Sentiments in Bitcoin Message Boards

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ABSTRACT

As an extension of Koo et al. (2018), we investigate the relationship between Bitcoin price and natural language processed emotion data extracted from an online chatboard at BitMEX, one of the biggest cryptocurrency exchanges. Combining emotion data with high-frequency quote and trade data from BitMEX, Binance, and Coinone between June 18, 2018 and November 27, 2018, vector autoregression (VAR) is performed with five minute sampling period to analyze complex interactions of emotions and Bitcoin prices. Our results suggest that Bitcoin return, volume, Korean premium, and volatility over the next five minute can be predicted by certain types of emotions expressed in the BitMEX chatboard. We also develop a simple investment strategy utilizing some emotions significantly correlated with Bitcoin returns and show that this strategy is profitable.

KEYWORDS: Bitcoin; Investor Sentiment; Online Chatting; Natural Language Processing; Multi-Class Emotions; High Frequency Data

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1. Introduction

Global Bitcoin markets are fragmented, which allows Bitcoin price different across markets and creates arbitrage opportunities. Many researchers believe that the "fundamental values" hardly explain the Bitcoin price since Bitcoin has no underlying asset, guarantees by government or central-bank, interest or dividends. This means that Bitcoin has no expected future cash flow to be discounted with risk-adjusted rates. Though the change in Bitcoin price may be inexplicable by the fundamental value, it should be explainable with non-fundamental values or speculative demands, which depends on sentiments and emotions of investors. Thus, a large part of Bitcoin price movement should be related to the change in investors' emotions/sentiments. Koo et al. (2018) shows that by extracting emotion data from Coinone chatboard, correlations between emotions and Bitcoin price movement exist from October 8, 2017 to January 23, 2018, during the Bitcoin bull market period. In this paper, we extend Koo et al. (2018) to test the hypothesis using a different emotion data source and more recent market data. Our emotion data is extracted from BitMEX[3] chatboard, where BitMEX is one of the biggest cryptocurrency exchanges in the world. Our analysis is performed on the recent time period between June 18, 2018 and November 27, 2018, when Bitcoin market is relatively quiet and stabilized compared to the period considered in Koo et al. (2018).

This paper is organized as follows: we first test the validity of our hypothesis by applying natural language processing (NLP) techniques to the chat message boards of BitMEX in order to extract investors' emotion data. Next, the statistical relationship between Bitcoin price return and emotion data is evaluated. Finally, the economic significance of our results is measured by building a simple emotion-based trading model.

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[3] BitMEX is a leading exchange for trading bitcoin futures and swaps. According to CoinMarketCap's statistics, BitMEX is the largest bitcoin exchange in the world.

2. Literature Review

Since Bitcoin was invented by Nakamoto in 2008, Bitcoin has drawn ever growing attention. According to existing literatures, Bitcoin market is inefficient, which creates opportunities for arbitrage (Hencic and Gouriéroux 2014; Cheah and Fry 2015; Cheung, Roca, and Su 2015). Kristoufek (2013) shows the relationship between Bitcoin price and search queries of Google Trends and Wikipedia associated with Bitcoin. Other studies show that Bitcoin markets do not follow the traditional efficient market hypothesis and imply weak-form inefficiency (Urquhart 2016; Bariviera 2017; Pieters and Vivanco 2017; Nadarajah and Chu 2017; Tiwari et al. 2018; Vidal-Tomás and Ibañez 2018; Panagiotidis, Stengos, and Vravosinos 2018). Moore and Christin (2013) shows that Bitcoin markets do not satisfy the law of one price (LOOP) as there is a shut-down risk for less popular exchanges. Financial regulations can also be a cause of LOOP violation (Pieters and Vivanco 2017; Nadarajah and Chu 2017). To test Bitcoin arbitrage opportunities, this paper investigates the Korean premium, the price difference between Korean and non-Korean markets.

The relationship between textual information and Bitcoin price has also been revealed in the literature. Garcia et al. (2014) explores that increase of word-of-mouth communication taking place in online social media and information searches tend to drive future Bitcoin price higher. This observation suggests Bitcoin price overshoots when experts report their opinions and corrects itself as the expectation of investors changes over time (Karalevicius, Degrande, and De Weerdt 2018). Mai et al. (2018) also discovers the relationship between social media and Bitcoin price in US exchanges by applying NLP analysis to Twitter texts and Internet forum contents. In this paper, we apply NLP analysis to data extracted from online Bitcoin message boards, which exhibits relatively unfiltered emotions compared to other social media. Our emotions data is aggregated over five minute interval to effectively measure the fluctuation of investors' emotion.

Throughout the study, we consider Bitcoin as an asset based on Glaser et al. (2014) suggesting similarities between Bitcoin and stock characteristics. As of now, there have been only a few papers investigating the interactions between the textual emotion data and asset prices, even including stocks. Bollen, Mao, and Zeng (2011) reveals significant correlation between mood difference in Twitter and Dow Jones Industrial Average (DJIA) on a daily basis. In addition, Lee et al. (2013) predicts the stock market using emotion data classified into nine different emotions extracted from Twitter. Social media can also be used to predict the future value of the firms (Luo, Zhang, and Duan 2012). Koo et al. (2018) reports presence of relationship between Bitcoin values and textual emotion data extracted from Coinone chatting board.

In classifying emotions, however, the number of defined emotions may vary. Bollen, Mao, and Zeng (2011) classifies the emotions into six, Bouazizi and Ohtsuki (2016) into seven, and Quan et al. (2015) into eight and Koo et al. (2018) into nine. We presume that the number of sentiments should be larger than six for statistical significance and apply nine-class emotions for the analysis.

3. Data Collection

3.1 Emotions in Chatting Massages

This study extracts and analyzes investors' emotions from the chatting board of BitMEX by applying NLP techniques using the trend-map system from Daumsoft. Table 1 shows how the system analyzes the input documents.

Table 1. Nine Human Emotions

Table 1 explains the nine categories of human emotions. The second and third columns explain the number of words and examples for each category.

