilities and Negative Financial Sentiments.

	Dependent variable: log(RV_{t+1})					
	PK (1980)		GK (1980)		RS (1991)	
	(HE)	(LM)	(HE)	(LM)	(HE)	(LM)
logPK_RV1	0.325***	0.326***				
	(14.752)	(14.833)				
logPK_RV7	0.373***	0.377***				
	(11.392)	(11.562)				
logPK_RV30	0.141***	0.142***				
	(4.644)	(4.719)				
logGK_RV1			0.283***	0.284***		
			(12.765)	(12.839)		
logGK_RV7			0.403***	0.407***		
			(11.945)	(12.123)		
logGK_RV30			0.152***	0.154***		
			(4.826)	(4.895)		
logRS_RV1					0.359***	0.364***
					(17.163)	(17.413)
logRS_RV7					0.293***	0.296***
					(9.475)	(9.610)
logRS_RV30					0.142***	0.146***
					(4.857)	(5.018)
N_HE_1	−0.206		0.079		−1.484	
	(−0.106)		(0.039)		(−0.750)	
N_HE_7	−1.574		−1.954		2.042	
	(−0.273)		(−0.320)		(0.347)	
N_HE_30	−14.557		−15.981*		−31.128***	
	(−1.643)		(−1.701)		(−3.413)	
N_LM_1		−0.507		−0.504		−0.615
		(−0.840)		(−0.787)		(−0.995)
N_LM_7		−1.453		−1.522		−1.243
		(−0.985)		(−0.973)		(−0.824)
N_LM_30		0.346		0.095		−1.992
		(0.193)		(0.050)		(−1.085)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.549***	−0.559***	−0.528***	−0.535***	−0.580***	−0.571***
	(−7.403)	(−6.340)	(−7.042)	(−5.921)	(−7.891)	(−6.492)
Observations	2802	2802	2802	2802	2802	2802
Adjusted R^2	0.498	0.497	0.468	0.468	0.476	0.475
F Statistic (df = 8; 2793)	347.900***	347.353***	309.130***	308.561***	319.438***	317.335***

Notes: This table reports the estimates for the HAR-RV-NS models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs along with two negative financial sentiments are considered. The extended HAR-RV-NS is presented in Eq. (11). T-stats are reported in the parenthesis.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

McDonald's overall finance sentiments significantly impacted weekly and monthly volatilities. As rationale for the insignificance of daily financial sentiments, we can again use the argument of news arrival delay in the context of psychological and discourse sentiments. However, it is surprising that the effect of financial sentiments was significant over a longer time period in comparison to the other two psychological and discourse dictionaries.

5.4. Decomposing overall sentiments into positive and negative sentiments

Overall sentiment is a combination of positive and negative sentiments. However, some readers might be influenced by either of these emotions. Pessimistic and optimistic readers have different choices and perceptions of events. Pessimistic readers are mostly influenced by negative events, whereas optimistic are influenced by positive events. In this regard, McAfee, Doubleday, Geiger, and Connell (2019) stated that optimism and pessimism inform our expectation that events will turn out positively or negatively. Therefore, I further decomposed the overall sentiment into positive and negative sentiments and extended the basic HAR-RV to see which polarity of emotion is more responsible for BTC volatility.

Table 5 shows the results of HAR-RV with positive psychological and quantitative discourse sentiments. Table 6 presents the results of negative sentiments from the same dictionaries. Sentiments being fragmented into only negative or only positive showed BTC market volatility to be subject to a mixture of negative and positive sentiments rather than a purely negative or purely positive sentiment. Comparing this result with the findings of Corbet et al. (2020) who constructed a sentiment index based on news surrounding macroeconomic indicators found that negative news related to these indicators is positive for BTC and vice-versa. Nevertheless, the result is not fully comparable as the sentiment generated by their study is based on the news surrounding macroeconomic announcements whereas the sentiment index generated in the current study is fully based on the news specific to BTC. On the other hand, Entrop et al. (2020) used the news-based BTC sentiment data from Thomson Reuters MarketPsych (TRMI) to study the dynamic relation between bitcoin spot and futures prices and found that higher news-based BTC sentiment increases the informational role of the BTC futures market. Furthermore, they found news-based BTC sentiment to be a relevant measure of BTC price discovery, which is in line with this current research as we can observe in Table 3 and Table 4 that the extended HAR-RV model with news-based BTC sentiment has improved

Table 9
Estimation of HAR-RV with Range-based Volatilities and NRC Emotion Lexicon.

