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Original research

The Relation between Gold Price Movement and Bitcoin Investment Sentiment

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Abstract

Considering the emotional behavior of investors in the cryptocurrency market, this paper comprehensively explores the sophisticated relationship between Bitcoin investor sentiment and gold price movements. The purpose of this study is to examine the impact of the gold price on investor sentiment of Bitcoin market traders and investors using monthly data from August 2020 to August 2022. The impact of oil prices on investor sentiment was examined using the Pooled Mean Group (PMG) method. The PMG approach considers short-term and long-term relationships between series and provides reliable results in the context of dynamic heterogeneous panel models. PMG implementations in all models show the short-term and long-term impact of the gold price on investor sentiment. The results also suggest that gold prices are positive and significant in the long run across all models, and that behavioral factors such as consumer sentiment and global economic stability are important in controlling gold prices at shorter time resolutions. Precious metals have had a positive impact on the Bitcoin market,

Keywords: Bitcoin, Gold Prices, Sentiment Analysis.

JEL Classification: C58, G12, G14

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Introduction

As a psychological term, investor sentiment is the reaction to market conditions. In fact, investor sentiment spillover is the process by which investors acquire the sentiment of others in order to achieve interaction and accumulation of opinions between different individuals. Sentiment spillovers have received a lot of attention in recent years, as they are one of the primary sources of investor sentiment for individual investors. Investor sentiment is one of the most important factors influencing investor decision-making, and extensive research has been conducted on investor sentiment in financial markets (e.g. (M Qadan, H Nama, 2018); (Jawad Shahzad, Elie Bouri, David Roubaud, Ladislav Kristoufek, 2019). In 2008, Satoshi Nakamoto introduced the first cryptocurrency called Bitcoin. It promises lower transaction fees than traditional online payment mechanisms, and unlike government-issued currencies, the system runs on a peer-to-peer decentralized network. Bitcoin's market value was less than 5 cents in 2010 and peaked at around $63,400 in 2021. Bitcoin's current price is $23,223. Bitcoin is a new and popular phenomenon, but large institutions are not part of the Bitcoin market, especially small businesses and individuals are Bitcoin investors. Some retail investors who hold Bitcoin are cryptocurrency enthusiasts, criminals, and mostly speculative investors. (Sean Foley, Jonathan R Karlsen, Talis Putnins, 2019)found that about 25% of all Bitcoin users are involved in illicit activities. Bitcoin was designed as a digital currency, but (Yermack, 2015) Bitcoin is a speculative investment. (Dirk G. Baur, KiHoon Hong, Adrian Lee, 2018) investigated whether Bitcoin is a medium of exchange or an asset by analyzing the statistical properties of Bitcoin, which is used by stocks, bonds, commodities, and It concluded that there was no correlation with traditional asset classes such as Bitcoin. It is a speculative investment and not as an alternative currency or medium of exchange. One of the most important financial innovations of the last decade is Bitcoin, so it's important to examine the determinants that influence Bitcoin's returns and its volatility. This paper focuses on identifying the impact of investor sentiment from a behavioral finance perspective to understand and identify Bitcoin as a new asset. Due to the speculative use of Bitcoin by lip traders, it is crucial to study the impact on investor sentiment. In existing literature, only one investor sentiment proxy is used to analyze the impact of investor sentiment on Bitcoin returns and return volatility. Since there is no perfect proxy for investor sentiment, we use three different proxies to see if different investor sentiment proxies are similar Result.

- Baker and Stein (2004), as they argued that if a market is unusually liquid and market liquidity can be measured by trading volume, will be available for a relatively long period of time is the Bitcoin trading volume.

