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Emotions in the crypto market: Do photos really speak?

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ABSTRACT

This study examines whether the emotions contained in new photos can affect the cryptocurrency market. Utilizing the daily data on top 100 cryptocurrencies, we find that the surge in ratio of photos comprising pessimistic tones is associated with negative coin returns. Photo sentiment positively predicts subsequent returns and trading intensity, implying the subsequent corrections. The photo sentiment also drives risks up with higher price volatilities. The predictive power is more pronounced during periods of elevated fear proxied by investors' risk aversion. Our results remain robust with alternative sentiment proxies, risk-adjusted returns, and a battery of sub-sample analyses.

1. Introduction

The cryptocurrency market has attracted much attention from traders, regulators, and scholars in recent years. This market has experienced significant growth in trading volume and has become an alternative investment for individual investors[1]. While some prior works indicate that the cryptocurrency market has been efficient over time (Vidal-Tomás & Ibañez, 2018; Jiang et al., 2018), most studies have admitted that cryptocurrencies are primarily risky assets (Baur et al., 2018; Corbet et al., 2019; Haq et al., 2023). This immature market may have greater sensitivity to sentiment than traditional asset markets due to higher transaction costs and lower involvement of institutional investors (Gurdgiev & O'Loughlin, 2020; Celeste et al., 2020). Using several proxies, including the VIX index, the Equity Market Uncertainty index, and textual analysis from social media (Google search index, Twitter, Wikipedia, or Reddit forums), prior studies confirm the power of investor sentiment on predicting the cryptocurrency market (Sifat, 2021; Loginova, 2021). Given the unique features of cryptocurrencies[2], previous research has acknowledged that the signal of investor sentiment from social media platforms has a significant predictive connection with cryptocurrency values (Mai et al., 2018; Gurdgiev & O'Loughlin, 2020; Kraaijeveld & De Smedt, 2020)[3]. By employing convolutional neural networks (CNNs) - a machine learning technique popular for classifying sentiment embedded in photos, Obaid and Pukthuanthong (2022) may address the current limitations in analysing

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[1] The market capitalization of all cryptocurrencies was about $18 billion in January 2017. However, after four years, its total market capitalization reached $2.6 trillion in October 2021 (Sapkota, 2022).

[2] Crypto traders are mostly young and computer-based enthusiasts, who are motivated by risk-taking behaviour and excitement (Pelster et al., 2019; Makarov & Schoar, 2020). As such, their trading behaviour are strongly affected when they observe negative and distrustful information from online platforms.

[3] For instance, using the signal of investor sentiment by Google and Wikipedia search data may not accurately reflect the type or nature of the investor sentiment. The audiences' search results from the above sources include non-investing public and investors (Gurdgiev & O'Loughlin, 2020).

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investor sentiment. Also, using photo sentiments may also be more effective than textual analysis because they can convey emotional information more from international investors regardless of the languages of traders (Obaid & Pukthuanthong, 2022). The findings of Obaid and Pukthuanthong (2022) confirm that sentiment extracted from photos can affect the movements of the U.S. stock market. A recent study by Chiah et al. (2022) re-affirm the predictive power of photo sentiment proxies on the performance of international equity markets. Motivated by the extant literature, this is the first study to investigate the effects of photo sentiment on the cryptocurrency market.

Using the data of the top 100 cryptocurrencies from 1st January 2014 to 29th June 2018, we find that photo sentiment, proxied by Photo Pessimism developed by Obaid and Pukthuanthong (2022), is statistically negatively associated with daily cryptocurrency returns on the same trading day. The sentiment-induced mispricing of photo sentiment exhibits subsequent return correction as a positive correlation is visible on day t+1. Our findings further confirm that we can predict higher trading intensity on the two following days, indicating the subsequent recuperation from negative emotion with a surge in trading activities. The results also confirm that higher Photo Pessimism causes higher risks when investing in cryptocurrencies due to the larger volatilities. One of the possible channels for the predictive power of photo sentiment on cryptocurrencies is the traders' mood swings and speculating preferences (Birru, 2018). As in this market, traders are particularly computer enthusiasts and excitement-seeking, who tend to react irrationally to negative moods spill out from online photos. As such, Photo Pessimism can drive mispricing and price fluctuations. Most notably, our main results remain robust to different subsamples, cross-sectional analyses, alternative proxies for photo sentiment, and a battery of subsample analyses.