	Dependent variable: log(RV_{t+1})		
	(PK)	(GK)	(RS)
logPK_RV1	0.325***		
	(14.809)		
logPK_RV7	0.377***		
	(11.597)		
logPK_RV30	0.144***		
	(4.802)		
logGK_RV1		0.284***	
		(12.840)	
logGK_RV7		0.406***	
		(12.130)	
logGK_RV30		0.156***	
		(4.983)	
logRS_RV1			0.367***
			(17.713)
logRS_RV7			0.296***
			(9.649)
logRS_RV30			0.146***
			(5.010)
NormalizedAnger	0.473	0.411	0.789**
	(1.213)	(0.993)	(1.976)
NormalizedAnticipation	−0.880**	−0.883*	−0.790*
	(−2.058)	(−1.944)	(−1.807)
NormalizedDisgust	−0.371	−0.352	−0.147
	(−1.117)	(−0.998)	(−0.433)
NormalizedFear	−0.268	−0.177	−0.926**
	(−0.627)	(−0.389)	(−2.120)
NormalizedJoy	−0.011	−0.044	0.084
	(−0.031)	(−0.115)	(0.226)
NormalizedSadness	−0.303	−0.316	−0.232
	(−0.893)	(−0.877)	(−0.671)
NormalizedSurprise	0.419	0.437	0.266
	(1.321)	(1.299)	(0.820)
NormalizedTrust	1.078***	1.059**	1.223***
	(2.765)	(2.558)	(3.067)
Controls	Yes	Yes	Yes
Constant	−0.649***	−0.638***	−0.762***
	(−10.180)	(−10.182)	(−12.016)
Observations	2802	2802	2802
Adjusted R^2	0.498	0.468	0.476
F Statistic (df = 13; 2788)	215.003***	190.749***	196.677***

Notes: This table reports the estimates for the HAR-RV-LI models. The estimation period spans from 1 January 2012 to 31 August 2021. Three different RVs along with eight different daily emotions based on NRC are considered. The extended HAR-RV-LI is presented in Eq. (12). T-stats are reported in the parenthesis. ***Significant at the 1% level, **Significant at the 5% level, *Significant at the 10% level.

the model. Furthermore, in Table 5, we can observe that both monthly psychological sentiments and monthly discourse sentiments were significant in the Rogers and Satchell (1991) volatility estimation. We can argue that the effect of positivity, or positive sentiment, lasts longer than negativity, or negative sentiment. However, we can see in the results that the effect of positive sentiment was significantly negative over the long term. We can relate this result with that of PH and Rishad, 2020 who found the impact of sentiment on volatility to cause market uncertainty and lead to fewer returns. If investors fail to earn a risk premium for their expected volatility, they will move away from the market, which further causes volatility in the market.

In Table 7 and Table 8, we see the results of purely positive and purely negative finance-specific sentiments and their significance in predicting future volatilities of BTC. On the contrary, for psychological sentiments, both the purely positive and purely negative sentiments showed a significant effect on BTC volatilities in monthly aggregated sentiments. However, the purely negative finance-specific sentiments incorporating Loughran's and McDonald's dictionary was insignificant in all time scales in all volatility estimators. The result is again similar to negative psychological sentiment.

