

The Relationship Between Bitcoin Returns, Volatility, And Volume Using Asymmetric Garch Modelling

Carel Dwinugrahadhi Kurnaman¹, Nora Amelda Rizal²

^{1,2} Faculty of Economics and Business, Telkom University, Bandung, Indonesia

*Corresponding: carelkurnaman@student.telkomuniversity.ac.id

Abstract

In 2020-2021 where the world experienced a Covid-19 pandemic, the price of Bitcoin increased and there was a fairly high price spike at the turn of the year 2020-2021 and had touched an all-time high (ATH) at the end of 2021. Bitcoin is one of the currencies crypto that is volatile when compared to the exchange rates of widely used currencies. In addition, Bitcoin price movements are difficult to predict. The samples used are Euro, Pound Sterling, Yuan, Yen, Ruble, Franc, and Bitcoin. The data used is in the form of Bitcoin price data and some of these currencies in 2020-2021. This study aims to find the relationship between volatility with Bitcoin trading volume, return with Bitcoin trading volume, and return with Bitcoin volatility for forecasting purposes. The research method used is the Augmented Dickey-Fuller (ADF) stationarity test, then using the ARMA model after that using the EGARCH model to find the relationship. The results of this study indicate that there is a positive relationship between volatility and Bitcoin trading volume. Just like the return and trading volume of Bitcoin there is a positive relationship. However, Bitcoin returns, and volatility have a negative relationship. For further research can use different crypto currency assets with different time periods.

Keywords: Volatility, Volume, Returns, Bitcoin, GARCH

Abstrak

Pada tahun 2020-2021 dimana dunia mengalami pandemi Covid-19, harga Bitcoin meningkat dan terjadi lonjakan harga yang cukup tinggi pada saat pergantian tahun 2020-2021 dan sempat menyentuh all time high (ATH) pada akhir tahun 2021. Bitcoin merupakan salah satu mata uang crypto yang bersifat fluktuatif bila dibandingkan dengan nilai tukar mata uang yang biasa digunakan secara luas. Selain itu, pergerakan harga Bitcoin sulit untuk diprediksi. Sampel yang digunakan adalah mata uang Euro, Poundsterling, Yuan, Yen, Rubel, Franc, dan Bitcoin. Data yang digunakan berupa data harga Bitcoin dan beberapa mata uang tersebut pada tahun 2020-2021. Penelitian ini bertujuan untuk mencari hubungan antara volatilitas dengan volume perdagangan Bitcoin, return dengan volume perdagangan Bitcoin, dan return dengan volatilitas Bitcoin dengan tujuan peramalan. Metode penelitian yang digunakan adalah uji stasioneritas Augmented Dickey-Fuller (ADF), lalu menggunakan uji ARMA model, setelah itu menggunakan model EGARCH untuk mencari hubungan tersebut. Hasil penelitian ini menunjukkan bahwa volatilitas dan volume perdagangan Bitcoin terdapat hubungan positif. Sama seperti return dan volume perdagangan Bitcoin terdapat hubungan positif. Namun, return dan volatilitas Bitcoin terdapat hubungan negatif. Untuk penelitian selanjutnya dapat menggunakan aset mata uang kripto berbeda dengan periode waktu yang berbeda.

Kata kunci: Volatilitas; Volume; Return; Bitcoin; GARCH

I. INTRODUCTION

Research on the relationship between, return, volatility, and volume has been carried out previously by several previous studies, namely (Acharya & Pradhan, 2019; Chiang et al., 2010; Chuang et al., 2012; Mahajan & Singh, 2013; Medeiros & Doornik, 2006; Miseman et al., 2019) but with the stock object. They use different stock objects, Medeiros & Doornik (2006) use Brazilian stock market, Chiang et al. (2010) use NASDAQ stock market, Chuang et al. (2012) use Asian stock market, Mahajan & Singh (2013) use Indian stock market, Miseman et al. (2019) use South Asian markets, and Acharya & Pradhan (2019) use Nepal Stock market. They argue that trading volume has a relationship or effect on return and volatility.

Some previous researchers have argued that trading volume can be a consideration for predicting return and volatility in capital market stocks. For example, according to Baklaci & Kasman (2006) argues that trading volume can affect stock returns and volatility. Osei-Wusu (2011) argues that trading volume has asymmetric impact on volatility and return. Tripathy (2018) argues that trading volume can be used to predict returns and volatility. Trading volume and stock returns volatility have a positive and significant relationship (Kalu, 2014; Oral, 2012; Samman & Al-jafari, 2015).

In addition, other previous studies conducted research on the relationship between return, volatility, and trading volume using bitcoin or cryptocurrency objects, namely (Bouri et al., 2019; Foroutan & Lahmiri, 2022; Kokkinaki et al., 2019; Sapuric et al., 2020; Yousaf & Yarovaya, 2022). They use bitcoin object and some other cryptocurrency. Kokkinaki et al. (2019) and Sapuric et al. (2020) argues that volume and volatility have a positive relationship, volume and return have a positive relationship, as well as return and volatility which have a positive and significant relationship. Bouri et al. (2019) argues that trading volume can predict volatility and returns. Foroutan & Lahmiri (2022) argues that return-volume has a significant relationship as well as return-volatility. Yousaf & Yarovaya (2022) argues that trading volume can predict the return and risk of cryptocurrencies.