This paper contributes to the literature in several ways. First, this is the first study to provide persuasive evidence on the impacts of investor sentiment embedded in photos on cryptocurrency returns, volatility, and trading volume. As such, it adds to the flourishing strand of literature on the impacts of investor sentiment on different asset classes in the financial market. This suggests that investors should consider hedging their cryptocurrency portfolio risks as the emotion from photos can successfully predict cryptocurrency volatilities. Second, our paper also speaks to the literature on the recent trend in alternative approaches to capture sentiment on financial markets. Given that technological advancement facilitates the development of innovative measures of sentiment, this study can extend and fill the gap in the current literature regarding the application of visual content (from photos) in the financial research. As stated by Newhagen and Reeves (1992) and Chaiken and Eagly (1976), graphical content is most efficient in recalling information than text content in the news. Hence, applying photo sentiment in the crypto market also extends the literature on investor sentiment through the psychology of visual provocations. Finally, photo sentiment captures emotions regardless of the languages of traders. As such, it can be used to capture the emotions of international investors, which is powerfully relevant to the crypto market.

The rest of the paper unfolds in the following manner. Section 2 describes the data and methodology. Section 3 elaborates on the empirical results. The additional analyses are reported in Section 4 and Section 5 concludes the study.

2. Data and method

We collect trading data of the top 100 cryptocurrencies based on the market capitalization from Coinmarketcap.com by the end of 2020[4]. The sample includes daily records on opening, closing, high and low prices, trading volume, and market capitalization (in USD). Our sample period spans from 1 January 2014 to 29 June 2018 to ensure consistency with available photo sentiment data. Therefore, our sample can include both booms and busts; and eliminate the impacts of the COVID-19 period on the cryptocurrency markets. We create several variables to proxy the movements of the cryptocurrency market, including daily returns, trading intensity which is the turnover ratio (Brauneis & Mestelb, 2018), three-day moving volatilities (Huynh et al., 2021), and daily range-based volatility by Garman and Klass (1980) by following Diebold and Yilmaz (2014) and Yi et al. (2018)[5].

We employ two proxies of the photo sentiment, *Photo Pessimism* (PP) and *Associated Text Pessimism* (ATP), developed by Obaid and Pukthuanthong (2022), to capture investor sentiment based on visual content from news photos and associated text. The daily *PP* is extracted from the pessimism in news photos, which reflects investor perception of photos in news articles.[6] In this study, we use the *PP* indicator developed from Getty Images as the key photo sentiment indicator, which is considered to reflect global sentiment to a larger extent (Chiah et al., 2022)[7]. We also include several additional variables to minimize the impacts of omitted variable bias, including the MSCI World index return (*MSCI*), Daily stock market Volatility Index (*VIX*), Daily Risk Aversion Index (*RAI*) (Bekaert et al., 2022).

[4] Coinmarketcap.com is a leading source of cryptocurrency price and volume data, aggregating information from over 200 major exchanges and daily data on opening, closing, high, and low prices, as well as volume and market capitalization (in US dollars) for most of the cryptocurrencies. In this study, we mainly focus on the top 100 cryptocurrencies by market capitalization, representing more than 90% of the total market capitalization of all cryptocurrencies.

[5] The range-based volatility can provide more precise and robust to market microstructure noise compared to the estimator based on daily close prices (Alizadeh et al. 2002; Molnár, 2012), which is utilized in prior cryptocurrency studies (See Sapkota, 2022; Phillip et al., 2019; Tan et al., 2020; among others)

[6] Using a machine learning approach, Obaid and Pukthuanthong (2022) construct Photo Pessimism based on photos from (1) the Wall Street Journal (WSJ) and (2) the editorial news section of Getty Images. Photos are downloaded from the editorial news section of Getty Images daily. The news database of Getty Images is a powerful source of photo databases used by major news outlets such as the Guardian, Bloomberg, and The Washington Post. The images in the Getty Images database are published very shortly as the relevant events occur. The ten most popular photos are processed using a machine learning technique called Convolutional Neural Networks, configured with a train batch size of 100 photos.