5.5. *The HAR-RV and emotion lexicon sentiments: A robustness check*

As an additional robustness check and to further explore the sentiments of different human emotions, I followed the NRC Emotion Lexicon. It is a list of English words and their associations with eight basic human emotions—anger, fear, anticipation, trust, surprise, sadness, joy, and disgust—and two sentiments—negative and positive. Fig. 5 shows a histogram of the corresponding eight basic human emotions in the news data sample. We can observe from the graph that trust and fear were the two emotions most triggered by BTC-related news. Because the weight of the emotions largely depends upon the number of words appearing in the news, I applied the min-max normalization process to scale these emotions. All the normalized emotions showed stationarity at their normalized levels. Next, I extended the HAR-RV with all eight daily normalized emotions, along with Google search intensity and news counts as controls. The results are presented in Table 9.

We can observe from the results that trust and anticipation were significant throughout all the volatility measures. In addition, fear and anger were significant at the 5% level in the volatility model incorporating the Rogers and Satchel (1991) method. Furthermore, Mohammad and Turney (2013) categorized trust and anticipation as positive sentiments and fear and anger as negative sentiments. In line with previous results presented in this paper, we can argue that it is not the negative

Table 10
Out-of-Sample Forecast Evaluation Statistics with Overall Sentiment.

			Sentiment			
	Measures	Basic-HAR	GI	QDAP	HE	LM
PK (1980)	ME	0.039	0.011	0.017	0.029	0.013
	RMSE	0.442	0.439	0.441	0.440	0.440
	MAE	0.315	0.313	0.314	0.314	0.316
	MAEP	0.115	0.113	0.114	0.114	0.114
	U2	0.816	0.816	0.817	0.814	0.818
GK (1980)	ME	0.095	0.010	0.019	0.034	0.014
	RMSE	0.467	0.463	0.464	0.464	0.464
	MAE	0.345	0.344	0.346	0.346	0.347
	MAEP	0.141	0.137	0.138	0.138	0.138
	U2	0.782	0.783	0.786	0.781	0.786
RS (1991)	ME	0.017	−0.014	−0.006	0.009	−0.014
	RMSE	0.472	0.469	0.470	0.469	0.468
	MAE	0.332	0.326	0.328	0.327	0.327
	MAEP	0.122	0.119	0.120	0.120	0.119
	U2	0.832	0.835	0.836	0.832	0.836

Notes: This table reports the values of various forecasting accuracy test results. The in-sample estimation period spans from 1 January 2012 to 31 December 2020, whereas the out-of-sample period ranges from 1 January 2021 to 31 August 2021. ME (mean error), RMSE (root mean square error), MAE (mean absolute error), MAEP (mean absolute error percentage), U2 (Thely's U2).

but positive sentiments that largely trigger volatility in the BTC market.

5.6. Out-of-sample forecast

To compare the out-of-sample accuracy of the different HAR-RV applications, first each alternative model was fitted to the in-sample RV data. Next, it was used to generate one-step-ahead out-of-sample forecasts. Because the data on volatility were generated with a daily range-based method, I focused on one-step-ahead forecasts in this study. However, multistep-ahead forecasts can be obtained similarly.

The in-sample data used for training purposes in this study were from January 1, 2012, until December 31, 2020. For testing the forecasting accuracy of the model, the out-of-sample data were from January 1, 2021, until August 31, 2021. The out-of-sample forecast accuracy measured by different methods is presented in Table 10.

$ME = \frac{1}{n}\sum_{t=1}^{n} e_{it}; RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_{it}^2}; MAE = \frac{1}{n}\sum_{t=1}^{n} |e_{it}|; MAEP = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{e_{it}}{a_{it}}\right|$

$$U2 = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{f_{t+1}-a_{t+1}}{a_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{a_{t+1}-a_t}{a_t}\right)^2}} \tag{13}$$

There are different techniques in measuring the forecast accuracy of the statistical model. Let's define the forecast error as $e_{it} = a_{it} - f_{it.}$

where a_{it} is the actual and f_{it} is the forecasted value. Then, the five accuracy measures are defined by:

In Table 10, for a better comparison, we can observe the value of mean absolute error percentage (MAEP) for all three range-based volatility estimations of the sentiment dictionaries. MAEPs ranged between 11% and 13%, which according to Lewis (1982, p.40), is good forecasting accuracy. On the other hand, Theil's U2, which looks at the accuracy of one-step-ahead forecasts, showed the HAR-RV extended with sentiment to be better than the naive forecasting method. Furthermore, the error statistics of the extended HAR models with sentiments as additional explanatory variables gave lower errors, implying higher forecasting accuracy. Appendix A.3 and Appendix A.4 show two out-of-sample forecast accuracy plots.