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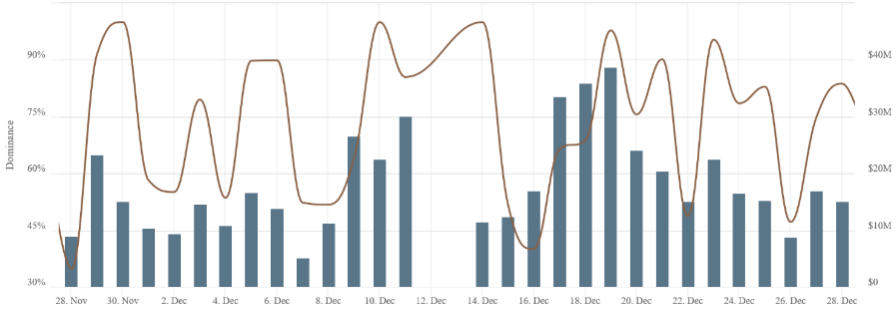

Figure 1. trading volume (Monthly), author computation from: https://bitcoinvisuals.com/market-volume

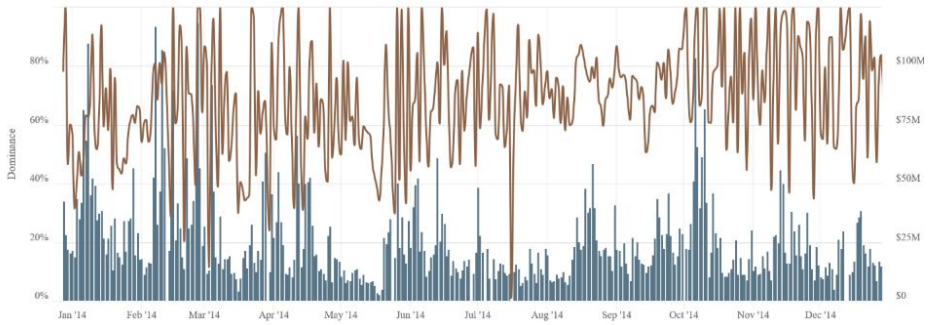

Figure 2. trading volume (Yearly), author computation from: https://bitcoinvisuals.com/market-volume

• The second indicator is a daily special crypto fear and greed index for crypto investors.

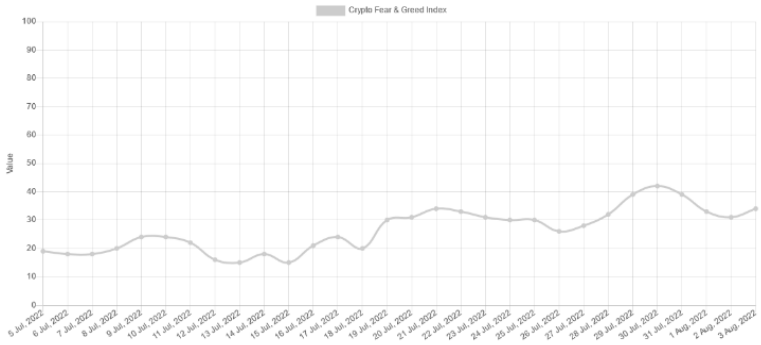

Figure 3. Crypto Fear & Greed Index (Monthly), author computation from: https://alternative.me/crypto/fear-and-greed-index/

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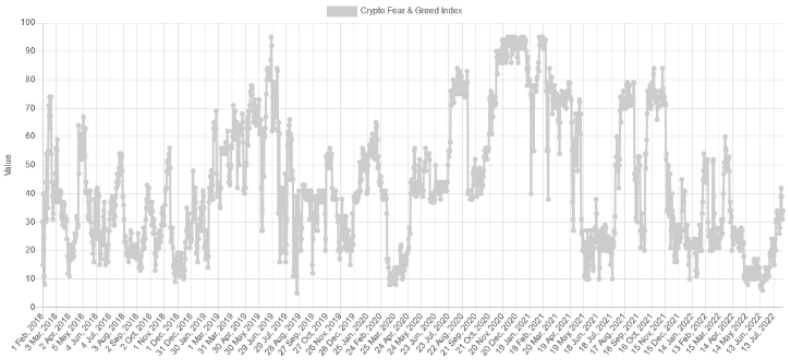

Figure 4. Crypto Fear & Greed Index (From 2018 to 2022), author computation from: https://alternative.me/crypto/fear-and-greed-index/

• The third index is the weekly American Association of Individual Investors Index. A vector autoregressive (VAR) model examines whether investor sentiment and Bitcoin returns are related in a dynamic environment, distinguishing between rational and irrational investor sentiment used for.