[7] We also perform the robustness checks by using photo sentiment indicators from Wall Street Journal (WSJ) for a longer period (1/1/2014 to 31/8/2020) in Appendix D.

The data is winsorized at the 1% level to avoid the impacts of outliers.

To investigate the relation between photo sentiment and the cryptocurrency market, we utilize the panel regression as follows:

$$Y_{i,t} = \alpha_i + \beta_n PSENT_{t-n} + \gamma_1 Y_{i,t-1} + \delta_i X_{i,t} + \varepsilon_{i,t} \tag{1}$$

where, $Y_{i,t}$ is the dependent variable we are interested in, including the daily coin returns ($RET_{i,t}$), daily turnover ratio ($TURN_{i,t}$), daily volatility ($VOL_{i,t}$), and three-day moving volatility ($VOL3_{i,t}$) of coin i at day t. The $PSENT_{t-n}$ is the n-lagged values of the daily photo sentiment measure, including *Photo Pessimism* (*PP*) and *Associated Text Pessimism* (*ATP*) of Obaid and Pukthuanthong (2022). We also include a vector of control variables ($Y_{i,t-1}$), including prior day return to control the return reversal, MSCI World index return (*MSCI*), Daily stock market Volatility Index (*VIX*), and Daily Risk Aversion Index (*RAI*) (Bekaert et al., 2022). $X_{i,t}$ are the coin fixed-effects and time-fixed effect dummy variables, which can effectually control all factors in the sample period for each coin. The error term is captured by $\varepsilon_{i,t}$. All models in this study are panel regressions estimated with robust t-statistics clustered at the currency levels. The variables are defined in detail in Appendix 1.

3. Empirical results

3.1. Summary statistics

Table 1 reports the summary statistics. Panel A presents the data sample's descriptive patterns in daily returns of top 100 cryptocurrencies. The average daily return of cryptocurrencies is 0.11%, which exhibits high volatility with maximum of 5.72% and minimum of -7.33%. The daily mean value of three-day moving volatility and daily volatility are relatively high, standing at 12.33% and 27.23%, respectively. The daily turnover yields at 0.0225 with a high standard deviation of 0.2288. In general, cryptocurrencies are risky and volatile assets, and their return patterns align with previous studies (Gurdgiev and O'Loughlin, 2020). Panel B tabulates the summary statistics for our independent variables (i.e., PP and ATP) and the control variables used in the regressions. The mean value of PP is 0.145, which is in line with Obaid and Pukthuanthong (2022). The average value of ATP is 0.017. The mean value of the MSCI World index is 0.0218, consistent with the study of Chiah et al. (2022). The patterns in the volatility of stock market returns are similar to the prior works of Griffin et al. (2007) and Fama and French (2017). The mean value of the Risk Aversion Index (RAI) is 0.727, which is in line with Bekaert et al. (2022).

3.2. Baseline results

First, we estimate the impacts of photo sentiment (*PSENT*), *PP*, and *ATP*, and its lagged value on daily returns of top 100 cryptocurrencies and present the results in Table 2. The results for *PP* and *ATP* are reported in columns 1-3 and 4-6, respectively. The result in column 1 indicates a negative association between *PP* and same-day cryptocurrency returns, with a slope coefficient of -0.008 which is significant at the 5% level. This finding suggests that sentiment embedded in photos is contagious to the crypto market. On days with a greater percentage of negative sentiment exists in photos, crypto market returns are more likely to be lower. A one standard deviation increase in *PP* is associated with a reduction in daily crypto market returns by 13.23 basis points, which is significantly higher than the global stock market returns (Chiah et al., 2022). When replacing the subsequent one- and two-day returns as dependent variables in columns 2 and 3, the slope coefficient on *PP* starts to reverse on day t+1 with a significantly positive slope of 0.013 (t = 3.05). However, we obtain an insignificant result for day t+2, suggesting that the cryptocurrency market mispricing caused by photo sentiment is only short-term. Our results are consistent with the return reversal effect in the prior works of Jegadeesh (1990) and Chiah et al. (2022) on the equity market. Across three models, the proxies of *VIX* and *RAI* are negatively associated with same-day returns, implying that higher volatility or fear from the stock market may reduce cryptocurrency returns. We also report a negative association between *ATP* and the same-day cryptocurrency returns but statistical insignificance[8].

