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Emotional trading in the cryptocurrency market

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We quantify the emotional factors inherited in 2,050,280 posts on Bitcointalk.org and investigate the impact of emotion on Bitcoin price fluctuations. Future Bitcoin returns are not associated with emotional factors, but Bitcoin trading volume and return volatility are significantly predicted by a catalog of emotions. Emotions affect the total return variation process of investors, and thus may influence the financial market by inducing extraordinary price movements.

1. Introduction

In the canonical finance model, rational (i.e., unemotional) investors always enforce the market value of any financial asset to be equal to the present value of all future cash flows. This model, however, is problematic in explaining extraordinary price fluctuations such as the Black Monday crash in October 1987 or the Dot.com bubble in the 1990s. Emotions appear to play a role in the general decision-making of individuals. According to Loewenstein (2000, p. 426), "emotions that are experienced at the time of decision--making…underpin daily functioning but also often propel behavior in directions that are different from that dictated by a weighing of the long-term costs and benefits of disparate actions." Behavioral economic studies also reveal that emotion drives sentiment, and thus affects investment decisions and asset pricing in the financial market (Saunders, 1993; Hirshleifer and Shumway, 2003; Kaplanski and Levy, 2010).

Motivated by the erratically fluctuating cryptocurrency prices over the last few years (e.g., Corbet et al., 2018), we examine the impact of emotional trading on Bitcoin price movements. Following the burgeoning literature on text analytics, we extract emotional information in the cryptocurrency market from a bitcoin bulletin board and investigate the pricing implications of these emotional factors. We conduct emotion analytics from online posts, given that written resources from online communication include the emotional characteristics of investors that objective media articles do not capture.

In evaluating the influence of emotion on Bitcoin investors' decision-making and cryptocurrency pricing, a number of studies (e.g., Baker and Wurgler (2007), among others) focus on long-term implications and attribute the association to cyclical variation in the real economy. By contract, we employ an emotion-mining technique in order to study the high-frequency implications of emotional factors in the cryptocurrency market. Emotion analytics, a burgeoning machine learning technique, was developed for the purpose of detecting various emotions in textual data. Comments, reviews, and posts that people have written online while using the Internet or social media are accumulated in large quantities, making it possible to analyze how emotions inherited in textual data are associated with individuals' future behavior.

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The remainder of the paper is organized as follows. Section 2 summarizes the emotion analytics that we employ. Section 3 addresses the empirical design and discusses the results. Section 4 concludes the paper.

2. Emotion analytics

Canonical sentiment analysis defines a sentiment word dictionary in order to calculate the sentiment score of the entire text using machine learning techniques. Among other approaches, the lexical approach assumes that an individual's personality matches her lexicality (i.e., vocabulary). In other words, it is possible to induce personality from the words that people use. The "Big Five" personality domains that classify human personality into openness, conscientiousness, extraversion, agreeableness, and neuroticism are widely used as an adequate taxonomy. A number of studies demonstrate that the association between emotional words and human personality is real and extant. For instance, extroverts tend to utilize more words, and they also make use of more positive words than introverts (Mehl et al., 2006). Pennebaker (2011) also document that functional words such as pronouns, prepositions, and articles are positively associated with personal status, power, and mindset. Beukeboom et al. (2013) show that introverts use more exclusive and negative words such as 'but' and 'except' than extroverts.

We employ a corpus linguistics approach whereby we determine how many words are related to the emotions from a predefined dictionary. We first collect all Bitcoin-related textual data from online sources (i.e., posts) and decompose all of the sentences in a post into word units. In order to identify the emotional factors in the post, we utilize the Linguistic Inquiry and Word Count (LIWC) software that has been shown to be a valid method for quantifying verbal expressions of emotion (Kahn et al., 2007). Based on the aforementioned Big Five domains, LIWC provides a function to classify any text into 93 psychologically meaningful categories in a hierarchical structure (e.g., anxiety, anger, sadness in the negative emotion category). For example, we compare 'strength,' which is already classified into the positive emotion category from a dictionary, with the first eight letters of all other separate word units in the post. Therefore, it is possible to classify 'strengthen' into the positive emotion category. We then count the number of words per each emotion category and standardize the quantity by dividing the cardinal number by the total number of words in the post.

