A Local Premium and Fluctuations: An Empirical Study on KorBit and the International Market

Jae-Young Kim and Joon-Hyuck Lee

Bitcoin, the first cryptocurrency created by Satoshi Nakamoto in 2009, has attracted considerable attention. The price of Bitcoin rose from $500 in the year 2014 to $70,000 in 2021, an astonishing 14,000% increase in the value, showing that it is a highly speculative asset. The Korean virtual currency exchange, KorBit, has emerged as a significant player in the global Bitcoin market, gaining considerable attention with a nontrivial premium known as the “kimchi premium”. We investigate how the Bitcoin’s value fluctuates and co-fluctuates across two markets of KorBit and international Bitcoin market (IntBit) based on a multivariate GARCH. We also explore what factors drive a relatively high yield and fluctuations in KorBit over IntBit. We have found that when the volatilities of Bitcoin’s yields in the two markets are contemporaneously high with a premium in KorBit, the correlation of the yields between the two markets decreases and highly fluctuates. We have also found that a relatively high yield of Bitcoin and its fluctuations in KorBit are mainly caused by depreciation of the Korean won and gains of KOSPI over S&P500.

Keywords: Bitcoin, multivariate GARCH, kimchi premium

JEL Classification: C32; C58; G15

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I. Introduction

Bitcoin, the first cryptocurrency created by Satoshi Nakamoto in 2009, has experienced an unprecedented surge in global popularity, becoming a highly speculative asset. Its value has skyrocketed from $500 in 2014 to over $70,000 in 2021, making it an attractive investment option for traders worldwide. The Korean virtual currency exchange, KorBit, has emerged as a significant player in the global Bitcoin market, gaining considerable attention with a nontrivial premium known as the “kimchi premium”. In this paper we examine time-varying nature of volatility and co-volatility of Bitcoin’s yield across KorBit and the international Bitcoin market (IntBit) based on a multivariate GARCH. We also explore what factors drive a relatively high yield of Bitcoin and its fluctuations in KorBit over IntBit.

There has been an increasing amount of research conducted on various aspects of Bitcoin and cryptocurrencies, including market dynamics and price formation. Woo *et al.* (2013), Bergstara and Leeuw (2013), and Huhtinen (2014) investigate the potential long-term scale of cryptocurrencies; Garcia *et al.* (2014) estimate the intrinsic value of Bitcoin. Kristoufek (2015) explores factors that influence the price of Bitcoin while Morten *et al.* (2015) analyze the role of different exchanges in the price of Bitcoin. Ciaian *et al.* (2015) analyze market supply and demand and the impact of investment on the price of Bitcoin. Also, He (2019) used statistical analysis to examine the relationship between the volatility of Bitcoin and various traditional financial instruments. Additionally, Lee and Rhee (2022) analyzed the relationship between the price of Bitcoin and US macroeconomic variables using a vector error correction model.

On the other hand, there has been considerable interest among researchers in arbitrage in the cryptocurrency markets. For instance, Choi *et al.* (2020) study the “kimchi premium” focusing on the period between January 2016 and February 2018. Kroeger and Sarkar (2017) analyze price differences between Bitcoin exchanges traded within the U.S. and found that these differences persist for a significant period of time. Kim *et al.* (2018) study effects of technical and institutional factors causing price difference between domestic and international markets. Jung (2018) compares traditional exchange rates with cryptocurrency price ratios for arbitrage analysis while Makarov and Schoar (2020) demonstrate repetitive arbitrage in the cryptocurrency market. Also, Park (2022) analyzes arbitrage transactions occurring in Korea.

In this paper we explore how the Bitcoin's yield fluctuates and co-fluctuates over time in KorBit and IntBit. We also explore what factors drive a relatively high yield of Bitcoin and its fluctuations in KorBit over IntBit. For the analysis of time-varying volatility and co-volatility we employ a multivariate GARCH (m-GARCH) introduced in Bolleslev (1988). Several authors have employed GARCH-type models to analyze the volatility of cryptocurrency prices, for example, Katsiampa (2017), Chu *et al.* (2017), Gyamerah (2019) and Lee (2018). All these existing analyses, however, adopted univariate GARCH type models.

Our analysis based on a bivariate m-GARCH enables us to find the pattern of evolution of individual fluctuations and co-fluctuation of Bitcoin values in two markets. To the best of our knowledge, our study is the first one in the literature adopting a multivariate GARCH for analyzing dynamics of Bitcoin values. We find clear and interesting features of fluctuations and co-fluctuation in the two markets. In particular, we have found that when the volatilities of Bitcoin's yields in the two markets are contemporaneously high with a premium in KorBit, the correlation of the yields between the two markets decreases and highly fluctuates.