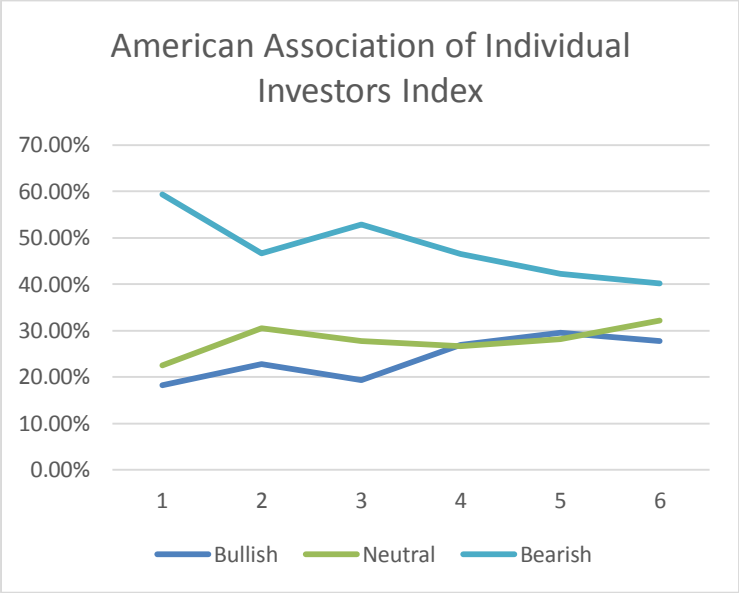

Figure 5. American Association of Individual Investors Index (Monthly), author computation from: https://www.aaii.com/sentimentsurvey

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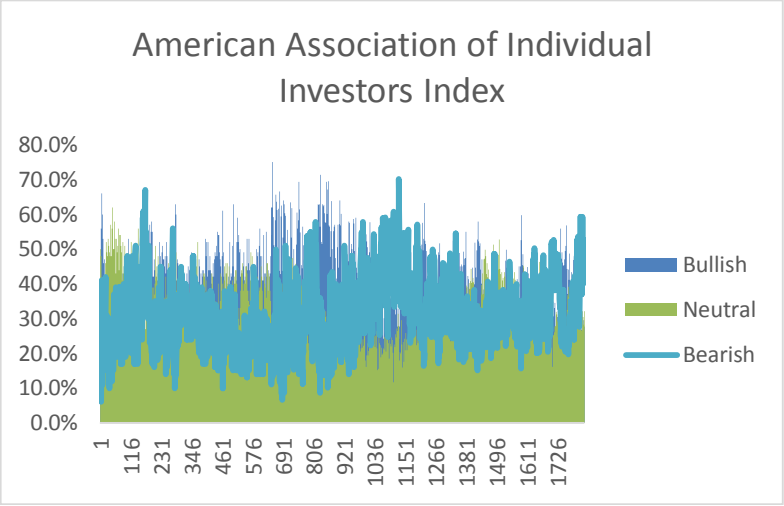

Figure 6. American Association of Individual Investors Index (The Total Data), author computation from: https://www.aaii.com/sentimentsurvey

Gold is one of the most malleable, dense, conductive, non-destructive, bright and beautiful metals (Fergal A. O'Connor, Brian M. Lucey, Jonathan A. Batten, Dirk G. Baur, 2015). These unique properties make its intrinsic value nearly impossible to change over time, making it globally accepted as the most representative hedge or haven against volatility in alternative assets. became. According to (Dirk G. Baur, Brian M. Lucey, 2010), hedges are financial assets that are uncorrelated or negatively correlated with alternative assets. Additionally, the asset is considered a haven when used as a hedge in extreme economic conditions. Bitcoin, by contrast, is a highly decentralized digital currency with little intrinsic value. It is considered a highly speculative form of investment and a highly innovative form of payment. Bitcoin is an online communication protocol that enables the use of virtual currencies, including electronic payments. Digital currencies have several characteristics that make them very popular, such as their pseudonymous nature, low costs and fast transaction speeds, leading to serious debates about the digitization of the financial system (Rainer Böhme, 2015).