6. Conclusion

In the past decade, BTC has made a lot of news in mainstream media. Some news media have portrayed it as a positive phenomenon, while many others have doubted its worth and authenticity. In recent years, cryptocurrency markets have also attracted considerable attention in academic literature, especially in finance and economics journals studying volatility of this new blockchain-based digital asset.

Modeling volatility is an important step to precisely measure the risk associated with an asset or portfolio of assets. An accurate estimation of volatility is vital for investors to develop an adequate strategy to hedge potential risks associated with an investment. In this study, I explored whether news media sentiments have an impact on BTC volatility by extending the work of Corsi (2009) with an HAR-RV with news-based sentiments as additional explanatory variables. I used past RVs of BTC and news sentiments to predict its future RVs. This study applied different range-based volatility estimation methods to obtain a better understanding of the nature of ranges and their significance in forecasting future volatilities. Furthermore, I differentiated financial sentiments and psychological sentiments cached in the news and their impact on BTC volatility in different time spans to capture the heterogeneity of news arrival times and sentiment memory lengths among investors. Moreover, to further explore the sentiments of different human emotions, I also extended the HAR model to the emotional level. As a result, I found trust and fear to be the two human emotions most triggered by BTC-related news and ultimately affecting its volatility.

Results for all the range-based estimators showed neither daily nor monthly psychological sentiments as being significant. The most likely reason behind this result might be the arrival of news to potential investors or readers. Not all audiences read newspapers on the same day they get published. Furthermore, general readers easily tend to forget the news over the long run, resulting in the decay of sentiment generated from the news within the month. However, it is surprising that the effect of finance-specific sentiments was significant over the long term in comparison to the other two psychological and discourse sentiments. One possible explanation of this result could be that BTC is more related to the field of finance than psychology. Another possible explanation could be that investors remember the news with more finance-specific sentiments for longer periods of time than news with more psychological sentiments. Moreover, I used the decomposition of overall sentiments into purely positive and purely negative sentiments to capture the heterogeneity between optimistic and pessimistic investors. The general idea is that optimistic investors are mainly guided by positive sentiments originating from the news, whereas pessimistic investors are mainly guided by negative sentiments. The results showed purely positive financial sentiment as being more responsible for BTC volatility. In other words, financially optimistic investors seem to be the main drivers of this market. Furthermore, the NRC Emotion Lexicon as a robustness check also showed trust and anticipation to be significant throughout all the volatility measures. Because NRC categorizes trust and anticipation as positive sentiments and fear and anger as negative sentiments, we can confirm the result that it is not the negative but the positive sentiment that largely triggers volatility in the BTC market. The out-of-sample forecasting accuracy of the model also showed the HAR-RV with sentiment extension to have a good forecasting accuracy irrespective of the choice of volatility measure.

Overall, the results reveal that information on time-varying sentiments could play a major role in analyzing the news media risk associated with BTC. Thus, the findings seem important for volatility modeling and developing a trading strategy. Given that capturing true sentiment in news plays a significant role in risk management and portfolio optimization, this paper has important implications for investors holding assets in the cryptocurrency market, more specifically, BTC. Moreover, one possible limitation of this study is the consideration of news sentiment generated from the news covered by the major English language newspapers only. Therefore, future research is encouraged on news media versus social media sentiment and volatility of digital assets like BTC. Furthermore, analyzing news sentiments with non-FinTech dictionaries might be another limitation of this study. Previous studies have shown that a borrowed dictionary from a different discipline is likely to misjudge true sentiment, I would also like to highlight the need for a FinTech-specific sentiment dictionary that helps to explore the true sentiments of the new digital financial market.