Emotion	Number of words	Examples
SADNESS	39	exhausted, painful, distressed
ANGER	46	unpleasant, humiliation, heartless, irritated
FEAR	34	worried, concerned, scared, feared
DISLIKE	36	annoyed, unbearable, confused, bored
JOY	69	gratitude, appreciation, thanks, touched
LOVE	13	kind, pounded, sweet
SHAME	12	ashamed, embarrassed, regretful
HATE	83	disgusted, ridiculous, contempt, unsatisfactory
HOPE	18	desire, wish, hope
Total:	**350**	

BitMEX chatting board, one of the globally used real-time message boards in crypto markets, is used in collecting emotion data. We use the emotion data from June 18, 2018 to November 27, 2018. Since the online chatting is more liberal than the official documents, it is closer to everyday conversation, revealing investors' raw emotions. Considering high volatility of Bitcoin price, our data frequency is set relatively high, so we collect data every five minutes from the trend-map system.

3.2 Bitcoin price and Premium

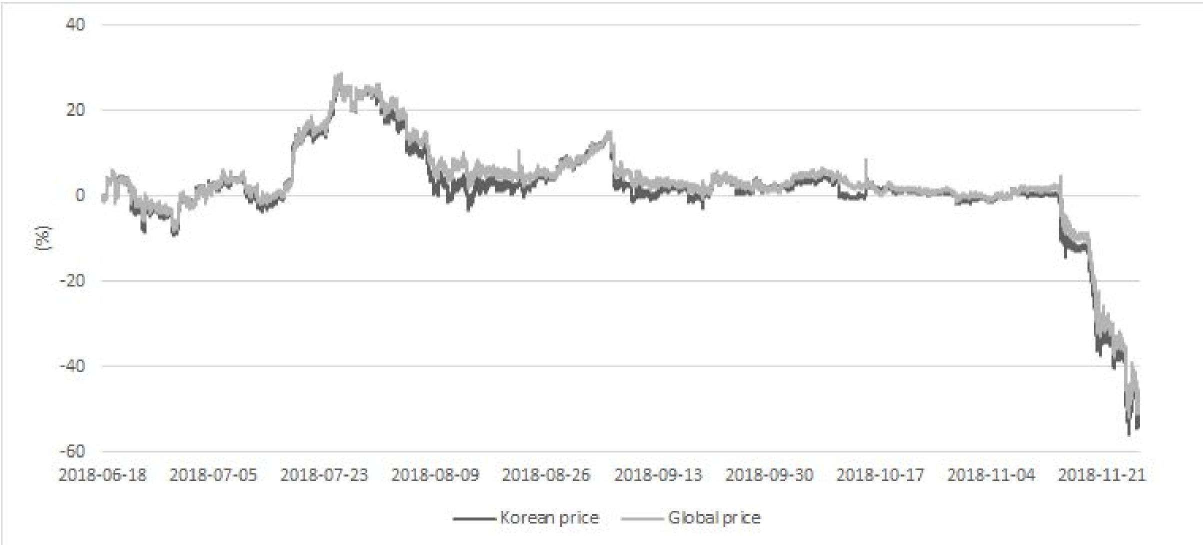
Bitcoin is traded globally. In this section, we compare Korean Bitcoin market with foreign Bitcoin markets. We collect Korean Bitcoin market data from Coinone (BTC-KRW, https://coinone.co.kr/) and foreign Bitcoin market data from BitMEX (XBT-USD[4],

[4] Bitcoin/US Dollar perpetual swap contract traded in BitMEX. Each contract represents the dollar value of one bitcoin. This contract does not have an expiration date, and provides a way for investors to speculate or hedge on the future value of bitcoin.

https://www.bitmex.com/) and Binance (BTC-USDT, https://www.binance.com). High-frequency quote and trade data are resampled at five minute periods. The Bitcoin unit is denoted by BIT, and the timezone is set to UTC + 9. We define the global Bitcoin price as the average Bitcoin price of BitMEX and Binance.

Figure 1. Bitcoin price of Korea and global markets.

Figure 1 illustrates cumulative five minute Bitcoin returns in Korea and global markets from June 18, 2018 to November 27, 2018. Two series show correlation of 0.98.



We define the Bitcoin return premium in Korea for five-minute intervals as follows.

$$Ret\,(KR - Global)_t = ln\left(\frac{Prc(Kr)_t}{Prc(Kr)_{t-1}}\right) - ln\left(\frac{Global(Kr)_t}{Global(Kr)_{t-1}}\right), \quad (1)$$

$Prc\,(Kr)_t$ is Bitcoin price in Korea and $Global\,(Kr)_t$ is Bitcoin price in global markets at time t.

4. Methodology

We examine the contemporary relationship between investors' emotions and bitcoin market by applying VAR analysis. VAR with $p = 5$ *and* $s = 5$[5] is denoted by

$$y_t = \delta + \sum_{i=1}^{s} \theta_i emotion_{t-i} + \sum_{j=1}^{p} \varphi_j y_{t-j} + \varepsilon_t , \tag{2}$$

We also investigate the five-minute lead-lag relationship between investors' emotions and the Bitcoin market to see whether emotions can predict the market. Next equation describes the regression used for VAR analysis:

$$y_t = \delta + \sum_{i=1}^{s} \theta_i emotion_{t-i} + \sum_{j=1}^{p} \varphi_j y_{t-j} + \varepsilon_t . \tag{3}$$

In addition, we evaluate the influence of mixed emotions on the Bitcoin market by extending Equation (3). Mixed emotions are defined as the interaction terms between nine emotions, which results in 36 mixed emotions (${}_9C_2$). Investors may experience various emotions at the same time, so mixed emotions are also expected to exhibit some predictive power on the market. To further investigate the causal relationship between emotions and Bitcoin prices, we use Granger causality test (Granger, 1969).

5. Results

5.1 Summary Statistics

Table 2 is the summary statistics of return (RET(KR), %), volume (VO(KR), BIT), return spread (RET(KR-Global), USD, %), and volatility of spread (VOL(KR-Global), %: absolute value of return spread). Summary statistics include average, standard deviation, median, minimum and maximum values.

[5] Our results are robust with a p-value of 1 to 4 and an s-value of 1 to 4.

Table 2. Summary statistics

Table 2 shows the summary statistics. RET(KR) is a log return of Bitcoin in percentage unit, VO(KR) is the volume of Bitcoin traded in the Korean market in BIT unit. RET(KR-Global) is the Korean return premium in percentage unit. Korean return Premium is calculated by subtracting Bitcoin return in global markets from Bitcoin return in the Korean market. VOL(KR-Global) is a volatility of Bitcoin, or the absolute value of RET(KR-Global).