3. Empirical design and results

Bitcointalk.org allows anyone to discuss any topics relevant to Bitcoin. Among the various bulletin boards on the site, we focus on the 'Bitcoin Discussion' bulletin board, which is a place for general discussion on Bitcoin without any restrictions. We crawl a total of 2050,280 posts from November 22, 2009 to September 30, 2020 for emotion analytics. We then calculate the percentage value of emotions for each post, derived by LIWC, as an average daily value and use it for empirical analysis.

"Affect" refers to the underlying experience of emotion or mood in psychology; this term has come to indicate anything emotional in modern psychology usage (Barrett and Bliss-Moreau, 2009). To be consistent with LIWC, we consider the following affect-related variables: a) positive emotion, b) negative emotion, c) anxiety, d) anger, and e) sadness. Emotion-related affective process words can be broadly categorized into positive or negative emotion; anxiety, anger, and sadness also appear to capture humans' affective processes (Pennebaker et al., 2015). To control for other psychological aspects, we quantify cognition-related variables: a) insight, b) cause, c) discrepancy, d) tentativeness, e) certainty, and f) differentiation. Cognitive processes vary in complexity and depth from person to person, but the words that people use exhibit heterogeneity in their cognitive processes (Tausczik and Pennebaker, 2010). We thus consider LIWC's 'certainty' and 'differentiation' categories in order to measure these heterogeneities from psychological perspectives. It appears that people who actively participate in the reappraisal process frequently use words in LIWC's 'cause', 'insight', and 'discrepancy' categories; actively using 'tentativeness'-related words is associated with a lack of confidence in the topic being addressed (Tausczik and Pennebaker, 2010). Lastly, perception-related control variables include a) seeing, b) hearing, and c) feeling. It is likely that people differentially perceive the written contents of posts. We consider 'seeing', 'hearing', and 'feeling' because these three quantities turn out to express various emotions as well as information contexts (Tausczik and Pennebaker, 2010).

The Chicago Mercantile Exchange CF Bitcoin Reference Rate (BRR) and the Chicago Mercantile Exchange CF Bitcoin Real-Time Index (BRTI) are a standardized reference rate and spot price index that aggregate the trade flow of major bitcoin spot exchanges including Bitstamp, Coinbase, Gemini, itBit, and Kraken. Following Grobys and Sapkota (2019) and Liu et al. (2020), we retrieve the cryptocurrency transactions data from Coinmarketcap.com. We consider the entire Bitcoin transactions data, i.e., from April 29, 2013 to September 30, 2020, which covers 89.8% (1841,362 posts) of the total posts on Bitcointalk.org. In addition to the conventional price- or transaction-related quantities such as the return, trading volume, realized volatility, and skewness, we consider Bitcoin market jumps (e.g., Kou, 2002; Patton and Sheppard, 2015).[1] Let p_t denote a continuous martingale for the log Bitcoin price:

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_t + J_t \tag{1}$$

in which W is a standard Wiener process, and J represents a jump process. The jump variation can be estimated as follows:

[1] We employ the concept of realized volatility. We download the tick-level data at Bitcoincharts.com and aggregate the data to compute 10-minute log returns. The daily realized volatility is the square root of the sum of the squared 10-minute returns in a day.

$$\Delta J^2 \xrightarrow{p} \sum_{0\le s\le t} \Delta p_s^2 \mathrm{II}\{\Delta p_s > 0\} + \sum_{0\le s\le t} \Delta p_s^2 \mathrm{II}\{\Delta p_s < 0\} \tag{2}$$

where II is the indicator function. Table 1 reports the summary statistics for the aforementioned variables.

For each of the return, trading volume, realized volatility, skewness, and jumps, we run the following predictive regression:

$$\boldsymbol{Y}_{t+1} = \boldsymbol{X}_t\beta + \varepsilon_t \tag{3}$$

where the time is daily; $\boldsymbol{Y}$ is a column vector whose elements are either return, volatility, skewness, or jump; $\boldsymbol{X}$ is an independent variable matrix; β is a matrix that captures the coefficients; and ε is a white noise vector. We consider the following controls that have proven to explain cryptocurrency price fluctuations: size, momentum, price, seasonality or the same weekday, idiosyncratic volatility (Wei and Li, 2020), Google search (Urquhart, 2018), and the economic policy uncertainty index (Demir et al., 2018). Size is the market capitalization of Bitcoin (Li et al., 2020). The momentum variable is the average of daily returns from t-140 to t-2 (Grobys and Sapkota, 2019). The seasonality variable is the mean same-weekday return over the last 20 weeks (Long et al., 2020). The idiosyncratic variable is defined as the standard deviation of idiosyncratic returns under a market model in the cryptocurrency market for the last 20 trading days, e.g., Bali and Cakici (2008). We follow Zhang and Li (2020) and consider 2264 cryptocurrencies to construct the market portfolio. We take the logarithm of the size and price variables in order to mitigate the stationarity issues associated with level variables. Google search is the amount of searching for the keyword “Bitcoin” on Google. The daily economic policy uncertainty index is from Policyuncertainty.com.

It should be noted that there is an endogeneity issue between emotional factors and Bitcoin price fluctuations. For example, investors might become unhappy or angry after they observe unfavorable Bitcoin price movements. To minimize this concern, we run a predictive regression in Eq. (3). We also take into account the fact that emotions tend to be sticky (Frijda, 1988). Today’s emotional status might persist for a prolonged period (e.g., Jiang et al., 2018). We thus utilize the five-day moving average of the independent emotion-related variables. The use of moving averages also helps mitigate the concern of reverse causality.

Table 2 summarizes the results. We find significant evidence that Bitcoin market participants appear to allow their emotional state to influence their future investment activities in the cryptocurrency market. In particular, emotional factors are significantly associated with Bitcoin price fluctuations such as volatility and skewness on top of trading volume. We echo that, interestingly, future Bitcoin returns are not associated with emotional factors at all. On the contrary, Bitcoin’s trading volume, realized volatility, and skewness, which characterize very unusual price fluctuations in the financial market, are significantly associated with emotional factors. These outcomes are consistent with Bollen et al. (2011), who document that mood on Twitter has statistical power in predicting whether the Dow Jones Industrial Average index goes up or down in a subsequent period.

The findings in Table 2 may not be stable over time, and there might exist some subsamples with the greatest significance. Therefore, we employ Bai and Perron (2003) to select the breakpoints for each of the dependent variables in Table 2. The Bai and Perron test shows that there exists at least one breakpoint for all dependent variables in Table 2. Table 3 summarizes the results from the Bai and Perron test with one breakpoint.

Table 1
Summary Statistics
This table reports summary statistics for the key variables. The sample spans from April 29, 2013 to September 30, 2020. The return is the daily holding period return: ($\text{Price}_t - \text{Price}_{t-1}$)/ Price_{t-1}. In order to minimize market microstructure noises, we aggregate the price data to compute 10-minute log returns. The daily realized volatility is the square root of the sum of the squared 10-minute returns in a day. Trading volume is in billions. We use the tick-level return data to compute the skewness. Jumps are defined by $\sum_{0\le s\le t} \Delta p_s^2 \mathrm{II}\{\Delta p_s > 0\} + \sum_{0\le s\le t} \Delta p_s^2 \mathrm{II}\{\Delta p_s < 0\}$, where II is the indicator function and p is the log price. The time is daily. N denotes the number of observations. SD stands for the standard deviation.