Figure 7. Gold Price and Bitcoin Price (Monthly), author computation from: https://tradingeconomics.com

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Figure 8. Gold Price and Bitcoin Price (From 2010), author computation from: https://tradingeconomics.com

Literature Review

Investor Sentiment

Investor sentiment has been studied extensively in the academic literature from time to time, with mixed results (Antti Klemola, Jussi Nikkinen, Jarkko Peltomäki , 2016). According to (Eom, 2019), the occurrence of keyword searches indicates the strength of investor interest, and this strength varies over time. Bitcoin's high-handed behavior cannot be explained by conventional economic or financial theory. Searches are linked to Bitcoin prices. Google Trends search queries are analyzed as indicators of investor interest and attention (Kristoufek, 2013). Kristoufek (2013) quantified the relationship between price and search queries. Through his Google Trends using some defined keywords, he found a significant correlation between Bitcoin and his Google queries.

Impact of Investor Sentiment

One of the first papers examining the impact of investor sentiment on Bitcoin volatility was by (Bukovina, J. and Marticek, M., 2016). They use an autoregressive AR (1) model to analyze the impact of sentiment on Bitcoin volatility, and use natural language processing (NLP) techniques to analyze submissions and comments with the Sentdex sentiment index data. selected. NLP techniques are used to extract information from text. The most widely used technique in NLP is sentiment analysis. It is based on customer surveys, reviews, and social media comments where people voice their opinions. Emotion signals are defined from 3 to 6, with 3 being the most negative emotion and 6 being the most positive emotion. The results show that only a small portion of the overall volatility is explained by the sentiment index. However, during periods of high volatility, sentiment has a greater impact.

Another study related to machine learning is provided by (M. Ángeles López-Cabarcos¸ Ada M. Pérez-Pico, Juan Piñeiro, Aleksandar Sevic, 2019). They used his GARCH and EGARCH models to explore the impact of investor sentiment, S&P 500 returns, and VIX returns on Bitcoin return volatility. They used the Stanford Core NLP

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measure for the investor sentiment variable. This variable is defined from 2 to 2, where 2 is the most negative sentiment and 2 is the most positive sentiment. Their results show that all explanatory variables affect Bitcoin's volatility during plateaus, making Bitcoin attractive to speculative investors. (Alessandra Cretarola, Gianna Figà-Talamanca, Marco Patacca, 2019) used autoregressive moving average (ARMA), GARCH, and EGARCH models to explore the impact of investor sentiment on the mean and variance of cryptocurrency returns. A key difference between (Alessandra Cretarola, Gianna Figà-Talamanca, Marco Patacca, 2019) and the study by Lopez-Cebarcos et al. (2019) is a measure of investor sentiment. (Alessandra Cretarola, Gianna Figà-Talamanca, Marco Patacca, 2019) used trading volume and the Google search index as a proxy for investor sentiment. Their results show that this trading volume affects both the average return and volatility of cryptocurrencies, while the search index primarily affects volatility. In short, the results show that investor sentiment has important informational value in explaining changes in Bitcoin's volatility, making Bitcoin look more like an investment than a financial asset.

Relation Between Bitcoin and Gold

High Relationship

Scientific research by (Dyhrberg, 2015) (Nguyen Phuc Canh, 2019); Shahzad et al. (2019b) and (Jamal Bouoiyour, 2019) provide strong evidence of commonalities between these two highly popular but seemingly disparate assets. Interestingly (Jawad Shahzad, Elie Bouri, David Roubaud, Ladislav Kristoufek, 2019). (Theodore Panagiotidis, On the determinants of bitcoin returns: A LASSO approach, 2018) use the least absolute shrinkage selection operator (LASSO) method for estimation. (Jamal Bouoiyour, 2019) use quantile-by-quantile regression specifications to investigate whether Bitcoin or gold can serve as better diversifiers, hedgers, or safe havens against oil price volatility. The survey period is from September 13, 2011 to August 29, 2017. Empirical results show that both Bitcoin and gold have adequate hedging capabilities against oil market price fluctuations. Still, these skills change over time depending on whether the Bitcoin or gold markets are thriving or stressed. The same is true for oil markets. It concludes that Bitcoin and Gold are safe investment choices in turbulent times. Similar results are extracted by the conditional value-at-risk method.