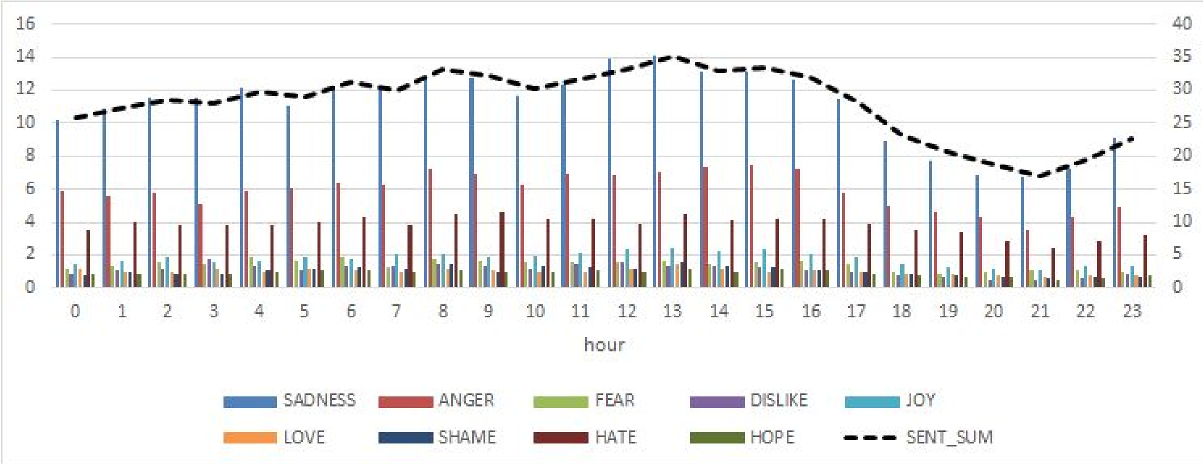
	count	mean	Std	median	min	max
SADNESS	46656	0.9241	1.2914	1.00	0.00	28.00
ANGER	46656	0.4942	0.8924	0.00	0.00	22.00
FEAR	46656	0.1160	0.4077	0.00	0.00	16.00
DISLIKE	46656	0.0939	0.3989	0.00	0.00	22.00
JOY	46656	0.1488	0.4287	0.00	0.00	7.00
LOVE	46656	0.0828	0.3733	0.00	0.00	16.00
SHAME	46656	0.0863	0.3569	0.00	0.00	10.00
HATE	46656	0.3173	0.6602	0.00	0.00	11.00
HOPE	46656	0.0751	0.3052	0.00	0.00	7.00
SENT_SUM	46656	2.3385	2.2082	2.00	0.00	47.00
RET(KR), (%)	46656	-0.0011	0.1590	0.00	-2.64	3.50
VO(KR), (BIT)	46656	3.1817	6.5348	1.38	0.00	164.93
RET(KR-Global), (%)	46656	0.0001	0.1232	0.00	-3.06	2.74
VOL(KR-Global), (%)	46656	0.0806	0.0932	0.05	0.00	3.06

The average Bitcoin return in the Korean market and Korean premium are shown virtually zero, and the average Bitcoin trading volume in the Korean market is approximately 3 BIT. Regarding emotions, the average value and the standard deviation of SADNESS is the highest, whereas those of LOVE, SHAME and HOPE are the lowest.

Figure 2. Hourly patterns of emotions and the Bitcoin market

Figure 2 presents the hourly patterns of the nine emotions and their sum as well as Bitcoin price and volume from June 18, 2018 to November 27, 2018.

Panel A. Bitcoin emotions expressed in the BitMEX chatboard.



Panel B. Bitcoin price and volume.

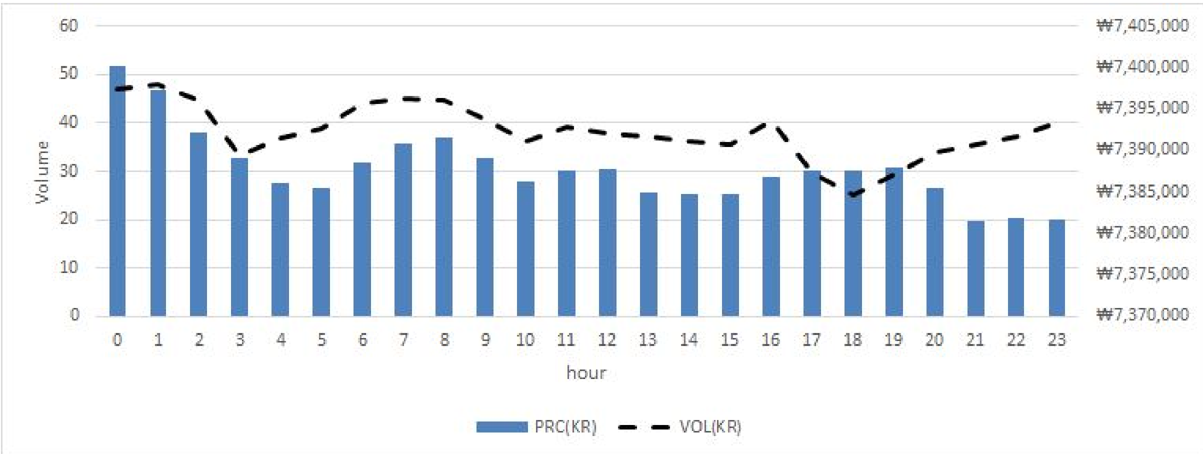


Figure 2 shows the seasonality of emotions, where emotions tend to be low during night time and high during day time. To de-seasonalize the emotion data, we run a regression on a five-minute dummy of each emotion and keep the residual. We define this residual as de-seasonalized emotions and mostly use this variable for the analysis.

Table 3. Principal component analysis of emotions

Table 3 presents the results of principal component analysis (PCA) performed on nine emotions. Panel A and Panel B show the eigenvalues and eigenvectors of the correlation matrix, respectively.