Variable	N	Mean	SD	Min	Q1	Median	Q3	Max
Return	2711	0.0025	0.0425	−0.3717	−0.0124	0.0017	0.0181	0.4297
Realized Volatility	2709	0.0408	0.0337	0.0049	0.0214	0.0318	0.0490	0.6018
Trading Volume	2712	6.5600	11.0663	0.0000	0.0254	0.1589	7.7243	74.1568
Skewness	2709	0.2323	0.9559	−10.3329	−0.0671	0.0820	0.3506	13.3595
Jump	2709	0.0388	1.3696	0.0001	0.0021	0.0048	0.0111	71.2790
Positive Emotion	2706	3.8984	0.6057	0.0000	3.5202	3.8044	4.1375	7.4204
Negative Emotion	2706	1.5430	0.2758	0.7580	1.3443	1.5167	1.6904	4.3514
Anxiety	2706	0.2897	0.1006	0.0000	0.2208	0.2747	0.3400	0.9306
Anger	2706	0.3760	0.1652	0.1008	0.2538	0.3364	0.4621	2.6777
Sadness	2706	0.3272	0.0919	0.0000	0.2658	0.3170	0.3752	0.8262
Insight	2706	2.6548	0.2476	1.3246	2.5018	2.6504	2.8096	3.8290
Cause	2706	2.5754	0.3678	0.0000	2.3083	2.6467	2.8520	3.5546
Discrepancy	2706	2.2103	0.2361	0.0000	2.0444	2.1986	2.3546	3.1198
Tentativeness	2706	3.7056	0.3195	1.6650	3.4933	3.6987	3.8930	8.3818
Certainty	2706	1.7643	0.1939	0.0000	1.6469	1.7578	1.8818	2.7399
Differentiation	2706	4.1606	0.3955	2.0287	3.9609	4.2197	4.4200	5.2040
Seeing	2706	0.6579	0.1802	0.2701	0.5251	0.6239	0.7524	1.9911
Hearing	2706	0.3669	0.1274	0.1510	0.2841	0.3375	0.4217	3.3350
Feeling	2706	0.2577	0.0906	0.0000	0.2007	0.2352	0.2947	1.0495

Table 2
Predictive Regression Results
This table summarizes the predictive regression results in eq. (3). The sample spans from April 29, 2013 to September 30, 2020. Controls include size, momentum, price, seasonality (SEAS) or same weekday, idiosyncratic volatility (IVol), google search, and the economic policy uncertainty (EPU) index. Trading volume is in billions. We compute the 5-day moving average for the regressors. Test statistics are between square brackets. [a], [b], and [c] represent significance at the 1%, 5%, and 10% levels, respectively.

Regressors	Dependent Variable Return	Volume	Volatility	Skewness	Jump
Positive Emotion	−0.0086[b]	−1.7923[a]	−0.0097[a]	0.0318	0.0028
	[−1.94]	[−4.04]	[−2.76]	[0.36]	[0.22]
Negative Emotion	−0.0092	5.9304[a]	0.0272[b]	−0.4214	−0.0482
	[−0.70]	[3.58]	[2.48]	[−1.30]	[−0.57]
Anxiety	0.0112	−12.0459[a]	−0.0084	−0.2779	−0.0485
	[0.57]	[−5.00]	[−0.53]	[−0.63]	[−0.87]
Anger	0.0031	−3.1784	−0.0465[a]	0.8446	−0.1369
	[0.18]	[−1.21]	[−3.27]	[1.53]	[−1.35]
Sadness	−0.0031	−13.5616[a]	0.0192	0.9936[c]	0.1601
	[−0.15]	[−4.06]	[1.23]	[1.68]	[0.91]
Insight	−0.0051	−0.7873	−0.0077	0.2758[c]	−0.0293
	[−0.77]	[−0.83]	[−1.56]	[1.82]	[−0.99]
Cause	−0.0001	−6.4424[a]	0.0005	−0.1525	0.3258
	[−0.01]	[−6.96]	[0.11]	[−1.06]	[1.03]
Discrepancy	−0.0019	6.5651[a]	−0.0030	0.1494	0.1796
	[−0.23]	[5.48]	[−0.58]	[0.75]	[0.99]
Tentativeness	−0.0022	3.4795[a]	−0.0155[a]	0.3489[c]	0.1589
	[−0.51]	[3.59]	[−4.91]	[1.74]	[0.97]
Certainty	0.0092	3.6672[a]	0.0149[c]	0.0717	0.2494
	[0.96]	[3.16]	[1.95]	[0.37]	[1.07]
Differentiation	−0.0035	−3.4138[a]	−0.0062	−0.3282[c]	−0.3618
	[−0.53]	[−2.91]	[−1.23]	[−1.68]	[−1.02]
Seeing	−0.0096	13.9180[a]	0.0140[c]	−0.8451[a]	0.2011
	[−0.95]	[9.07]	[1.82]	[−3.10]	[1.13]
Hearing	−0.0105	4.9335[c]	−0.0004	0.4951	0.1334
	[−0.87]	[1.67]	[−0.04]	[1.54]	[0.92]
Feeling	0.0318	13.6997[c]	0.0203	0.4107	−0.5517
	[1.26]	[4.88]	[1.17]	[0.78]	[−0.98]
Log(Price)	0.0148	−31.6176[a]	0.1001[a]	−0.8046	−0.4741
	[0.53]	[−9.69]	[4.85]	[−1.42]	[−0.84]
Size	−0.0173	36.7272[a]	−0.0997[a]	0.6750	0.4066
	[−0.63]	[11.67]	[−4.98]	[1.22]	[0.82]
Momentum	0.2239	−192.2955[a]	1.3374[a]	−10.1825[c]	13.6468
	[0.68]	[−6.52]	[5.56]	[−1.93]	[1.10]
IVol	−0.0920	−155.3335[a]	−0.0738	0.8714	2.8154
	[−0.57]	[−9.76]	[−0.83]	[0.37]	[0.98]
SEAS	−0.0659	1.5374	0.0459	1.3108	−1.7441
	[−0.63]	[0.12]	[0.68]	[0.58]	[−0.95]
Google Search	0.0002	0.1933[a]	0.0015[a]	0.0092[a]	−0.0021
	[0.86]	[7.36]	[7.84]	[3.57]	[−0.62]
EPU	0.0001	0.0281[a]	0.0001	0.0006[a]	0.0002
	[1.64]	[12.94]	[1.64]	[3.01]	[1.00]
F statistic	1.12	364.40[a]	52.55[a]	8.82[a]	0.46[a]
R^2	0.01	0.75	0.30	0.06	0.01