Generally, our findings are consistent with the equity market studies of Obaid and Pukthuanthong (2022) and Chiah et al. (2022), that sentiment extracted from photos can successfully predict the asset returns. Our results are also in line with prior sentiment studies on the crypto market, such as online platforms (Gurdgiev & O'Loughlin, 2020; Loginova, 2021), social media (Mai et al., 2018; Kraaijeveld & De Smedt, 2020). The possible channel on how sentiment extracted from photos can lead to mispricing in cryptocurrency market is investors' mood swings and speculating inclination (Baker & Wurgler, 2006; Birru, 2018). On the same day that photos are released, cryptocurrency participants, mostly young individuals and computer enthusiasts, that exposed to more distrustful photos may have negative moods (Chiah et al., 2022; Obaid & Pukthuanthong, 2022). Further, crypto traders are motivated by risk-seeking behavior and excitement, who lose heart when negative information, such as photos, comes out (Pelster et al., 2019; Makarov & Schoar, 2020). Those individuals reflect their mood in their trading behavior by buying less and/or selling more on that day. Therefore, coin returns are lower during the same day to reflect negative mood swings.

[8] In the Appendix A3, we utilize two Panel Granger causality tests, including simple bivariate and block exogeneity tests – to test for the potential reverse causality of cause-and-effect relationships. Overall, the results show that neither returns, turnover nor volatility granger causes investor sentiment indicator, indicating no reverse causality.

Table 1
Summary statistics

Variable	N	Mean	Std. Dev.	Max	Min
Dependent Variables					
RET	94,464	0.0011	0.2253	5.7226	-7.3321
TURN	94,464	0.0225	0.2287	21.882	0.0000
VOL3	93,640	0.1233	0.1805	4.6536	0.0000
VOL	94,464	0.2723	3.3280	49.2290	0.0023
Independent and Control Variables					
Photo Sentiment (PP)	1,047	0.1463	0.1654	0.8426	0.0000
Associated Text Pessimism (ATP)	1,047	0.0167	0.0181	0.1145	-0.0490
MSCI	1,047	0.0218	0.6717	0.2600	-0.4900
VIX	1,047	0.3643	0.0887	1.1560	-0.2591
RAI	1,047	0.7265	0.2283	5.2390	2.4254

This table reports the summary statistics of the key variables in this study between 1 January 2014 and 29 June 2018. The descriptions and data sources of all variables are reported in Appendix 1.

Table 2
Panel regression for daily returns

Variables	RET_t (1)	RET_{t+1} (2)	RET_{t+2} (3)	RET_t (4)	RET_{t+1} (5)	RET_{t+2} (6)
PP_t	-0.008**	0.013***	-0.002			
	(-2.27)	(3.05)	(-0.69)			
ATP_t				-0.039	0.041	-0.021
				(-0.87)	(1.18)	(-0.35)
RET_{t-1}	-0.221***	-0.221***	0.255***	-0.221***	-0.219***	0.255***
	(12.54)	(12.53)	(15.73)	(12.53)	(12.46)	(15.71)
VIX	-0.108***	-0.097***	0.027**	-0.088**	0.027**	0.042**
	(-3.65)	(3.37)	(2.63)	(-2.52)	(2.62)	(2.99)
MSCI	0.314***	0.322***	0.433***	0.205**	0.296**	0.325***
	(7.81)	(8.37)	(10.58)	(2.97)	(2.53)	(4.25)
RAI	-0.188***	-0.116*	-0.107	-0.212**	-0.127	0.037
	(-3.91)	(-2.12)	(-1.77)	(-2.37)	(-1.37)	(1.67)
Constant	0.002***	0.001	0.002**	0.002**	0.001	0.005***
	(4.30)	(-1.22)	(2.54)	(2.38)	(0.84)	(5.73)
Observations	94,464	94,464	94,464	94,464	94,464	94,464
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Coin-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.377	0.319	0.322	0.383	0.383	0.382