Declaration of Competing Interest

I declare that I have no significant competing financial, professional, or personal interests that might have influenced the performance or presentation of the work described in this manuscript.

Appendix A. Appendices

Appendix A.1. Major newspapers in English listed by lexisnexis.com from around the world

S.No.	Major Newspapers in English	S.No.	Major Newspapers in English
1	The Advertiser/Sunday Mail (Adelaide, South Australia)	47	The Independent (London)
2	The Age (Melbourne, Australia)	48	The Indianapolis Star (Indiana)
3	APN Australian Newspapers	49	The Irish Times
4	The Arizona Republic (Phoenix)	50	The Japan News
5	Arkansas Democrat-Gazette	51	The Jerusalem Post
6	The Atlanta Journal-Constitution	52	The Kansas City Star
7	The Australian	53	Los Angeles Times
8	Australian Financial Review	54	The Miami Herald
9	The Baltimore Sun	55	The Milwaukee Journal Sentinel
10	The Boston Globe	56	New Straits Times (Malaysia)
11	The Boston Herald	57	Newsday (New York)
12	The Buffalo News (New York)	58	The New York Post
13	Business Times (Malaysia)	59	The New York Times
14	The Business Times Singapore	60	The New Zealand Herald
15	The Canberra Times	61	Northern Territory News (Australia)
16	The Charlotte Observer	62	The Observer
17	Chicago Sun-Times	63	The Orange County Register
18	Chicago Tribune	64	The Oregonian
19	The Christian Science Monitor	65	Orlando Sentinel (Florida)
20	The Chronicle (Australia)	66	Ottawa Citizen
21	The Cincinnati Enquirer (Ohio)	67	The Philadelphia Daily News (PA)
22	The Columbus Dispatch	68	The Philadelphia Inquirer
23	The Courier Mail/The Sunday Mail (Australia)	69	Pittsburgh Post-Gazette
24	The Courier-Journal (Louisville, Kentucky)	70	The Plain Dealer
25	Daily News (New York)	71	The Press (Christchurch, New Zealand)
26	The Daily Oklahoman (Oklahoma City, OK)	72	Sacramento Bee
27	The Daily Telegraph (London)	73	San Antonio Express-News
28	Daily Telegraph and Sunday Telegraph (Sydney, Australia)	74	San Diego Union-Tribune
29	The Dallas Morning News	75	The San Francisco Chronicle
30	The Denver Post	76	The Seattle Times
31	Detroit Free Press	77	South China Morning Post
32	The Detroit News (Michigan)	78	St. Louis Post-Dispatch (Missouri)
33	The Dominion Post (Wellington, New Zealand)	79	The Star-Ledger (Newark, New Jersey)
34	Financial Times (London)	80	Star Tribune (Minneapolis MN)
35	Fort Worth Star-Telegram	81	The Straits Times (Singapore)
36	The Gazette (Montreal)	82	Sun-Sentinel (Fort Lauderdale)
37	Gazeta Mercantil Online	83	The Sunday Herald (Glasgow)
38	The Globe and Mail (Canada)	84	The Sydney Morning Herald (Australia)
39	Grand Rapids Press (Michigan)	85	Tampa Bay Times
40	The Guardian	86	The Tampa Tribune (Florida)
41	The Hartford Courant	87	Times - Picayune (New Orleans)
42	The Herald (Glasgow)	88	The Toronto Star
43	Herald Sun/Sunday Herald Sun (Melbourne, Australia)	89	USA Today
44	Het Financieele Dagblad	90	The Wall Street Journal
45	Hobart Mercury/Sunday Tasmanian (Australia)	91	The West Australian (Perth)
46	The Houston Chronicle		

Appendix A.2. Sample news file (LexisNexis.com)

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Virtual currency Bitcoin registers with European regulators

LexisNexis

Virtual currency Bitcoin registers with European regulators

Guardian.com

December 7, 2012 Friday

Length: 478 words

Byline: Jemima Kiss, guardian.co.uk

Body

ABSTRACT

Site takes step towards legitimacy as euro accounts now subject to same protection as bank holdings

FULL TEXT

The virtual currency ***Bitcoin*** took a step towards legitimacy today as its eurozone wing joined the ranks of PayPal and Worldpay by becoming a registered payment services provider (PSP) under European law.