Table 3
Bai and Perron Test Results for One Break Point
This table reports the break day for each of the returns, trading volume, volatility, skewness, and jump. The first subsample is from April 29, 2013 to the break day, and the second one spans from the day after the break day to September 30, 2020.

	Dependent Variables (April 29, 2013 ~ September 30, 2020) Return	Volume	Volatility	Skewness	Jump
Break Day	Jun. 22, 2014	Nov. 6, 2018	Sep. 24, 2014	Nov. 7, 2014	Jan. 28, 2016

Tables 4 and 5 document the results for the first and second subsamples, respectively. Though there exists a subsample with greater significance, we highlight that the main message of this study does not change: future Bitcoin returns are not related with emotional factors, while trading volume, realized volatility, skewness, and jumps are significantly associated with emotional factors. We also check a variety of cases with 2, 3, 4, and 5 breakpoints and confirm that the main findings remain unchanged.

Table 4
Predictive Regression Results during Period 1
This table summarizes the predictive regression results in Eq. (3). The return's first period is from April 29, 2013 to June 22, 2014, The volume period is from April 29, 2013 to November 6, 2018, The volatility period is from April 29, 2013 to September 24, 2014, The skewness period is from April 29, 2013 to November 7, 2014, and the jump period is from April 29, 2013 to January 28, 2016. Controls include the size, momentum, price, seasonality (SEAS) or the same weekday, idiosyncratic volatility (IVol), Google search, and the economic policy uncertainty (EPU) index. The trading volume is in billions. We compute the 5-day moving average for the regressors. Test statistics are between square brackets. [a], [b], and [c] represent significance at the 1%, 5%, and 10% levels, respectively.