Weak and Neutral Relationship

Furthermore, (Eom, 2019)examines the diversification and hedging potential of gold compared to Bitcoin. Perform estimation using dynamic conditional correlation (DCC) and wavelet coherence methods. The survey period is from July 26, 2010 to October 25, 2017. Empirical results show that bubble movements in the gold price can be used in part to hedge bubble movements in the Bitcoin market value. More specifically, volatility, causality, and persistence of change across alternating phases are highlighted in gold futures prices and Bitcoin. The closest connections are tracked for the period 2012-2015 over a frequency band of 8-16 weeks. During the European sovereign debt crisis, the contagion between Bitcoin and gold has become more intense. The academic work by (Irene Henriques, 2018) is representative of the detailed specification of the GARCH method. (Irene Henriques, 2018)use dynamic conditional correlation (DCC), asymmetric

DCC (ADCC), and generalized orthogonal generalized autoregressive Compare the result of replacing with. Bitcoin. Minimum volatile stock portfolios and long and short positions are examined. This data spans the period from January 4, 2011 to October 31, 2017. Empirical evidence suggests that risk-averse investors are willing to pay high performance fees to switch from gold portfolios to Bitcoin portfolios. Bitcoin is favored as an investment instead of gold Portfolios may offer higher risk-adjusted returns. Similarly, (Debdatta Pal and Subrata K. Mitra , 2019) compare optimal hedge ratios for Bitcoin and other financial assets using conditional volatility estimates from various GARCH methods. The investigation period begins on January 3, 2011 and ends on February 19, 2018. Econometric results show that the Generalized Orthogonal GARCH (GO-GARCH) specification has the greatest hedging effect. There is support that a $1 long bitcoin could be hedged with a 70 cent short 70.5% of gold. Overall, it is argued that gold offers a better hedge against bitcoin.

Bitcoin Sentiment

(Anamika Anamika, Sowmya Subramaniam, 2021) show that if investors are bullish on Bitcoin, the price of Bitcoin will rise. After considering relevant factors, Bitcoin sentiment has great power in predicting Bitcoin price. The author also used Baker and Wagler and his VIX Sentiment Index, respectively, as measures of stock market sentiment. Their findings show that cryptocurrency prices rise when stock market investor sentiment is bearish, and that cryptocurrencies can serve as an alternative investment vehicle. They also noted that the results remain unaffected even after considering potential factors affecting cryptocurrency prices. (Brahim Gaies, 2021) used a nonlinear autoregressive variance-lag model to analyze the impact of the Bitcoin Misery Index as a measure of investor sentiment on Bitcoin returns. The results show that bearish shocks have a greater impact on Bitcoin returns over the long term than bullish shocks. (Shaen Corbet. Charles James Larkin, Brian Lucey, Andrew Meegan, 2019) created a sentiment index based on post-release news of four macroeconomic indicators. H. GDP, unemployment, CPI, durable goods. The results show that Bitcoin returns respond differently than stock market returns. It has also been argued that cryptocurrencies' reactions to news and announcements may vary depending on the type of digital asset. (Akyildirim, Erdinc & Corbet, Shaen & Lucey, Brian & Sensoy, Ahmet & Yarovaya, Larisa, 2020) note that increased investor anxiety leads to increased volatility in cryptocurrency markets.