Finding discrepancy in the time-varying volatility and co-volatility of Bitcoin's yields in the two markets, we study what factors affect the 'premium', or relatively high yield of Bitcoin in KorBit over IntBit. We consider key financial factors, such as the spread of 3-month bill rates, the spread of rates of return of stock markets in the two markets, and the growth rate of the dollar exchange rate of Korean won. We have found that the latter two factors are statistically significant for the premium while the first one is not. Our model for determinants of the premium has overall significance by the F-test.

Our discussion in this paper proceeds as follows. Section 2 studies, based on a bivariate m-GARCH, dynamic volatility and co-volatility of Bitcoin's yields in the two markets of KorBit and IntBit. We first explain the model and data to be used in our analysis and present results of the analysis. Section 3 investigates what factors affect the 'premium', or difference of Bitcoin values, in KorBit over IntBit. As in section 2 we explain first the model and data to be used in our analysis and present results of the analysis. Section 4 provides concluding remarks.

II. Time-Varying Volatility in Bitcoin Markets

A. The Bivariate m-GARCH Model

In general, for volatile assets like stock prices, time-varying nature of volatility is of crucial interests for investors as well as researchers. An increase in volatility can lead to a phenomenon known as "volatility clustering". In this case the high level of volatility persists for a certain period of time, challenging the traditional assumption of constant volatility. Autoregressive conditional heteroscedasticity (ARCH) introduced by Engle (1982) and Generalized ARCH (GARCH) of Bolleslev (1986) are now commonly used to describe and forecast changes in the volatility of financial time series. For a survey of ARCH-type models, see Bollerslev *et al.* (1992, 1994), Bera and Higgins (1993), Pagan (1996), among others.

In the case of Bitcoin, long-term persistence of volatility and clustering have been observed as in the case of other volatile assets such as stock prices. Several authors have studied these features of Bitcoin prices and yields based on ARCH and GARCH type models, for example, Katsiampa (2017), Chu *et al.* (2017), and Gyamerah (2019).

On the other hand, it is now widely undersood that volatilities of financial assets in different markets move together over time. A multivariate setup would be more appropriate for anlyzing such phenomina than a univariate model. We emply an m-GARCH model introduced by Bolleslev (1988) for modelling time-varying volatility and co-volatility. See Bauwens *et al.* (2006) for survey. Employing an m-GARCH for the analysis of volatilities across markets allows us to study such issues as (1) Is the volatility of an asset in a market transmitted to another market?; Does the transmission proceed directly (through its conditional variance) or indirectly (through its conditional correlations)? (2) Does the correlations between markets change over time. Are they higher during periods of higher volatility?

In this section we use a bivariate m-GARCH model for analyzing evolution of individual fluctuations and co-fluctuation of Bitcoin yields in KorBit and IntBit. For simplicity, consider a bivariate m-GARCH (1,1). Thus, let y_t be a (2x1) vector of time series such that

$$y_t = C + \varepsilon_t, \ \ \varepsilon_t \mid \Omega_t \sim N(0, H_t) \tag{1}$$

where Ω_t is the information set available at t; C is a (2×1) vector of constants, and H_t is a (2×2) matrix such that

$$
\begin{aligned}
& H_t = D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}}, \\
& D_t = diag(\sigma_{1,t}^2, \quad \sigma_{2,t}^2) \\
& \qquad for \ \ \sigma_{i,t}^2 = c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2, \ i = 1, 2 \\
& \qquad and \ R_t = diag(Q_t)^{-\frac{1}{2}} Q_t \ diag(Q_t)^{-\frac{1}{2}}, \\
& Q_t = (1 - \lambda_1 - \lambda_2)\Sigma_u + \lambda_1 u_{t-1} u_{t-1}' + \lambda_2 Q_{t-1},
\end{aligned}
\tag{2}
$$

where $u_t = V^{-\frac{1}{2}} \varepsilon_t, V = diag(\upsilon_1, \cdots, \upsilon_T)$ for $\upsilon_t = \mathrm{var}(\varepsilon_t)$, and $\sum_u$ is the unconditional variance-covariance matrix of u_t. Here, $\sigma_{i,t}^2$ is the conditional variance of $\varepsilon_{i,t}$, given Ω_t. The off-diagonal element of H_t is the conditional correlation of $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$. See Bauwens (2006). We may have an m-GARCH of higher orders than the one in (1)-(2) with additional lagged terms of $\varepsilon_{i,t}^2$ and/or $\sigma_{i,t}^2$ on the right hand side (RHS) of the equation for $\sigma_{i,t}^2$ and corresponding additional terms of RHS of the equation for Q_t.