Panel A. Eigenvalues of the correlation matrix

	Eigenvalue	Difference	Variance explained	Cumulative
0	1.2720	-0.2564	0.1413	0.1413
1	1.0157	-0.0064	0.1129	0.2542
2	1.0093	-0.0218	0.1121	0.3663
3	0.9875	-0.0121	0.1097	0.4761
4	0.9754	-0.0085	0.1084	0.5844
5	0.9668	-0.0076	0.1074	0.6919
6	0.9592	-0.0133	0.1066	0.7984
7	0.9459	-0.0776	0.1051	0.9035
8	0.8683	0.0000	0.0965	1.0000

Panel B. Eigenvectors of the correlation matrix

	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7	Prin8	Prin9
SADNESS	0.5449	-0.1547	0.0047	-0.1144	-0.0343	-0.0156	0.2678	-0.0295	0.7694
ANGER	0.4412	-0.1274	-0.3084	-0.2657	-0.1818	-0.1109	0.5045	0.1133	-0.5573
FEAR	0.2807	0.0671	-0.1114	0.5326	0.7162	0.2274	0.1348	0.1606	-0.1096
DISLIKE	0.2461	-0.2810	0.5832	-0.1396	-0.1099	0.6471	-0.1401	0.1134	-0.1938
JOY	0.2856	0.1524	-0.5322	0.0534	-0.2832	0.2250	-0.5873	0.3617	0.0498
LOVE	0.2149	0.5304	0.3999	-0.3450	0.2208	-0.3644	-0.1293	0.4406	-0.0349
SHAME	0.2455	-0.3220	0.2971	0.5799	-0.2953	-0.5176	-0.1777	0.1110	-0.1119
HATE	0.3917	-0.0029	-0.0237	-0.1940	0.2496	-0.1505	-0.4360	-0.7092	-0.1740
HOPE	0.1660	0.6842	0.1424	0.3427	-0.4029	0.2075	0.2293	-0.3275	-0.0360

Table 3 implies that there is no dominant variable: Panel A illustrates that the influence of each emotion is similar, and the explained variance has small changes across different principal components, with minimum of 0.09 and maximum of 0.15. Panel B shows the eigenvector for each emotion is also similar across principal components.

5.2 Emotions and the Bitcoin market

5.2.1 Contemporaneous relationship between emotions and the Bitcoin market

Table 4. Contemporaneous relationship between emotions and the Korean premium

Table 4 shows the contemporaneous relationship between emotions and Bitcoin market variables using VAR with Equation (2), where $p = 5$ *and* $s = 5$. The dependent variables are listed at the top of each table for columns and the independent variables are listed in the left side of each table for rows. Panel A presents the results from multivariate regressions, which includes all nine sentiments as independent variables simultaneously. Panel B shows the results from univariate regressions with each individual sentiment as an independent variable.

Panel A. Multivariate regression

	(1) RET(KR), (%)	(2) VO(KR), (BIT)	(3) RET(KR-Global), (%)	(4) VOL(KR-Global), (%)
SADNESS	0.0001 (0.11)	0.1136*** (5.6)	0.0005 (1.12)	0.0013*** (3.96)
ANGER	0.0019** (2.15)	0.2251*** (7.76)	-0.0009 (-1.48)	0.003*** (6.51)
FEAR	0.0004 (0.21)	0.0465 (0.75)	-0.0008 (-0.58)	0.0013 (1.36)
DISLIKE	-0.0051*** (-2.69)	-0.0042 (-0.07)	-0.0023* (-1.65)	0.0004 (0.41)
JOY	-0.0013 (-0.76)	0.3347*** (5.73)	0.0019 (1.45)	0.0037*** (4.01)
LOVE	-0.0063*** (-3.11)	-0.0608 (-0.9)	-0.0003 (-0.21)	-0.0017 (-1.54)
SHAME	0.0003 (0.16)	0.1552** (2.21)	-0.0014 (-0.91)	0.0017 (1.51)
HATE	-0.0014 (-1.25)	-0.0002 (-0.01)	0.0003 (0.36)	0.0003 (0.52)
HOPE	-0.0029 (-1.2)	-0.1475* (-1.81)	0.0031* (1.72)	-0.0001 (-0.06)

* : l t l > 1.64, ** : l t l > 1.96, *** : l t l > 2.58

Panel B. Univariate regression

	(1) RET(KR), (%)	(2) VO(KR), (BIT)	(3) RET(KR-Global), (%)	(4) VOL(KR-Global), (%)
SADNESS	-0.0007 (-1.09)	0.126*** (6.16)	0.0006 (1.4)	0.0022*** (6.7)
ANGER	0.0018** (2.11)	0.235*** (8.04)	0.0019*** (2.91)	0.0035*** (7.6)
FEAR	-0.0008 (-0.42)	0.1372** (2.21)	-0.0006 (-0.44)	0.0013 (1.29)
DISLIKE	-0.0007 (-0.35)	-0.0167 (-0.26)	0.0018 (1.26)	0.0008 (0.77)

JOY	0.0046*** (2.62)	0.2941*** (5.02)	-0.0019 (-1.46)	0.0035*** (3.75)
LOVE	0.0045** (2.21)	0.0666 (0.98)	0.0014 (0.93)	-0.0002 (-0.21)
SHAME	-0.004* (-1.92)	0.1171* (1.66)	-0.0027* (-1.75)	0.0012 (1.09)
HATE	-0.0012 (-1.09)	0.0372 (0.97)	0.0005 (0.6)	0.0021*** (3.48)
HOPE	-0.0004 (-0.17)	-0.1536* (-1.88)	-0.0016 (-0.87)	0.0009 (0.68)
SENT_SUM	0.0002 (0.51)	0.1014*** (8.11)	0.0005** (2.0)	0.0017*** (8.37)
PCA	0.0001 (0.17)	0.2382*** (8.44)	0.0014** (2.32)	0.0039*** (8.75)

In Panel A, column (1) reports a significantly negative relationship between Bitcoin returns and certain emotions, such as *DISLIKE, LOVE* with correlation coefficients of -0.0057% and -0.0050%, respectively. Thus, the increase in *DISLIKE or LOVE* corresponds to contemporaneous decrease in Bitcoin price. On the other hand, *SADNESS and ANGER* shows a significantly positive relationship with Bitcoin returns. Hence, the Bitcoin price tends to rise when *SADNESS or ANGER* increases.

Column (2) shows that the five-minute trading volume correlates with emotions such as *SADNESS, ANGER,* and *JOY.* Mai et al. (2018) argues that sentiments are not correlated to the daily trading volume, but our result implies that some emotions are related to trading volume at five-minute intervals.

According to Column (3), contemporaneous correlations between emotions and Korean premium are insignificant in general, where only *HOPE* is significant at 10% level. The low correlation between emotions and returns may be due to somewhat decreasing level of interest on Bitcoin in the second half of 2018.

On the other hand, column (4) implies that the volatility of the Korean premium has a significantly positive correlation with *SADNESS, ANGER and JOY*. Compared to Mai et al. (2018), who argues that daily binary sentiments are not correlated with the volatility of

Bitcoin returns, our result suggests that human emotions correlate with volatility, when we use multi-class emotions at five-minute intervals. Our results are rather consistent with Liu's (2015), who shows that a stock market has higher volatility when emotion indices increase, or with the results in Black (1986) and De Long et al. (1990), which shows emotions cause excessive volatility.