Sentiment Investment and Bitcoin Predictability

(Muhammad Ali Nasir, Toan Luu Duc Huynh, Sang Phu Nguyen¸ Duy Duong, 2019) Predictability of Returns from Bitcoin Volume and Google Search Volume Using Vector Auto Regression (VAR) Framework, Copulas Approach, and Nonparametric Plots of Weekly Data from 2013 to 2017 I checked. Their results show that increasing search volume has a positive impact on Bitcoin returns and trading volume. (Muhammad Abubakr Naeem, Imen Mbarki and Syed Jawad Hussain Shahzad , 2021) examined the impact of investor sentiment on the returns of six major cryptocurrencies using two proxies: the FEARS index and Twitter happiness. Happiness Index Significantly Predicts Returns for Selected Individuals The predictability of the FEARS index is weak and short-term. In a recent publication, (Anupam Dutta, 2022)examined volatility spillovers across

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15 major cryptocurrencies, given the impact of investor sentiment. The Twitter feed was peroxide for investor sentiment with a dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model to measure the impact of investor sentiment on volatility spillover across cryptocurrencies. Used as a result, we find that highly dissatisfied investors show higher market volatility and greater attachment to the market, whereas very satisfied investors show lower overall attachment. If the excess volatility between assets is low, these assets can be used as mutual hedging tools. The results of this paper suggest that diversification opportunities between cryptocurrencies are possible for satisfied investors. Results from both studies suggest that feelings of euphoria or anxiety have different effects, and that level of happiness also plays a role.

Methodology

Econometric Model and Method of Research

In this work, we use the Pooled Mean Group (PMG) estimator econometric method to investigate both research hypotheses. That model is:

$$\text{Sentiment}_{it} = \sum_{j=1}^{p} \theta_{ij}\ \text{sentim}_{i.t-j} + \sum_{j=1}^{n} \beta_{ij} OP_{i.t-j} + \sum_{j=1}^{n} \beta_{ij} CPI_{i.t-j} + \sum_{j=1}^{n} \beta_{ij} CURR_{i.t-j} \sum_{j=1}^{n} \beta_{ij} LIQ_{i.t-j} + \sum_{j=1}^{n} \beta_{ij} INTERB_{i.t-j} + \sum_{j=1}^{n} \beta_{ij} GDPR_{i.t-j} + \mu_i + \varepsilon_t$$

To remove the bias caused by non-uniform gradients in dynamic panel models such as the generalized method of moments (GMM) with long time horizons, (M.Hashem Pesaran, 1995)and (M. Hashem Pesaran, Yongcheol Shin and Ron P. Smith , 1999) proposed two estimates presenting the quantity group (MG) and pooled mean group (PMG). The MG and PMG estimation methods apply the ARDL model to panel data and, like ARDL, include lags in the dependent variable that can indicate the dynamics of the panel model. The MG method first estimates the ARDL model for each intersection and computes the mean of the estimated coefficients. Using this estimator, the intercept, slope coefficient, and variance may differ between groups. In the PMG method, the intercept, short-term coefficients, and residual variances can differ between mean groups, but they are the same across groups because no constraint is applied to the long-term coefficients in this method (e.g., fixed-effects estimate vessel). MG and PMG methods with sufficiently large lags provide super-consistent estimators of long-term parameters even when the regressor is I (1) (Pesaran, Shin, and Smith, 1999). The Hausman test is used to

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choose between the two estimators, MG and PMG. The null hypothesis is the use of the PMG method and the alternative is the use of the MG method

Research Variables

Gold and Bitcoin prices were extracted from www.tradingeconomics.com. Various studies have used two types of direct and indirect measures of mood (Malcom Baker, Jeffery Wurgler, 2006). This study uses his four proxies of trade volume, trade value, number of new investor accounts and number of monthly trades using the method given that the study is conducted at the industry level. I extracted the sentiment quotient. The first principal component of principal component analysis (PCA) was used as a sentiment indicator in this study. One advantage of the PCA method is that it indexes and combines variables that exhibit high multicollinearity with each other.

Results

Descriptive Statistics

Table 1. Descriptive statistics

Statistics	GOLD	BTC
Mean	1840.775	1825.969
Median	1830.700	1817.310
Maximum	2063.020	1681.740
Minimum	1682.740	2048.840
Std. Dev.	70.03040	64.43762
Skewness	0.365710	0.354764
Kurtosis	2.653154	2.773871
Jarque-Bera	12.96903	10.97573
Probability	0.001527	0.004137
Sum	874368.2	867335.2
Sum Sq. Dev.	2324618.	1968146.
Observations	475	475

[1] Table 1 shows descriptive statistics for the model variables. The average raw gold price for this period is around $1678, peaking at $1840 in March 2020 as the global gold price rises.