This table presents panel regressions of results of daily returns of top 100 cryptocurrencies on photo and associated text pessimism and its lagged value, along with set of control variables. The *Photo Pessimism (PP)* and *Associated Text Pessimism (ATP)* indicators are obtained from Obaid and Pukthuanthong (2022), which captures the pessimism embedded in influential photos. The control variables include the prior-day returns; daily stock market volatilities index (*VIX*); MSCI market daily return (*MSCI*); and the daily investor sentiment proxied by the US Risk Aversion Index (*RAI*) by Bekaert et al. (2022). All variables are winsorized at the top and bottom 1% of the sample distribution. All regressions use coin-fixed effects and time-fixed effects. The robust t-statistics, clustered at the currency levels, are reported in the brackets under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

We further consider the impacts of photo sentiment on trading intensity (*TURN*) and daily volatility (*VOL3* and *VOL*)[9]. The results for turnover and volatilities are reported in columns 1-3 and 4-5 in Table 3, respectively. The result in column 1 indicates *PP* does not seem to alter the contemporaneous turnover with a statistically insignificant coefficient. However, we can obtain the stronger impacts of *PP* emerging in the next two days, with positive and significant slopes in columns 2 and 3. In other words, one standard deviation increase in *PP* is correlated with a 0.51% and 0.31% increase in coins' trading volume in the following two days. Our findings are in line with prior studies that confirm the correlation between trading volume and investor sentiment in the equity markets (Tetlock, 2007; Siganos et al., 2017)[10]. In the last two columns (4 and 5), we examine how the photo sentiment impacts the volatility of the cryptocurrency market returns. The daily volatilities are proxied by three-day moving (*VOL3*) and daily volatility (*VOL*). The results show that *PP* is positively associated with both volatility proxies. This suggests that the negative photo sentiment may cause higher risks for the cryptocurrency market as the returns are more volatilized when more negative emotions are captured in online photos. The negative moods spill out from online photos can lead to a short overreaction of irrational investors and thus drive higher price

[9] In Tables 3, 4, and 5, we do not report the results for *ATP* to converse space as this variable does not exhibit significant impacts. However, the results are available upon request.

[10] In Appendix B1, we report that the predictive power of Photo sentiment on returns, turnover, and volatilities diminishes from day t + 3 to t + 5. This finding demonstrates that mispricing induced by photo sentiment is temporary.

Table 3
Panel regression for daily turnover and volatilities

Variables	$TURN_t$ (1)	$TURN_{t+1}$ (2)	$TURN_{t+2}$ (3)	$VOL3_t$ (4)	VOL_t (5)
PP_t	-0.017	0.051**	0.031*	0.028**	0.046***
	(-0.91)	(2.53)	(1.96)	(2.62)	(4.15)
RET_{t-1}	0.304***	0.313***	0.314**	0.046***	0.022**
	(2.93)	(2.97)	(3.54)	(6.14)	(2.01)
VIX	0.015***	0.016***	0.015***	0.016**	0.024*
	(5.97)	(6.84)	(6.23)	(2.02)	(1.87)
MSCI	0.374***	0.315***	0.321***	0.001	0.003
	(12.81)	(10.37)	(11.58)	(0.16)	(0.75)
RAI	-0.005	-0.003	-0.017*	0.231**	0.319***
	(-1.15)	(-1.01)	(-1.87)	(2.39)	(3.44)
Constant	0.025*	0.009***	0.007**	0.286**	0.282***
	(1.79)	(2.86)	(2.38)	(2.56)	(3.22)
Observations	94,464	94,464	94,464	93,640	94,464
Time-fixed effects	Yes	Yes	Yes	Yes	Yes
Coin-fixed effects	Yes	Yes	Yes	0.659	0.593
Adjusted R^2	0.429	0.363	0.366	93,640	94,464

This table presents panel regressions of results of daily return volatilities of top 100 cryptocurrencies on photo pessimism and its lagged value, along with set of control variables. Following Brauneis and Mestel (2018), the turnover ratio (*TURN*) is defined as dollar volume divided by market cap to capture the trading intensity. The volatilities are computed by using the moving average approach for three-day (VOL3) volatilities, Garman and Klass (1980) daily volatility (VOL). The *Photo Pessimism* (*PP)* are obtained from Obaid and Pukthuanthong (2022), which captures the pessimism embedded in influential photos. The control variables include the prior-day returns; daily stock market volatilities index (*VIX*); MSCI market daily return (*MSCI*); and the daily investor sentiment proxied by the US Risk Aversion Index (*RAI*) by Bekaert et al. (2022). All variables are winsorized at the top and bottom 1% of the sample distribution. All regressions use coin-fixed effects and time-fixed effects. The robust t-statistics, clustered at the currency levels, are reported in the brackets under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

fluctuations.