Regressors	Dependent Variable Return	Volume	Volatility	Skewness	Jump
Positive Emotion	−0.0347[a]	0.3183[a]	−0.0066	0.1815	−0.0033
	[−2.84]	[2.68]	[−0.81]	[1.07]	[−0.85]
Negative Emotion	−0.0798	1.8960[a]	0.0507	−1.1580	0.0273
	[−1.43]	[4.29]	[1.43]	[−1.55]	[1.59]
Anxiety	0.0522	−1.7010[b]	0.0223	−1.1660	0.0334
	[0.44]	[−2.28]	[0.29]	[−0.73]	[0.95]
Anger	0.1091	−2.2170[a]	−0.1204[b]	2.3620[b]	−0.0595[b]
	[1.43]	[−3.47]	[−2.45]	[2.27]	[−2.42]
Sadness	−0.0580	−1.0160	0.0019	3.0970[b]	−0.0230
	[−0.56]	[−1.25]	[0.03]	[2.38]	[−0.74]
Insight	−0.0038	0.4909[c]	−0.0175	0.9493[b]	−0.0069
	[−0.12]	[1.95]	[−0.87]	[2.24]	[−0.69]
Cause	0.0262	−0.5821[b]	0.0099	0.5556	0.0128
	[0.77]	[−2.42]	[0.03]	[1.27]	[1.13]
Discrepancy	0.0165	0.6070[b]	−0.0024	−0.0551	0.0019
	[0.46]	[1.98]	[−0.11]	[−0.12]	[0.17]
Tentativeness	−0.0307	0.0481	0.0007	0.1250	−0.0022
	[−1.44]	[0.27]	[0.05]	[0.44]	[−0.32]
Certainty	0.0252	−0.4544	0.0026	−0.4251	0.0138
	[0.75]	[−1.47]	[0.12]	[−0.90]	[1.20]
Differentiation	0.0071	−1.3530[a]	0.0082	−0.3282	−0.0075
	[0.20]	[−4.98]	[0.39]	[−0.75]	[−0.71]
Seeing	−0.0378	−0.5063	0.0493[b]	−1.0300[b]	0.0343[b]
	[−0.92]	[−1.23]	[2.11]	[−2.02]	[2.58]
Hearing	−0.0308	−0.7739	0.0195	−0.3050	0.0045
	[−0.41]	[−1.50]	[0.42]	[−0.31]	[0.27]
Feeling	0.1989[b]	−2.5690[a]	−0.0538	1.8220	−0.0169
	[2.34]	[−3.10]	[−0.97]	[1.59]	[−0.59]
Log(Price)	0.3645	−1.6140	0.0806	2.2200	0.0613[c]
	[1.41]	[−1.60]	[0.57]	[0.84]	[1.67]
Size	−0.3942	2.6990[a]	−0.0950	−2.6420	−0.0687[c]
	[−1.58]	[2.73]	[−0.70]	[−1.04]	[−1.86]
Momentum	0.1170	−103.2000[a]	−0.2037	−34.9100[b]	−1.0760[a]
	[0.10]	[−11.11]	[−0.27]	[−2.11]	[−2.64]
IVol	−1.0190	−3.5350	−0.3914	13.1300	−0.1194
	[−0.84]	[−0.73]	[−0.47]	[0.72]	[−0.31]
SEAS	0.0763	0.3214	0.3768	3.4810	0.3394[b]
	[0.21]	[0.08]	[1.59]	[0.67]	[2.33]
Google Search	0.0036	0.2156[a]	0.0140[a]	0.0864[c]	0.0179[a]
	[1.13]	[35.35]	[6.39]	[1.83]	[11.85]
EPU	−0.002[c]	0.0017[b]	0.0001	−0.0003	0.0000
	[−1.76]	[2.43]	[1.25]	[−0.19]	[0.50]
F statistic	1.83[b]	395.20[a]	6.93[a]	4.47[a]	17.48[a]
R^2	0.13	0.82	0.29	0.19	0.30

4. Conclusions

Bitcoin is the most popular cryptocurrency asset and offers diversification benefits to investors. For example, Bitcoin has the hedging capability against global uncertainty (Bouri et al., 2017), Asia Pacific stocks (Bouri et al., 2017), gold and the US dollar (Baur et al., 2018), and economic policy uncertainty (Demir et al., 2018). The merits of Bitcoin as an alternative asset or a hedging instrument are dampened, given that it entails high volatility and crash risk (Kalyvas et al., 2020). We document empirical evidence that Bitcoin's price fluctuations are highly associated with emotional factors among investors. We further advance the literature by showing that people's emotions associated with their decision-making influence their eventual decisions mainly at higher moments, such as the non-jump volatility component and skewness. The results imply that emotions heterogeneously affect the total return variation process of investors, and thus may affect the financial market by inducing extraordinary price movements.

Table 5
Predictive Regression Results during Period 2
This table summarizes the predictive regression results in Eq. (3). The return's second period is from June 23, 2014 to September 30, 2020, The volume period is from November 7, 2018 to September 30, 2020, The volatility period is from September 25, 2014 to September 30, 2020, The skewness period is from November 8, 2014 to September 30, 2020, and the jump period is from January 29, 2016 to September 30, 2020. Controls include the size, momentum, price, seasonality (SEAS) or the same weekday, idiosyncratic volatility (IVol), Google search, and the economic policy uncertainty (EPU) index. Trading volume is in billions. We compute the 5-day moving average for the regressors. Test statistics are between square brackets. [a], [b], and [c] represent significance at the 1%, 5%, and 10% levels, respectively.