Under a deal made in France with the investment firm Aqoba and the Crédit Mutuel bank, ***Bitcoin***-Central now has an international bank ID number, meaning the network will be able to send and receive transfers to and from other banks and issue debit cards for users.

In a post on the Bitcoin forum, ***Bitcoin*** staffer davout announced: "At Paymium we spent lots of time and energy talking about ***Bitcoin*** to our regulating bodies, the Banque de France, the ACP (French equivalent of the American SEC), TRACFIN (AML French supervising body) etc. We engaged all these resources with one goal in mind: get these people to know ***Bitcoin***, advocate our beloved crypto-currency and listen to them, help them think until they finally reach the same conclusion as we did: there's nothing wrong with people being free.

"There's nothing wrong with people freely exchanging value, we don't hurt anybody, we're not forcing anyone to use ***Bitcoin***, we simply want to see our dream and the future of money become a reality."

The virtual currency has seen significant growth since it launched in 2009 with an estimated 10.5m bitcoins currently being traded. One ***bitcoin*** is currently worth £8.54, after peaking at nearly £18 in June 2011, meaning the ***Bitcoin*** empire represents £89.6m of trading value.

Bitcoin magazine's editor, Vitalik Buterin, told the BBC the deal would encourage more growth and make it more accessible to new users.

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Virtual currency Bitcoin registers with European regulators

It will also mean balances held in euros by ***Bitcoin*** will be subject to the same protection and compensation laws as cash held in conventional banks.

"The more we see governments and banks being willing to deal with ***Bitcoin***, the more comfortable a lot of organisations are going to be making the step forward themselves," he said.

Despite a fiercely dedicated userbase in the tech community, ***Bitcoin***'s ubiquity and the anonymity of its users have also made it an attractive exchange platform for criminals, leading to a call by the US Senate in 2011 to investigate the site for tax evasion and money laundering.

The chairman of the non-profit ***Bitcoin*** Foundation, *Peter Vessenes, said in October that the site was battling against barriers to more widespread adoption*.

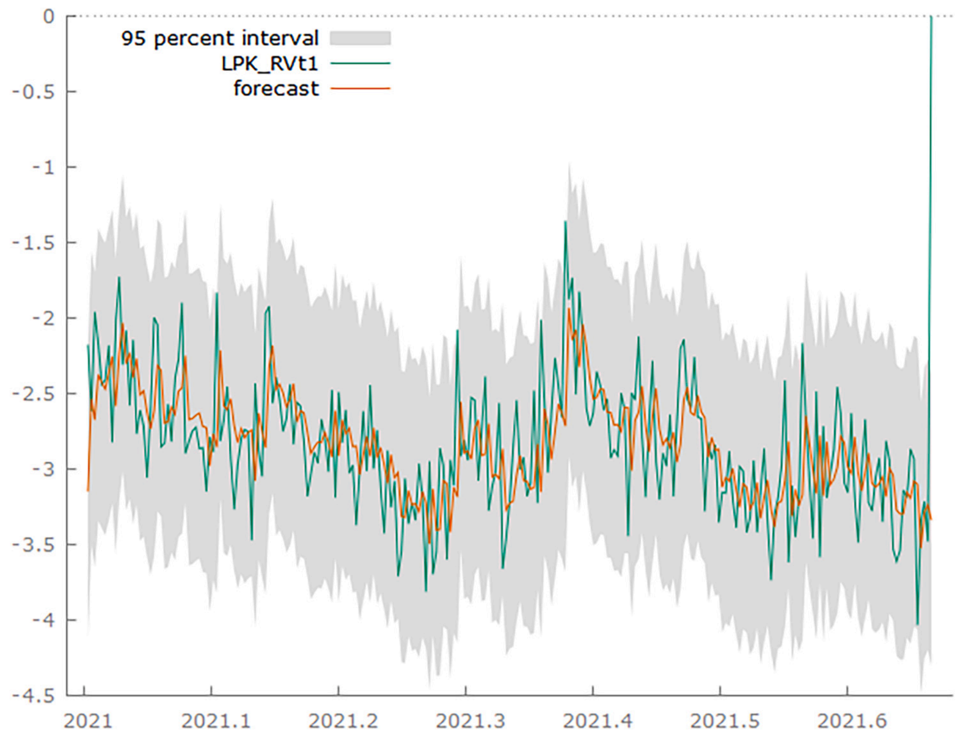
"There's a lot to love [but] ... there are botnet operators, hackers, and Ponzi-scheme runners floating around our space," he said.