Panel B shows additional results for *SENT_SUM* and *PCA*. *PCA*, the integrated index of emotions, and *SENT_SUM*, the total level of emotions, have no significant relationship with Bitcoin price and Korean premium. However, they show significantly positive correlations with trading volume and volatility. The results of other univariate emotions are similar to those from the multivariate analysis. Overall, it is observed that the emotions are correlated with returns and volatility.

5.2.2 Predictive relationship between emotions and the Bitcoin market

Table 5. Predictive relationship between emotions and the Korean premium

Table 5 shows relationship between emotions of past five-minutes and current Bitcoin market by applying VAR analysis with Equation (3), where $p = 5 \textit{ and } s = 5$. Columns are dependent variables: *RET(KR), VO(KR), RET(KR-Global) and VOL(KR-Global)* of five minute ahead. Rows are independent variables, or individual emotions, *SENT_SUM*, and *PCA*. Panel A presents the multivariate regression results between all nine pure emotions and each independent variable. Panel B shows the univariate regression results between each characteristic and each dependent variable.

Panel A. Multivariate regression

	RET(KR), (%)	VO(KR), (BIT)	RET(KR-Global), (%)	VOL(KR-Global), (%)
SADNESS	-0.0008 (-1.26)	0.1283*** (6.32)	0.0007 (1.61)	0.002*** (6.33)
ANGER	0.0023*** (2.69)	0.2546*** (8.77)	0.0017*** (2.72)	0.0036*** (7.89)

FEAR	-0.0008 (-0.43)	0.1048* (1.7)	-0.0007 (-0.5)	0.0007 (0.71)
DISLIKE	-0.0016 (-0.82)	-0.0448 (-0.7)	0.0013 (0.93)	0.0003 (0.31)
JOY	0.0045** (2.57)	0.2854*** (4.88)	-0.0018 (-1.4)	0.0028*** (3.07)
LOVE	0.0037* (1.83)	0.0362 (0.54)	0.0013 (0.91)	-0.0011 (-1.01)
SHAME	-0.0037* (-1.78)	0.1015 (1.45)	-0.003* (-1.91)	0.0005 (0.44)
HATE	-0.0015 (-1.33)	0.0018 (0.05)	0.0005 (0.62)	0.0014** (2.36)
HOPE	-0.0006 (-0.26)	-0.1961** (-2.4)	-0.0014 (-0.77)	0.0003 (0.24)

Panel B. Univariate regression

	(1) RET(KR, t), (%)	(2) VO(KR, t), (BIT)	(3) RET(KR-Global, t), (%)	(4) VOL(KR-Global, t), (%)
SADNESS	-0.0006 (-1.08)	0.1514*** (7.52)	0.0007 (1.61)	0.0025*** (7.82)
ANGER	0.0021** (2.45)	0.2749*** (9.51)	0.0017*** (2.72)	0.0041*** (8.91)
FEAR	-0.0007 (-0.4)	0.15** (2.43)	-0.0007 (-0.51)	0.0016 (1.62)
DISLIKE	-0.0016 (-0.87)	-0.009 (-0.14)	0.0014 (0.98)	0.001 (0.99)
JOY	0.0045*** (2.58)	0.3213*** (5.5)	-0.0017 (-1.35)	0.0038*** (4.13)
LOVE	0.0035* (1.76)	0.0627 (0.93)	0.0014 (0.91)	-0.0003 (-0.32)
SHAME	-0.004* (-1.92)	0.1359* (1.94)	-0.0028* (-1.84)	0.0015 (1.31)
HATE	-0.0014 (-1.23)	0.0424 (1.12)	0.0005 (0.63)	0.0022*** (3.69)
HOPE	-0.0006 (-0.26)	-0.1611** (-1.97)	-0.0014 (-0.76)	0.0009 (0.7)
SENT_SUM	0.0001 (0.33)	0.1259*** (10.29)	0.0006** (2.1)	0.002*** (10.22)
PCA	0.0001 (0.14)	0.2957*** (10.71)	0.0015** (2.43)	0.0047*** (10.65)

Table 5 reports correlations between the past five-minute emotions and the current Bitcoin market by applying VAR analysis with Equation (3). Column (1) of Panel A implies that *ANGER, JOY, and SHAME* have some predictive power on Bitcoin returns. Interestingly, *ANGER* shows significantly positive correlations with all dependent variables, which also implies prediction capability of *ANGER* for all dependent variables. In Panel B, univariate regression results show similar patterns as Panel A, validating multivariate regression results. Also, it shows that *SENT_SUM and PCA* can predict future trade volume of Bitcoin in Korea and volatility.

Table 6. Mixed emotions and the Korean premium

Table 6 presents the results of VAR regression using the Equation (3), where $p = 5$ *and* $s = 5$. The independent variables, emotions including thirty-six mixed emotions represented by interaction terms, are listed in rows. The dependent variables are listed in the columns, which are the Bitcoin return, Bitcoin trade size in Korean market, Korean return premium and volatility.

	RET(KR), (%)	VO(KR), (BIT)	RET(KR-Global), (%)	VOL(KR-Global), (%)
SADNESS	-0.0008 (-1.22)	0.1338*** (6.4)	0.0006 (1.38)	0.002*** (6.15)
ANGER	0.0027*** (3.04)	0.2481*** (8.32)	0.0018*** (2.68)	0.0037*** (7.89)
FEAR	-0.0005 (-0.28)	0.0804 (1.24)	-0.001 (-0.7)	0.0008 (0.74)
DISLIKE	-0.0022 (-1.09)	-0.0448 (-0.66)	0.0018 (1.19)	0.0004 (0.35)
JOY	0.004** (2.26)	0.2519*** (4.21)	-0.0022* (-1.66)	0.0022** (2.29)
LOVE	0.0018 (0.85)	-0.0148 (-0.21)	0.0016 (1.03)	-0.0008 (-0.74)
SHAME	-0.0035 (-1.61)	0.0918 (1.27)	-0.0031* (-1.92)	0.0003 (0.29)
HATE	-0.0018 (-1.53)	0.0164 (0.42)	0.0006 (0.64)	0.0016** (2.52)
HOPE	-0.0013 (-0.54)	-0.192** (-2.31)	-0.001 (-0.57)	0.0006 (0.47)
SADNESS*ANGER	-0.0005* (-1.81)	0.0098 (1.04)	0.0004* (1.82)	-0.0002 (-1.51)
SADNESS*FEAR	-0.0011 (-0.92)	0.0404 (1.03)	0.001 (1.15)	-0.0002 (-0.3)
SADNESS*DISLIKE	0.002* (1.89)	-0.0051 (-0.14)	0.0 (0.02)	0.0001 (0.13)
SADNESS*JOY	0.0008 (0.65)	0.1594*** (3.7)	0.0014 (1.47)	0.0016** (2.28)