4. Robustness Checks and Additional Tests

4.1. Risk-adjusted returns and photo sentiment

Given the extant literature, several studies propose several factors to capture the expected cross-sectional cryptocurrency returns (Liu et al., 2020; Shen et al., 2020; Liu et al., 2022). Following Liu et al. (2022) and Shen et al. (2020), we utilized several approaches to consider the risk-adjusted returns for cryptocurrencies. Hence, we expect to provide more robust results on the predictive power of photo sentiment on cryptocurrencies. First, the cryptocurrency market return is the value-weighted return of all coins. The cryptocurrency excess market return (*CMKT*) is the difference between the cryptocurrency market return and the risk-free rate measured as the one-month U.S. Treasury bill rate from the Center of Research in Security Prices (Liu et al., 2020; Liu et al., 2022). Next, we finally construct two daily factors of Momentum[11] (*CMOM*) and Size[12] (*CSMB*) for the cryptocurrency market by following the method of Fama and French (1993). We use daily alphas with respect to the following factor model instead of returns as the dependent variable in Eq. (1).

- The one-factor model with only the *CMKT* or the cryptocurrency CAPM:

$$R_{it} - R_{ft} = \alpha_i + \beta_i CMKT_t + \varepsilon_{it} \tag{2}$$

- Three-factor model that combines the *CMKT, size*, and *momentum* factors:

$$R_{it} - R_{ft} = \alpha_i + \beta_i CMKT_t + \gamma_i CSMB_t + \delta_i CMOM_t + \varepsilon_{it} \tag{3}$$

[11] Following Liu et al. (2022), the three-week momentum factor is constructed by forming the momentum factor portfolio based on the intersection of 2×3 portfolios. Then, we sort coins into two portfolios based on the coin size. Then, three momentum portfolios are formed within each size portfolio based on past three-week returns. Based on past three-week returns, the first, second, and third momentum portfolios are sorted into the bottom 30%, middle 40%, and top 30% of the coins. The momentum factor is constructed as follows:CMOM $= (Small\ High + Big\ High)/2 + (Small\ Low + Big\ Low)/2$Following Liu et al. (2022) and Huynh (2023), the coins are sorted into three size groups by market capitalization: bottom 30% (small), middle 40% (neutral), and top 30% (big). Then, value-weighted portfolios for each of the three groups are constructed. The size factor (CSMB) is the return difference between the portfolios of small and big size portfolios.

[12] Bitcoin represents about 30-40% of the total market capitalization of all cryptocurrencies. See: https://www.slickcharts.com/currency

Table 4
Panel regression for daily risk-adjusted return

Variables	α_t	α_{t+1}	α_{t+2}
PANEL A: ***Cryptocurrency CAPM***			
	(1)	(2)	(3)
PP_t	-0.031**	0.009	-0.005
	(-2.89)	(0.67)	(-0.34)
Observations	94,464	94,464	94,464
Baseline controls	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Coin-fixed effects	Yes	Yes	Yes
Adjusted R^2	0.306	0.276	0.279
PANEL B: ***Three-factor model (CMKT, CSIZE and CMOM)***			
	(1)	(2)	(3)
PP_t	-0.049***	0.032**	0.011
	(-3.14)	(-2.16)	(1.01)
Observations	94,464	94,464	94,464
Baseline controls	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes
Coin-fixed effects	Yes	Yes	Yes
Adjusted R^2	0.243	0.219	0.221

This table presents panel regressions of results of daily risk-adjusted returns of top 100 cryptocurrencies on photo pessimism and its lagged value, along with set of control variables. The results for two modified cryptocurrency pricing models are reported in Panel A and B, respectively. The *Photo Pessimism* (*PP)* are obtained from Obaid and Pukthuanthong (2022), which captures the pessimism embedded in influential photos. The control variables include the prior-day returns; daily stock market volatilities index (*VIX*); MSCI market daily return (*MSCI*); and the daily investor sentiment proxied by the US Risk Aversion Index (*RAI*) by Bekaert et al. (2022). All variables are winsorized at the top and bottom 1% of the sample distribution. All regressions use coin-fixed effects and time-fixed effects. The robust t-statistics, clustered at the currency levels, are reported in the brackets under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