Correlation between Variables

Table 2 shows the correlations between study variables. As you can see there is relatively high correlation between the variables and possible multicollinearity between them.

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Table 2. Matrix correlation

	GOLD	BTC
BTC	0.1780472667407893	1
GOLD	1	0.1780472667407893

Investigating the stationary of Variables and Model Co integration

Table 3. Co integration

	t-statistic	Prob.*	z-statistic	Prob.*
GOLD	-3.686888	0.0201	-20.77794	0.0457
BTC	-3.113236	0.0877	-17.71187	0.0858

Cointegration tests are used to examine long-term relationships between model variables. Panel models use methods like Kao and Pedroni to explore cointegration between variables. In this study, we used the method of Pedroni (2004) to examine the cointegration of the tested models. This procedure allows non-uniformities to exist in the intersections and slopes of the cointegration equations. Pedroni's cointegration test uses residuals from long-term regression estimates and its general equation is defined as: $Y_{it} = \alpha_i + \theta_i t + \beta_1 X_{1t} + \beta_2 X_{2t} + \cdots + \beta_{mi} X_{mit} + \varepsilon_{it}$

Where i represents the cross, t denotes the time period, and m refers to the number of explanatory variables. The variables α_{i} and θ_{i} make it possible to study the fixed effects of the section as well as deterministic trends. $\varepsilon_{\mathrm{it}}$ denotes the estimated residuals of the long-term relationships (Pedroni, 2004).

Table 4. Pedroni's cointegration test

		Within-dimension (panel)			Between-dimension (group)		
	v-statistic	p-statistic	PP-statistic	ADF-statistic	p-statistic	PP-statistic	ADF-statistic
GOLD	2.980***	-9.132***	-7.978***	-2.175***	-7.843***	-5.913***	-0.4251
BTC	4.274***	-7.528***	-5.264***	0.126***	-8.196***	-7.181***	0.2942

$***$,$**$ and $*$ indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 shows the results of Pedroni's cointegration test between the variables tested in the model. All estimated models have probability levels higher than 0.05%, thus proving the hypothesis of cointegration between model variables. Also, when estimating with the panel ARDL method as described above, it is necessary to select which estimation method, MG or PMG, is more appropriate. A Hausman test performed on all

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models show that the p-value for the Hausman test is greater than 0.05%, making PMG a better method for estimating the models.

Results of Model Estimation in Long-term and Short-term

The long-term model estimation results for the various groups reported in Table 5 and the short-term model estimation results are shown in Table 6.

Table 5. PMG long-run estimates

	coefficient	t-statistic
GOLD	0.719640	10.19***
BTC	0.641285	8.763***

***,** and * indicate statistical significance respectively at 1%, 5% and 10% level.

As the long-term relationship results in Table 5 show, there is a positive and significant relationship between the price of gold and investor sentiment, and the impact of the price of gold on investor sentiment Medium, 0.05 percent.

Table 6. PMG short-run estimates

Variable	Coefficient	t-Statistic
GOLD(-1)	0.719640	10.19***
GOLD(-2)	-0.618557	-7.956***
GOLD(-3)	0.411788	5.472***
GOLD(-4)	-0.172500	-3.016***
BTC	0.229752	3.580***
BTC(-1)	0.641285	8.763***
BTC(-2)	-0.439330	-5.405***
BTC(-3)	0.317095	4.296***
BTC(-4)	-0.111711	-2.554***

***,** and * indicate statistical significance respectively at 1%, 5% and 10% level.

Table 6 shows the short-term relationship between 'gold price and other control variables' and 'investor sentiment' for three different models. The delays for these models are automatically chosen based on the Akaike information criterion. For short-term testing, the primary focus is on error correction model (ECM) coefficients. This indicates the speed of adjustment in variable relationships between short and long term. As the results show, gold's adjustment speed is faster and faster than BTC.

Conclusion and Suggestion

This study examines the sentiment spillover dynamics between the gold price and the Bitcoin market over the period 04/08/2020 to 04/08/2022. In particular, variance-resolved spectral plots are used to measure sentiment spillover for the short, medium, and long-term components. The empirical results of this study have several important implications. First, the study shows that the price of gold is a key factor influencing investor sentiment.