SADNESS*LOVE	-0.0011	-0.0085	-0.0002	0.0011
	(-0.74)	(-0.16)	(-0.18)	(1.34)
SADNESS*SHAME	0.0007	-0.0241	0.0004	0.001
	(0.5)	(-0.5)	(0.34)	(1.28)
SADNESS*HATE	0.0011	-0.0752**	-0.0001	-0.0002
	(1.51)	(-2.96)	(-0.19)	(-0.39)
SADNESS*HOPE	0.0019	-0.0426	0.0009	0.0007
	(1.01)	(-0.67)	(0.61)	(0.7)
ANGER*FEAR	-0.0012	-0.0095	0.0015	0.0002
	(-0.72)	(-0.17)	(1.22)	(0.2)
ANGER*DISLIKE	-0.0026	-0.2343	0.0002	-0.002*
	(-1.22)	(-3.3)	(0.14)	(-1.76)
ANGER*JOY	0.0037**	0.2163***	-0.0	0.0031***
	(2.09)	(3.65)	(-0.0)	(3.29)
ANGER*LOVE	0.0032	-0.0253	-0.0043***	-0.0018
	(1.52)	(-0.36)	(-2.75)	(-1.66)
ANGER*SHAME	-0.0035	-0.0672	0.0023	-0.0031**
	(-1.55)	(-0.88)	(1.33)	(-2.54)
ANGER*HATE	-0.002*	-0.025	0.0002	-0.0005
	(-1.74)	(-0.66)	(0.22)	(-0.91)
ANGER*HOPE	-0.0023	-0.0714	-0.0	-0.0026**
	(-1.02)	(-0.94)	(-0.02)	(-2.16)

	RET(KR), (%)	VO(KR), (BIT)	RET(KR-Global), (%)	VOL(KR-Global), (%)
FEAR*DISLIKE	0.0044	0.0317	0.0005	0.005**
	(0.99)	(0.21)	(0.15)	(2.12)
FEAR*JOY	-0.0069*	0.1142	-0.005*	0.0007
	(-1.75)	(0.87)	(-1.71)	(0.34)
FEAR*LOVE	-0.0005	-0.1482	0.0058*	-0.0015
	(-0.11)	(-0.94)	(1.66)	(-0.62)
FEAR*SHAME	-0.0056	0.2447	-0.0032	-0.0015
	(-1.21)	(1.58)	(-0.92)	(-0.6)
FEAR*HATE	0.0004	0.0508	-0.0002	-0.0008
	(0.21)	(0.71)	(-0.15)	(-0.68)
FEAR*HOPE	0.008*	0.117	-0.0051	0.0021
	(1.65)	(0.72)	(-1.42)	(0.82)
DISLIKE*JOY	0.0022	-0.0958	0.0002	-0.0027
	(0.48)	(-0.62)	(0.06)	(-1.09)
DISLIKE*LOVE	0.0009	0.0077	-0.0047	-0.0026
	(0.22)	(0.05)	(-1.52)	(-1.16)
DISLIKE*SHAME	0.0013	0.0509	-0.0017	0.0027
	(0.36)	(0.42)	(-0.65)	(1.42)
DISLIKE*HATE	-0.0008	0.2586***	-0.0016	0.0007
	(-0.31)	(3.0)	(-0.82)	(0.5)
DISLIKE*HOPE	0.0052	0.2234	-0.0034	-0.0041
	(0.81)	(1.03)	(-0.72)	(-1.19)
JOY*LOVE	0.0001	0.0074	0.0021	0.0003
	(0.01)	(0.05)	(0.66)	(0.14)
JOY*SHAME	0.0017	0.101	-0.004	0.0025
	(0.39)	(0.69)	(-1.22)	(1.09)
JOY*HATE	-0.0002	-0.2086**	0.0016	0.0004
	(-0.11)	(-2.78)	(0.98)	(0.31)
JOY*HOPE	0.0052	-0.0243	0.0052	-0.004
	(1.05)	(-0.15)	(1.42)	(-1.53)
LOVE*SHAME	-0.0156**	0.041	0.0007	-0.0015
	(-2.53)	(0.2)	(0.15)	(-0.47)
LOVE*HATE	0.0099***	0.2633***	0.0006	-0.0023*
	(3.95)	(3.13)	(0.32)	(-1.74)
LOVE*HOPE	0.0012	-0.0197	-0.0022	-0.0019
	(0.26)	(-0.13)	(-0.63)	(-0.75)
SHAME*HATE	-0.0012	0.0638	-0.002	0.0018
	(-0.42)	(0.65)	(-0.91)	(1.18)

SHAME*HOPE	-0.0021 (-0.33)	0.2006 (0.93)	-0.008* (-1.68)	-0.0017 (-0.51)
HATE*HOPE	-0.0063* (-1.73)	-0.1314 (-1.08)	0.0007 (0.24)	0.0018 (0.94)

Table 6 reveals relationship between 36 mixed emotions and the Bitcoin market. Many mixed emotions are shown to have statistically significant correlations with Bitcoin market characteristics. Especially, column (3) implies that some mixed emotions, *ANGER*LOVE and FEAR*JOY*, have significantly negative correlations with Korean return premium. Thus, when investors feel *ANGER and Love or FEAR and JOY* at the same time, Korean premium tends to decrease.

5.2.3 Granger Causality Test

We use the Granger causality test to determine the causal relationships between Bitcoin market and emotions.

[Insert Table 7 here]

In the univariate analysis, only *ANGER* causes Bitcoin price movement in Korean market (row (1) of Panel A), while Bitcoin price return in Korean market does not cause *ANGER* (row (1) of Panel B). Interestingly, changes in trade volume of Korean market cause *SADNESS, ANGER, JOY, SENT_SUM and PCA*, and also the other way around (row (2) of Panel A and B). According to row (3) of the Panel A, emotions do not appear to cause Korean premium. In addition, *SADNESS, ANGER, DISLIKE, JOY, HATE, SENT_SUM and PCA* are shown to cause volatility and vice versa. In the multivariate case, the multivariate combination is observed to cause trade volume and volatility.