Regressors	Dependent Variable Return	Volume	Volatility	Skewness	Jump
Positive Emotion	0.0002	−5.7730[a]	−0.0080[a]	0.0314	0.0095
	[0.05]	[−2.65]	[−3.55]	[0.39]	[0.04]
Negative Emotion	0.0039	−10.7500[b]	0.0219[b]	−0.0078	−0.2519
	[0.32]	[−2.11]	[2.98]	[−0.03]	[−0.34]
Anxiety	−0.0033	−9.6420	−0.0170	−0.4231	0.1365
	[−0.17]	[−1.18]	[−1.48]	[−1.03]	[0.12]
Anger	−0.0054	8.5940	−0.0290[a]	−0.2316	0.1596
	[−0.29]	[1.22]	[−2.70]	[−0.61]	[0.15]
Sadness	−0.0056	10.2800	0.0185	0.0998	0.5765
	[−0.27]	[1.37]	[1.50]	[0.23]	[0.48]
Insight	−0.0060	1.7910	−0.0102[a]	−0.0544	0.0536
	[−0.92]	[0.77]	[−2.66]	[0.40]	[0.15]
Cause	−0.0052	4.4640	−0.0013	−0.3009[b]	0.4610
	[−0.83]	[1.67]	[−0.35]	[−2.33]	[1.26]
Discrepancy	−0.0022	5.1770	−0.0042	0.3884[b]	0.3010
	[−0.27]	[1.59]	[−0.85]	[2.22]	[0.63]
Tentativeness	0.0019	0.4659	−0.0130[a]	−0.0369	0.3692
	[0.30]	[0.16]	[−3.58]	[0.29]	[1.06]
Certainty	−0.0037	3.2600	0.0122[b]	0.4961[a]	0.5095
	[−0.42]	[0.85]	[2.36]	[2.72]	[0.96]
Differentiation	−0.0014	−1.1030	−0.0087[c]	0.0155	−0.7350[c]
	[−0.19]	[−0.37]	[−1.95]	[0.10]	[−1.75]
Seeing	−0.0102	16.0300[a]	0.0031	−0.5057[b]	0.5171
	[−0.91]	[3.70]	[0.44]	[−2.04]	[0.70]
Hearing	−0.0076	22.8000[a]	−0.0070	0.9353[a]	−0.4201
	[−0.52]	[2.85]	[−0.81]	[3.08]	[−0.35]
Feeling	−0.0175	28.9700[b]	0.0411[a]	−0.0985	−0.4939
	[−0.72]	[2.47]	[2.86]	[−0.19]	[−0.31]
Log(Price)	−0.0577[c]	−156.7000[a]	0.0836[a]	1.0710	0.4636
	[−1.89]	[−3.68]	[3.77]	[1.27]	[0.13]
Size	0.0533[c]	169.4000[a]	−0.0823[a]	−1.0868	−0.5070
	[1.83]	[4.11]	[−3.89]	[−1.35]	[−0.15]
Momentum	0.2415	−1048.0000[a]	1.1730[a]	4.2126	22.8301
	[0.71]	[−5.54]	[5.94]	[0.61]	[1.07]
IVol	0.0018	372.7000[a]	−0.0344	−2.6606	1.1877
	[0.01]	[4.79]	[−0.47]	[−1.04]	[0.19]
SEAS	−0.0886	−16.1100	−0.0326	1.1080	−3.0555
	[−0.85]	[−0.44]	[−0.52]	[0.51]	[−0.55]
Google Search	0.0002	2.2030[a]	0.0014[a]	0.0040	−0.0033
	[1.08]	[12.48]	[13.72]	[1.15]	[−0.41]
EPU	0.0000	0.0097[a]	0.0000	0.0005[a]	0.0004
	[1.09]	[3.58]	[1.22]	[2.81]	[0.77]
F statistic	0.89	52.16[a]	47.98[a]	6.68[a]	0.51
R^2	0.01	0.62	0.32	0.06	0.01

5. Author statement

The authors contributed equally to this work.

Declaration of Competing Interest

None.

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