B. Data

The data for our analysis of a bivariate m-GARCH are as follows. The data for Bitcoin prices traded in KorBit were obtained from bitcoincharts.com/ while those of the international market were obtained from historical data provided by investing.com/. The data period is from January 1, 2015 to November 30, 2022. The Bitcoin prices in KorBit was adjusted by dividing it by the dollar exchange rate. The variable for our analysis with the bivariate m-GARCH is the rate of return, or yield, of Bitcon defined as in the following:

$$Rate\ of\ Return = \frac{P_t}{P_{t-1}} - 1\,(t:\ daily),$$

where P_t is the price of Bitcoin at time t.

The Bitcoin prices and the yield rates are shown in Figure 1 and 2, repectively.

The basic statistics of yield series in KorBit and international

red line: International, blue line: KorBit

Figure 1
Bitcoin Prices in KorBit and International Markets

red line: International, blue line: KorBit

Figure 2
Bitcoin Yield Series in KorBit and International Markets

markets are presented in Table 1. Upon conducting an ARCH(5) test for the absence of ARCH effects, we have strong evidence in favor of the existence of ARCH effects with very small p-values (the last line in Table 1).

For applying the GARCH model it is necessary to ensure that the yield series is stationary. The results of applying the Augmented Dickey-Fuller t-test to the yield series are presented in Table A of Appendix along with results for the other time series used in Section 3. We can see in Table A that the null of unit root is strongly rejected with the p-value much less than 1% for the yield series. We select m-GARCH(1,1) based on Bayesian information criterion used in Kim and Park (2018).

TABLE 1
BASIC STATISTICS FOR THE YIELD RATES BITCOIN

Basic Statistics	KorBit	International
number	2911	2911
mean	0.002109	0.002140
median	0.001070	0.001643
maximum	0.309495	0.272286
minimum	-0.342666	-0.391816
std. dev.	0.038324	0.039081
skewness co.	0.04360668	-0.1837199
kurtosis co. (cf. Normal : 0)	10.428	8.110499
p-value of ARCH(5) test	< 2.2*e-16	< 2.2*e-16

C. Results of Fitting Bivariate m-GARCH

Tables 2 shows the results of fitting the bivariate m-GARCH(1,1). All the coefficients are estimated to be statistically significant as reflected by the p-values.

Figures 3 and 4, respectively, show the series of conditional variances and conditional covariances estimated by the bivariate m-GARCH. As we can see in Figure 3 there are sub-periods of considerable volatility clustering. In the sub-periods of volatility clustering the conditional variances of Bitcoin yield in KorBit are substantially higher than that in IntBit. Also, as we can see in Figure 4 the conditional correlation of yields between the two markets decreases, fluctuating considerably. This is confirmed in Table 4, where variances and correlation in the table are obtained by estimating them in each of the sub-periods.

TABLE 2
MODEL FIT

Model : DCC m-GARCH (Bouwens (2006))
Number of obs. : 2921, Log likelihood = 14895.58

KorBit	estimates	st. error.	z	P>|z|	IntBit	estimates	st. error.	z	P>|z|	Corr	estimates	st. error.	z	P>|z|
C	.001418	.0005084	2.79	0.005	C	.0017501	.000559	3.13	0.002	λ_1	.0917861	.008327	11.02	0.000
α	.2258654	.0161769	13.96	0.000	α	.2065101	.014704	14.04	0.000					
β	.7710401	.0139157	55.41	0.000	β	.7861149	.012376	63.52	0.000	λ_2	.8709513	.0125237	9.54	0.000
c	.0000813	9.74e-06	8.35	0.000	c	.0000918	.000010	8.82	0.000					