In conclusion, Bitcoin market movement can be explained by emotions and vice versa. Also, mixed emotions show similar results. In the next section, we test the economic significance of our findings by constructing a simple trading strategy utilizing emotions and evaluating its performance.

5.3 Trading Profits

5.3.1 Trading profits of long-short strategies

In order to test the economic significance of our model, we construct a simple emotion-based trading strategy. Since correlations between emotions and Korean premium are shown low, it is assumed that we only trade in Korean market, Coinone, rather than trade both Korean and non-Korean markets to monetize the Korean premium. Based on the results of section 5.2.2, we apply different strategies for each emotion. When the emotion shows positive correlations with returns, if five-minute emotion at time t is higher (lower) than the average value of the last 24-hour emotion, we buy (sell) Bitcoin at the five-minute closing price of the Korean market, $Prc(Kr)_t$, and the other way around when the emotion shows negative correlations with returns. In other words, when the emotions are relatively high (low), we take a long (short) Bitcoin position in the Korean market if the emotion is positively correlated with returns, and if the emotion is negatively correlated with returns, we take a short (long) Bitcoin position. The cumulative return of long / short positions is denoted as follows.

$$CUM_{Long} = \sum_t \{ \left[ln(Prc(Kr)_{t+1}) \; - \; ln(Prc(Kr)_t) \right] \} \tag{4}$$

$$CUM_{Short} = \sum_t \{ \left[ln(Prc(Kr)_t) \; - \; ln(Prc(Kr)_{t+1}) \right] \} \tag{5}$$

We assume transaction cost of 0.075% (7.5 basis points) when changing positions. Table 9 shows that our simple trading model is profitable, which validates the significance of emotions from our NLP analysis in predicting the Bitcoin returns. Our trading strategy is designed in a simple form, taking either long or short position based on the emotion-based trading signals. More sophisticated trading strategies such as allowing flat positions based on some profit-taking, stop-loss, or timed exit conditions can further improve performance.

[Insert Table 8 here]

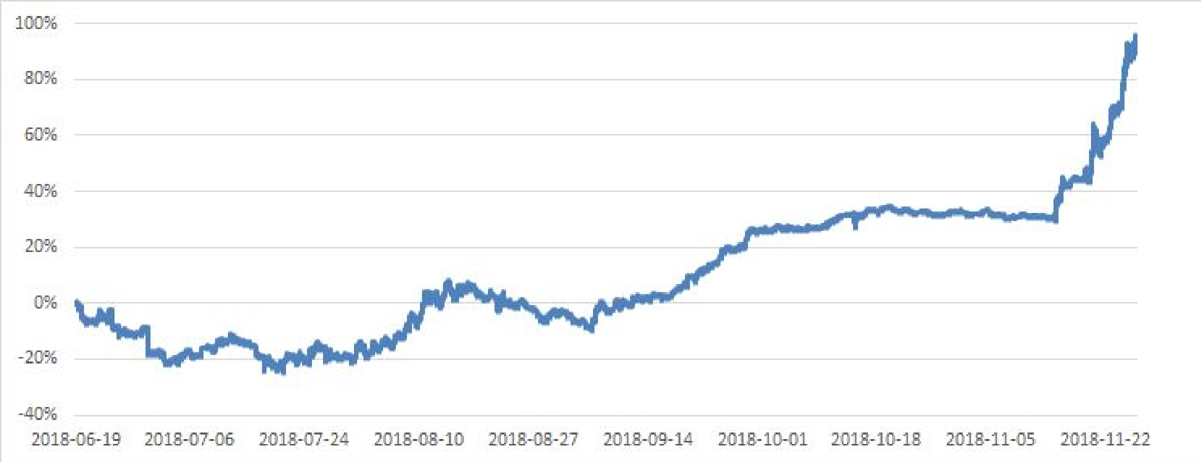
Table 8 illustrates the investment performance of our trading model. In Panel A, trading profits of SADNESS, ANGER, JOY, LOVE and HATE are shown positive without transaction costs. Even after applying transaction costs of 7.5 bps per each trade, SADNESS, ANGER, JOY and LOVE are still shown profitable. Our results suggest that investors' emotions obtained from NLP techniques can potentially be used as good trading signals for Bitcoin.

Figure 3. Cumulative performance of the trading strategies

Figure 3 illustrates cumulative investment results in terms of percentage returns. Panel A and B show the cumulative return performance of our investment based on *ANGER and JOY*, respectively.

Panel A. ANGER

Panel B. JOY



In Table 9, instead of de-seasonalized emotions, we use the raw emotions to test the robustness of Table 4. The results remain robust.

Table 9. Robustness : De-seasonalized emotions

Table 9 presents the results obtained by applying the same procedures in Table 4 on the raw emotions, not on de-seasonalized emotions. VAR with Equation (3) is used with $p = 5$ *and* $s = 5$. The dependent variables are Bitcoin return in Korean market, Bitcoin trade volume of Bitcoin in Korean market, Korean return premium and volatility.

Panel A. Multivariate regression

	RET(KR), (%)	VO(KR), (BIT)	RET(KR-Global), (%)	VOL(KR-Global), (%)
SADNESS	0.0002 (0.25)	0.1112*** (5.51)	0.0005 (1.08)	0.0012*** (3.75)
ANGER	0.0019** (2.22)	0.223*** (7.72)	-0.0009 (-1.44)	0.0029*** (6.38)
FEAR	0.0005 (0.27)	0.0432 (0.7)	-0.0008 (-0.6)	0.0012 (1.26)
DISLIKE	-0.005*** (-2.66)	-0.0114 (-0.18)	-0.0023 (-1.63)	0.0001 (0.12)
JOY	-0.0012 (-0.72)	0.3155*** (5.42)	0.0019 (1.52)	0.0035*** (3.76)
LOVE	-0.0059*** (-2.96)	-0.0611 (-0.91)	-0.0002 (-0.14)	-0.0017 (-1.59)
SHAME	0.0006 (0.3)	0.1472** (2.11)	-0.0014 (-0.89)	0.0014 (1.26)
HATE	-0.0015 (-1.31)	0.0012 (0.03)	0.0003 (0.33)	0.0002 (0.38)
HOPE	-0.0027 (-1.12)	-0.1579* (-1.94)	0.0033* (1.83)	-0.0005 (-0.35)