"As the ***Bitcoin*** economy has evolved, we have all noticed barriers to its widespread adoption - [programs] that attempt to undermine the network, hackers that threaten wallets, and an undeserved reputation stirred by ignorance and inaccurate reporting."

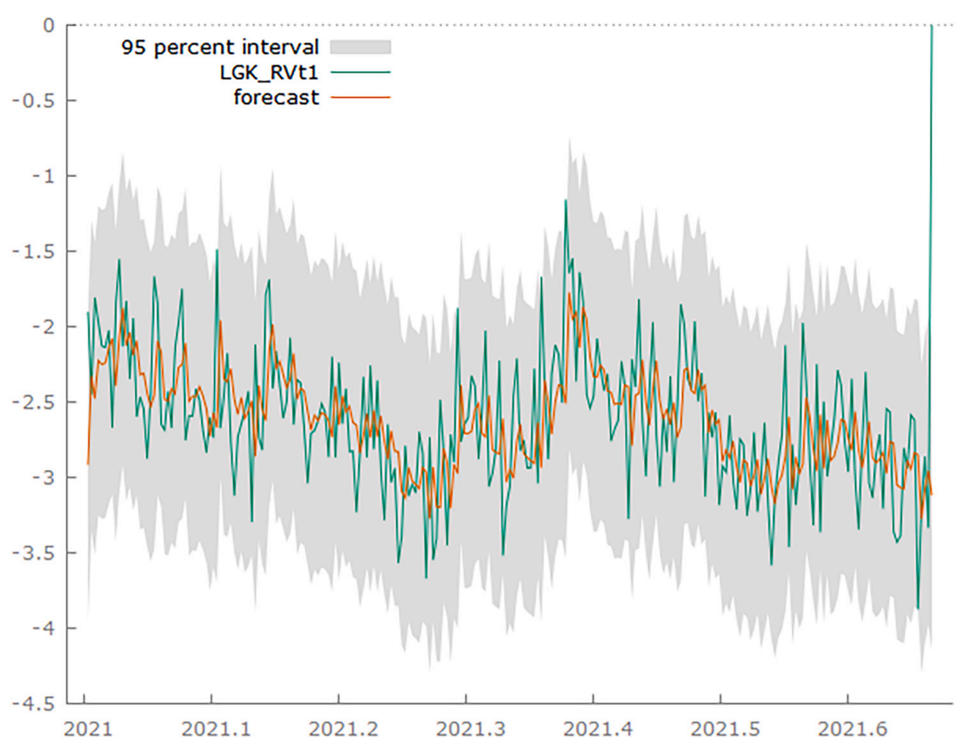
Load-Date: December 7, 2012

End of Document

Appendix A.3. Out-of-sample forecast accuracy plot (Parkinson volatility and Harvard psychological sentiment)



Appendix A.4. Out-of-sample forecast accuracy plot (Garman-Klass volatility and Harvard psychological sentiment)



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