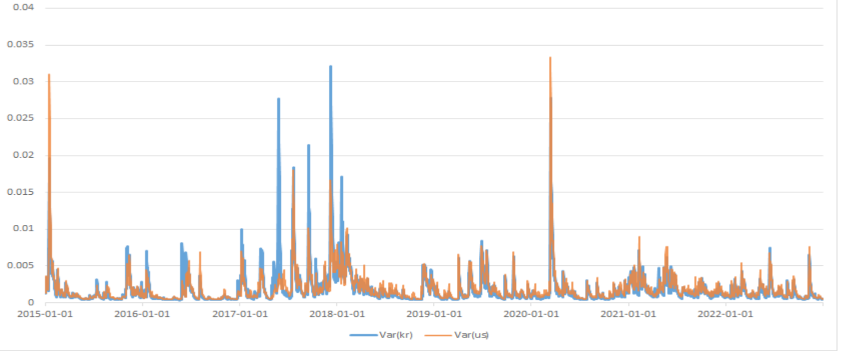

Figure 3
Conditional Variance

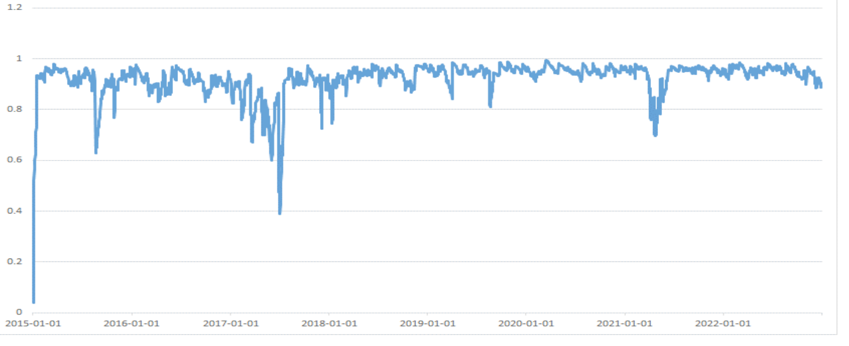

Figure 4
Conditional Correlation

Table 3
Variance and Correlation of Bitcoin in Sub-periods

sub-periods	variance in KorBit	variance in IntBit	correlation
2015.01.01 ~ 2015.05.01	0.00209	0.00273	0.96433
2015.05.01 ~ 2016.01.01	0.00083	0.00076	0.89430
2016.01.01 ~ 2017.01.01	0.00069	0.00066	0.91570
2017.01.01 ~ 2018.02.01	0.00343	0.00259	0.83402
2018.02.01 ~ 2021.02.01	0.00127	0.00154	0.96679
2021.02.01 ~ 2021.08.01	0.00175	0.00210	0.91732
2021.08.01 ~ 2022.12.31	0.00092	0.00115	0.97458

*The sub-periods are determined rather arbitrarily by looking at Figures 3 and 4.

III. Determinants of a Premium in Bitcoin Yields

In the previous section we have found that there is nontrivial discrepancy in fluctuations and co-fluctuation of Bitcoin yields in the two markets. In this section we study what factors affect the difference of Bitcoin yields in KorBit and IntBit. We consider the difference in the level of yields as well as the conditional volatilities and investigate their determinants.

A. The Model for the Difference

As determinants of the difference in the level and the conditional volatility of Bitcoin yields we consider key financial factors, such as the spread of 3-month interest rate of Korea over that of the U.S., the spread of rate of return of KOSPI over S&P500, and the growth rate of the dollar exchange rate of Korean won. There are other factors that might affects the difference such as technical and institutional aspects as considered in Kim *et al.* (2018). These other factors, creating market friction, would amplify the difference caused by the financial factors considered in this paper.

Let S_t be either the difference in the levels of Bitcoin yields between KorBit and IntBit or the difference in the conditional volatilities of Bitcoin yields between the two markets. Also, let X_t, I_t, and E_t, respectively, be the spread of stock yield of KOSPI over S&P500, the interest rate spread of Korean 3month call rate over U.S. 3-month T-bill rate, and the growth rate of the dollar exchange rate of Korean won:

$$\begin{aligned} S_t &= \Delta \ln BTC_t^{KR} - \Delta \ln BTC_t^{US}, \\ X_t &= \Delta \ln KOSPI_t - \Delta \ln SP500_t, \\ I_t &= r_t^{KR} - r_t^{US}, \\ E_t &= \Delta \ln e_t, \end{aligned}$$

where Δ denotes the difference.

We consider a linear model for S_t to depend on the factors X_t, I_t, and E_t:

$$S_t = \beta_0 + \beta_1 X_t + \beta_2 I_t + \beta_3 E_t + \beta_4 S_{t-1} + \upsilon_{t,} \tag{3}$$

where υ_t is an error term with zero mean and a finite variance.