* : | t | > 1.64, ** : | t | > 1.96, *** : | t | > 2.58

Panel B. Univariate regression

	RET(KR), (%)	VO(KR), (BIT)	RET(KR-Global), (%)	VOL(KR-Global), (%)
SADNESS	-0.0006 (-0.92)	0.1229*** (6.04)	0.0006 (1.4)	0.002*** (6.24)
ANGER	0.0019** (2.2)	0.2369*** (8.14)	0.0019*** (3.0)	0.0034*** (7.42)
FEAR	-0.001 (-0.54)	0.1406** (2.27)	-0.0004 (-0.33)	0.001 (1.05)
DISLIKE	-0.0006 (-0.3)	0.0008 (0.01)	0.0017 (1.18)	0.0006 (0.56)
JOY	0.0047*** (2.74)	0.303*** (5.2)	-0.002 (-1.56)	0.0033*** (3.61)
LOVE	0.0046** (2.29)	0.0706 (1.04)	0.0016 (1.05)	-0.0002 (-0.18)
SHAME	-0.004* (-1.92)	0.1195* (1.7)	-0.0028* (-1.84)	0.0011 (0.99)
HATE	-0.0012 (-1.04)	0.0321 (0.84)	0.0003 (0.4)	0.002*** (3.25)
HOPE	-0.0006 (-0.24)	-0.1553* (-1.91)	-0.0017 (-0.97)	0.0007 (0.56)
SENT_SUM	0.0002 (0.66)	0.0995*** (8.01)	0.0005** (1.96)	0.0015*** (7.68)
PCA	0.0001 (0.17)	0.2382*** (8.44)	0.0014** (2.32)	0.0039*** (8.75)

6. Conclusions

This paper investigates how Bitcoin investors' emotions expressed in the online chatboard interact with Bitcoin price returns. We apply advanced NLP techniques to BitMEX online chatboard to extract nine emotions of Bitcoin investors at five-minute intervals. The influence of these emotions on Bitcoin market variables are rigorously examined by utilizing high-frequency quote and trade data from BitMEX, Binance, and Coinone, aggregated into five-minute intervals.

In this paper, it is shown that the return and volatility of the Bitcoin price and Korean premium can be predicted by emotions. More complex emotions, defined as mixed emotions, are also investigated and shown to have predictive power for the Bitcoin price return.

Additionally, the Bitcoin price movement is seen to cause the fluctuation of emotions.

In order to examine the economic significance of our findings, we construct a simple trading strategy utilizing the emotion-based signals, which is shown profitable.

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Table 7. Granger-causality test

Table 7 presents the Granger-causality test results. Each entry shows the p-value of the test.

Panel A. Source of causation is emotions

	SADNESS	ANGER	FEAR	DISLIKE	JOY	LOVE	SHAME	HATE	HOPE	SENT_SUM	PCA	Multivariate
RET(KR), (%)	0.3000	0.0596*	0.6051	0.1041	0.0632*	0.2904	0.1937	0.5337	0.8185	0.8163	0.8617	0.0396**
VO(KR), (BIT)	<.0001***	<.0001***	0.0732*	0.7352	<.0001***	0.0067***	0.0162**	0.0922*	0.0898*	<.0001***	<.0001***	<.0001***
RET(KR-Global), (%)	0.5624	0.0283**	0.0832*	0.6893	0.6099	0.6202	0.2416	0.8891	0.1342	0.4048	0.2322	0.1377
VOL(KR-Global), (%)	<.0001***	<.0001***	0.0651*	0.0300**	0.0001***	0.0211**	0.0018***	<.0001***	0.4951	<.0001***	<.0001***	<.0001***

Panel B. Source of causation is the Bitcoin market

	SADNESS	ANGER	FEAR	DISLIKE	JOY	LOVE	SHAME	HATE	HOPE	SENT_SUM	PCA	Multivariate
RET(KR), (%)	0.0629*	0.066*	0.8659	0.5986	0.0042***	0.0247**	0.3898	0.026**	0.6453	0.0013***	0.0037***	NaN
VO(KR), (BIT)	<.0001***	<.0001***	0.0013***	0.0001***	<.0001***	0.1121	0.0003***	<.0001***	0.1748	<.0001***	<.0001***	NaN
RET(KR-Global), (%)	0.0342**	0.4920	0.1408	0.2286	0.0054***	0.5807	0.1869	0.9581	0.9227	0.4621	0.3709	NaN
VOL(KR-Global), (%)	<.0001***	<.0001***	0.0051***	0.0011***	<.0001***	0.1513	<.0001***	<.0001***	0.6478	<.0001***	<.0001***	NaN

Table 8. Trading profits

Table 8 shows the investment performance of our emotion-based trading strategy described in Equations (5) and (6). The sum of CUM_{Long} and CUM_{Short} is trading profits. Panel A shows the investment result with standard error without transaction cost and Panel B with transaction cost of 7.5 basis points (bps).

Panel A. Trading profits without transaction costs.

	SADNESS	ANGER	FEAR	DISLIKE	JOY	LOVE	SHAME	HATE	HOPE	SENT_NUM	PCA
CUM long	-36.34	113.08	-86.29	-78.33	166.08	115.90	-74.83	-46.20	-91.43	36.80	-53.68
se	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0005)	(0.0005)
CUM short	86.40	-9.66	36.45	44.41	43.34	-6.84	47.91	76.54	31.31	-85.94	69.06
se	(0.0005)	(0.0005)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0005)	(0.0005)
Trading profit	50.06	103.41	-49.84	-33.92	209.42	109.06	-26.92	30.33	-60.11	-49.14	15.39
se	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)

Panel B. Trading profits with transaction costs of 7.5 bps

	SADNESS	ANGER	FEAR	DISLIKE	JOY	LOVE	SHAME	HATE	HOPE	SENT_NUM	PCA
CUM long	-53.67	96.01	-97.35	-88.86	153.81	106.02	-85.28	-61.93	-101.28	19.73	-70.79
se	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0005)	(0.0005)
CUM short	68.06	-30.40	4.85	12.60	13.10	-39.85	15.88	51.78	-1.58	-103.34	51.50
se	(0.0005)	(0.0005)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0005)	(0.0005)
Trading profit	14.39	65.61	-92.50	-76.27	166.91	66.18	-69.40	-10.16	-102.86	-83.62	-19.29
se	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)