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Gold price volatility should therefore be taken into account when examining the sources of investor sentiment. Moreover, this finding enables investors to make more effective decisions by using gold market information. In addition, considering that gold prices have significant long-run and short-run effects on investor sentiment, individual and institutional investors should focus more on this linkage and adjust their investment strategies over time and investors may benefit from these insights for hedging activities in the bitcoin market. The effects of gold price changes on investor sentiment at the market and industry level, examining the two-way relationship between gold price and the bitcoin market. By understanding the intensity and frequency components of these spillover effects, investors with different investment horizons can improve their portfolio diversification and hedging strategies when forecasting portfolio market risk exposures among these hedging assets. With regard to policymakers, by closely identifying the major transmitter and receiver of these spillover effects between the gold price and the Bitcoin market over different periods, they can be better prepared to protect against contagion risk and to foster market stability. Further studies should focus on the transmission mechanisms underlying the discovered spillover dynamics and identify the determinants of such spillover effects.

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Appendix

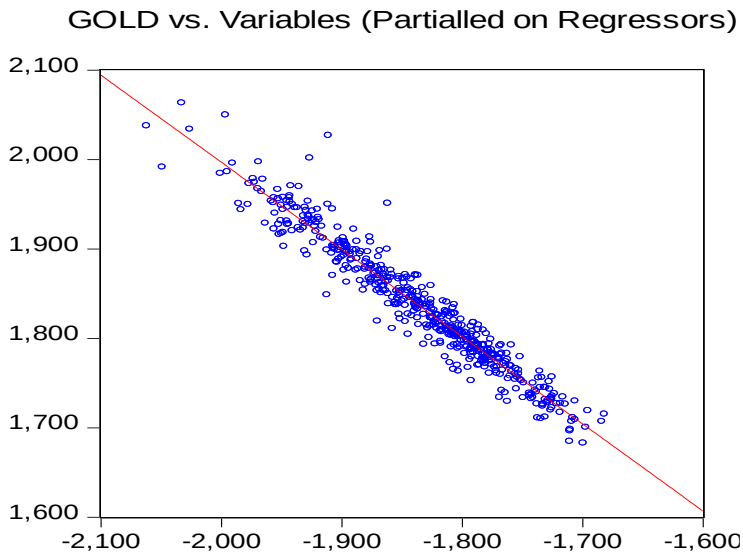

Figure 9. Partialled on Regressors

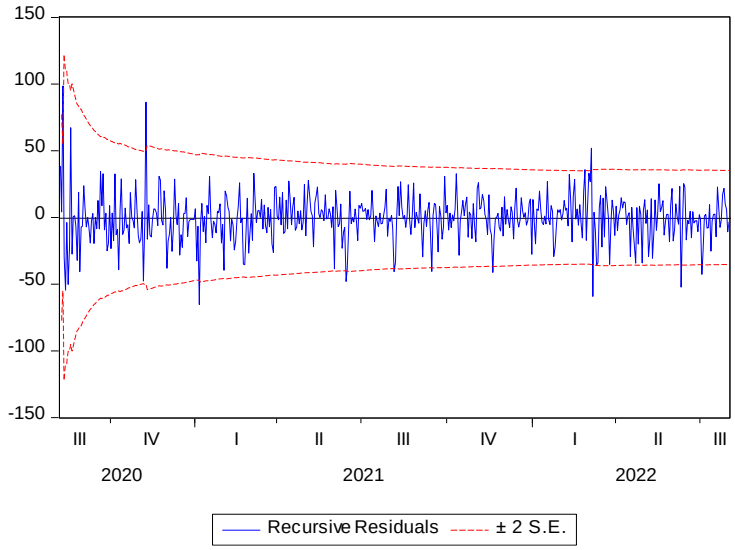

Figure 10. Recursive residuals are independent and identically distributed, and unlike normal residuals, some imperfections in the data don't smear all residuals. Additionally, recursive residuals can be interpreted to show the effect of successively removing observations from the dataset.

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