B. Estimation Results

We estimate coefficients in (3) by the instrumental variable (IV) method. We use lagged values of the regressors X_t, I_t and E_t as IVs as in many cases of time series analysis. In other words, our IV set is $\{X_{t-1}, I_{t-1}, E_{t-1}, S_{t-1}\}$. We have the estimation results in Tables 4 and 5, respectively, the estimation result for the level difference of yields and for that of difference in conditional volatilities.

As is shown in Table 4 and Table 5 the two factors X and E, the spread of stock yields of KOSPI over S&P500 and the growth rate of the

TABLE 4

	estimates	std error	t-stat	p-value
constant	0.000273	0.000508	0.5367	0.5915
X (stock yield spread)	0.063059	0.030071	2.0970	0.0361
I (interest spread)	-0.00043	0.000702	-0.6188	0.5360
E (Δln(exchange rate))	0.360548	0.078184	4.6115	4.3E-06
S_1	-0.11626	0.024253	-4.7938	1.7E-06

Overall Statistics	
Number of obs.	1656
R-square	0.0309
R-bar square	0.0285
F-ratio (p-value)	13.14353 (1.5E-10)

TABLE 5

	estimates	std error	t-stat	p-value
constant	0.002626	0.001062	2.4727	0.0136
X (stock yield spread)	0.108414	0.046202	2.3465	0.0249
I (interest spread)	-0.000802	0.001386	-0.5778	0.5632
E (Δln(exchange rate))	0.810836	0.174722	4.6407	4.2E-06

Overall Statistics	
Number of obs.	1655
R-square	0.0247
R-bar square	0.0236
F-ratio (p-value)	13.9898 (1.6E-10)

dollar exchange rate of Korean won, are statistically significant both for the differences in the levels and for the difference in conditional variances of Bitcoin yields in KorBit and IntBit. Our model shows overall significance of the model by the F-test both in Tables 4 and 5. The sign of estimated coefficients are the same in the two tables, reflecting that increase in the level difference of yields goes along with increase in the difference in the conditional volatility.

The positive sign of estimated β_3 implies that investors of Bitcoin in KorBit choose a relatively cheaper Bitcoin in KorBit, pushing up the price harder in KorBit. On the other hand, the positive sign of estimated β_1 implies that a bullish domestic stock market pushes up activity in KorBit, which might be led by easy financial conditions. These push-up forces in KorBit might be amplified by government regulations for cryptocurrency trades in Korea.

IV. Concluding Remarks

In this paper, we studied two subjects: (1) How the Bitcoin's yield fluctuates and co-fluctuates across two markets of KorBit and IntBit, and (2) what factors drive a relatively high yield of Bitcoin and its fluctuations in KorBit over IntBit.

For (1) our estimation results show that the volatilities in the two markets vary together with the correlation remains above 0.8 in the majority of data period. We have also found that when the volatilities of Bitcoin's yields in the two markets are high with a premium in KorBit, the correlation of the yields between the two markets decreases and highly fluctuates. These finding for (1) imply that (i) the volatility of an asset in a market transmitted to another market quickly, (ii) the indirect route of the transmission (through the conditional correlation) is weaker at times of high volatilities in individual markets. (iii) the conditional correlations between markets change considerably over time, and they are lower during periods of higher volatility. However, we did not go in more detail about the transmission mechanism and about causal relation between individual volatilities and co-volatility. These are left for future research.

On the other hand, for (2) we have found that a relatively high yield of Bitcoin and its fluctuation in KorBit are caused by depreciation of the Korean won and gains of KOSPI over S&P500. The former finding for (2) implies that investors of Bitcoin choose a relatively cheaper Bitcoin in KorBit (with a cheaper Korean won), pushing up the price harder in KorBit. The latter finding for (2) implies that a bullish domestic stock market pushes up activity in KorBit, increasing relative price in KorBit. In analyzing (2) we did not consider other factors that may in reality affect the premium in KorBit such as institutional and technical factors, or government regulations. These other factors may cause market frictions, restricting trades or increasing transaction costs and affect magnitude of difference in levels and volatilities across markets. A more comprehensive study including these other factors is also left for future research.

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Appendix

Table A1
ADF-τ FOR A UNIT ROOT

Variables/ADF-t

KorBit Yield	IntBit Yield
-37.2751	-38.6306

critical values: 1% (-2.58), 5% (-1.95), 10% (-1.62)

Variables/ADF-t

Bit Yield Spread	Stock Yield Spread	Interest Spread	Rate of Exch Growth
-33.3767	-34.9554	-1.989	-29.0139

critical values: 1% (-2.58), 5% (-1.95), 10% (-1.62)

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