Table 4 presents the panel regressions of results of daily risk-adjusted returns and photo sentiment. The results for two modified cryptocurrency pricing models are reported in Panel A and B, respectively. The *PP* is significantly and negatively associated with daily returns adjusted by the CAPM and three-factor model (*CMKT, CSMB*, and *CMOM*). Our findings align with Liu et al. (2022) that expected cryptocurrency returns could be captured by three fundamental factors: market returns, size, and momentum. Taking Model (1) in Panel B as an example, the coefficient of -0.049 is significant at 1%. The economic meaning is that one standard deviation increase in *PP* would cause 81 basis points (-0.049 $\times$ 0.1654) reduction in the risk-adjusted return (measured by three-factor Alpha). Also, the slope coefficient on *PP* is reversed on day t + 1 with a significantly positive slope of 0.032 (t = -2.16). This means that it also takes only a day for the impact of *PP* on the risk-adjusted return to reverse, which confirms that our previous findings are robust.

4.2. *Photo sentiment, investor risk-aversion, and cryptocurrencies*

This section considers the potential impacts of time-varying risk aversion in the financial markets. Utilizing the recently developed Risk Aversion Index (RAI) of Bekaert et al. (2022), we employ a time-series test by dividing our data sample into high and low *RAI* based on the median value. The results are tabulated in Table 5. Overall, the predictive power of photo sentiment is more visible during the higher risk aversion periods. This finding is consistent with the studies of Demiralay and Golitsis (2021); Sifat (2021), and Long et al. (2022) for the time-series correlation between risk aversion and cryptocurrency returns.

4.3. *Robustness checks*

We report the results for other additional analyses in the Appendix for brevity. In Appendix B, we perform two robustness tests on the predictive power of photo sentiment by utilizing the subsample analyses and alternative econometric approaches. In Table B2, we employ the data of the top 99 cryptocurrencies to exclude the dominance of Bitcoin[13] in this market. We also consider the impacts of photo sentiment on the top 20 coins by market capitalization in Table B3. Overall, the main findings remain consistent with our results in the prior section that photo sentiment is associated with a drop in cryptocurrency returns and an increase in trading volume and daily volatilities in the subsequent days, which require at least one day to reverse. In Appendix B4, we overcome the endogenous issues by employing two alternative econometric approaches. First, we employ the two-step system Generalised Method of Moments (GMM) - dynamic panel model using two lags of the dependent variables (Wintoki et al., 2012; Yao et al., 2021). Corresponding to the results in Table B4, the coefficients of sentiment are still statistically significant, which validates the robustness of our findings. Further, we re-estimate our model by using the moving-block bootstrap simulation procedure developed by Gonçalves and White (2005) by

[13] This approach includes two steps: (1) The estimated coefficients are obtained from the original panel fixed-effect regressions; (2) The raw data are repeatedly rerun in the moving block-bootstrap with 15 observations for each block length to generate 10,000 new time series produced under the null of no predictability for all dependent variables and predictors to obtain the bootstrap distribution of all estimated coefficients.

Table 5
Cross-sectional tests: High vs. Low Risk Aversion

Variables	Return			Turnover			Volatility	
	RET_t	RET_{t+1}	RET_{t+2}	$TURN_t$	$TURN_{t+1}$	$TURN_{t+2}$	$VOL3_t$	VOL_t
PANEL A: High risk aversion								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PP_t	-0.045***	0.017**	0.005	0.011	0.046***	0.023*	0.011**	0.054***
	(-3.77)	(2.31)	(1.04)	(1.25)	(3.74)	(1.90)	(2.33)	(4.14)
Observations	53,136	53,136	53,136	53,136	53,136	53,136	52,672	53,136
Baseline controls	Yes	Yes	Yes	*Yes*	*Yes*	*Yes*	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	*Yes*	*Yes*	*Yes*	Yes	Yes
Coin-fixed effects	Yes	Yes	Yes	*Yes*	*Yes*	*Yes*	Yes	Yes
Adjusted R^2	0.321	0.289	0.292	0.232	0.297	0.244	0.358	0.546
PANEL B: Low risk aversion								
	(1)	(2)	(3)	*(4)*	*(5)*	*(6)*	(7)	(8)
PP_t	-0.024*	0.003	0.007	-0.001	0.019*	0.001	0.011*	0.018
	(-1.87)	(0.59)	(0.77)	(-0.22)	(1.72)	(0.16)	(1.70)	(1.47)
Observations	41,328	41,328	41,328	41,328	41,328	41,328	40,968	41,328
Baseline controls	Yes	Yes	Yes	*Yes*	*Yes*	*Yes*	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	*Yes*	*Yes*	*Yes*	Yes	Yes
Coin-fixed effects	Yes	Yes	Yes	*Yes*	*Yes*	*Yes*	Yes	Yes
Adjusted R^2	0.291	0.262	0.264	0.146	0.211	0.187	0.299	0.370

This table presents panel regressions of results of daily returns, turnover, and volatilities of top 100 cryptocurrencies on photo pessimism and its lagged value, along with set of control variables. The sample are divided into two subperiods by using the daily investor sentiment proxied by the US Risk Aversion Index by Bekaert et al. (2022). The results for High- and Low-risk-aversion periods are reported in Panel A and B, respectively. The *Photo Pessimism and Associated Text Pessimism* indicators (*PSENT)* are obtained from Obaid and Pukthuanthong (2022), which captures the pessimism embedded in influential photos. The control variables include the prior-day returns; daily stock market volatilities index (*VIX*); and MSCI market daily return (*MSCI*). All variables are winsorized at the top and bottom 1% of the sample distribution. All regressions use coin-fixed effects and time-fixed effects. The robust t-statistics, clustered at the currency levels, are reported in the brackets under the associated coefficients. ***,**,* represents 1%, 5%, 10% significance levels, respectively.

following Schmeling (2009)[14]. Overall, our results remain robust as this approach can justify the correlations between dependent variables and predictor variations and consent for standard forms of heteroskedasticity.

In Appendix C, we perform a cross-sectional test by utilizing the sub-samples of market capitalization. In Table C1, we partition the sample into large and small coins based on the 50% top and bottom of market capitalization. In general, our results indicate that the effects of photo sentiment on returns, returns, and volatilities are pronounced for all coins regardless of the market capitalizations. In Appendix D, we perform the last robustness checks by utilizing an alternative proxy for photo sentiment in Table D1. This proxy is based on photos from the Wall Street Journal from 1/1/2014 to 30/8/2020, which is constructed similarly to the indicators from Getty Images. Overall, the predictive power of the new photo sentiment proxy on the cryptocurrency market remained significant. Compared to the main sentiment proxy, this alternative indicator exerts weaker predictive power[15].

5. Conclusion

This study examines the predictive power of investor sentiment, proxied by the number of pessimistic photos and associated text, on the cryptocurrency market movements. Overall, the photo sentiment is negatively associated with the same-day coin returns, which promptly reverse on a subsequent day. Further, the trading intensity of cryptocurrencies on the following day rises with a higher magnitude of negativity embedded in photos. The photo sentiment also exhibits its power to heighten the daily return volatilities. The results remain robust under a battery of robustness checks of subsample analyses and alternative photo sentiment indicators. The impacts of photo sentiment on the cryptocurrency market are more pronounced during periods of elevated investors' risk aversion. Thus, our findings provide new insights into the recent trend in innovative measures for investor sentiment and its application in the cryptocurrency market. This study also opens doors for further research to bridge the gap between new sentiment proxies and other asset classes in the financial markets. Given the data limitation of photo sentiment, further studies can consider the impacts of news and photos sentiment during uncertain periods (i.e., COVID-19 and Russia-Ukraine conflicts) and the market segmentation nature of the cryptocurrencies.

[14] As the WSJ is a daily newspaper that focuses on major events in the US market and with limited copyrights of photos (Obaid & Pukthuanthong, 2022), the extracted photo sentiment is limited in scope compared to photos from Getty Images. The Wall Street Journal does not have the full copyrights of photos, and they only hold the licenses for a limited time from other news and media agencies (i.e., Associated Press, Reuters, and Getty Images). As such, when their license expires, the photos are removed.

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Declaration of Competing Interest

None

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Supplementary materials

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