Bitcoin (BTC) is the first decentralized digital currency, because the system works without a central bank or single administrator. Peer-to-peer (P2P) networking and transactions occur between users directly, without intermediaries/third parties. These transactions are verified by the network through the use of cryptography and recorded in a publicly distributed ledger called the blockchain. Bitcoin was invented by Satoshi Nakamoto and released as the first cryptocurrency in 2009 (Bhosale & Mavale, 2018). Bitcoin price movements are very volatile from year to year. In recent years the price of Bitcoin has not always gone up. Bitcoin does have the potential to provide big returns, but also big losses. Bitcoin has properties like speculative investment, because it has a very high volatility so that investors prefer to invest short-term in Bitcoin (Yermack, 2015).

In 2020-2021, where the world experienced a Covid-19 pandemic, Bitcoin experienced an increasing trend and there was a fairly high price spike at the turn of the year 2020-2021. The closing average price of Bitcoin in January 2020 was \$8,388 and the closing average price of Bitcoin in December 2021 was \$49,263. Bitcoin experienced a price increase of about 487.25% when calculated from the beginning of 2020 to the end of 2021. Bitcoin reached an all-time high (ATH) in November 2021 with an average closing price of \$60,621 Bitcoin (finance.yahoo.com, 2021).

Bitcoin has a very high volatility when compared to the volatility of some widely used currencies (Yermack, 2015). Bitcoin volatility is also much higher when compared to the volatility of emerging market currencies. This makes Bitcoin unable to qualify as an alternative currency (Kasper, 2017). Bitcoin cannot replace its position as a conventional currency or

medium of exchange, because Bitcoin is very volatile and has high volatility (Baur & Dimpfl, 2018). Bitcoin returns are more volatile compared to gold and some commonly used currencies (Kokkinaki et al., 2019). Bitcoin price movements are also very difficult to predict. There are no variables that can be considered to predict Bitcoin returns (Aalborg et al., 2019). In addition, Bitcoin price movements cannot be predicted using fundamental analysis, but you can rely on technical analysis to measure Bitcoin prices in the future. Information about the previous day's Bitcoin price can affect the next day's Bitcoin price (Balcilar et al., 2017).

Bitcoin trading volume can be an option to predict Bitcoin's future returns and volatility (Kokkinaki et al., 2019). Information about Bitcoin trading volume can be considered in predicting Bitcoin volatility and returns. Bitcoin transaction volume is often overlooked in predicting the volatility and return of Bitcoin. However, in some financial literature, returns and transaction volume are related, for example, exchange rates. In addition, an increase in Bitcoin returns can also cause an increase in Bitcoin volatility (Sapuric et al., 2020).

This study will use GARCH to find the relationship between Bitcoin return, volatility, and volume. In addition, GARCH is used extensively by many studies on volatility in financial literature. Some previous researchers, such as (Belhaj & Abaoub, 2015; Eddien et al., 2013; Naka & Oral, 2013; Wang et al., 2005) using GARCH to find the relationship between volatility and stock returns with trading volume. Some other researchers using GARCH to test the relationship between trading volume and volatility in stocks (Naik & Padhi, 2015; Ureche-Rangau et al., 2011). Korkmaz (2018) using GARCH to find the relationship between Bitcoin, gold, and currency exchange rates.

II. LITERATURE REVIEW

This research will continue the research conducted by (Kokkinaki et al., 2019; Sapuric et al., 2020). The purpose of the study is to show the relationship between trading volume, volatility, and Bitcoin return. The method used is secondary data by comparing the volatility between Bitcoin and several currencies and looking for the relationship between volume, return, and volatility using the asymmetric model GARCH. The results show that Bitcoin has the highest volatility compared to currencies, volume and volatility then have a positive and significant relationship such as volume and return which have a positive and significant relationship. In addition, several previous researchers who examined the stock object argued that trading volume and stock returns volatility have a positive and significant relationship (Kalu, 2014; Oral, 2012; Samman & Al-jafari, 2015). Then, some researchers who research with bitcoin or cryptocurrencies objects argue that trading volume can predict volatility and returns (Bouri et al., 2019). Foroutan & Lahmiri (2022) argues that return-volume has a significant relationship as well as return-volatility. Based on previous research that has been described, the hypotheses obtained in this study are:

H1: Volatility with Bitcoin trading volume is positively and significantly related.

H2: Return with Bitcoin trading volume is positively and significantly related.

H3: Return with Bitcoin volatility is positively and significantly related.

III. RESEARCH METHODOLOGY

This research is quantitative research using secondary data. The samples used are Bitcoin, Euro, Pound sterling, Yuan, Yen, Ruble, and Franc against the US Dollar. The data in this study was obtained from the finance.yahoo.com website in the form of daily price data for Bitcoin and several other currencies from January 1, 2020 to December 31, 2021. The sequence of data analysis techniques carried out in this study is as follows:

1. To prove that Bitcoin has a more volatile return compared to currencies, the first step is to calculate the daily return of Bitcoin and six other currencies with the following equation:

$$\Delta \text{ Exchange Rate} = \frac{ER_t - ER_{t-1}}{ER_{t-1}}$$

2. After that calculate the daily volatility of Bitcoin and six currencies by finding the standard deviation with the following equation:

$$\sigma = \sqrt{\frac{\sum(X_i - \bar{X})^2}{n - 1}} \quad (2)$$

This study uses the two equations above to test that Bitcoin returns are more volatile compared to other currencies by calculating descriptive statistics and making graphs between Bitcoin volatility and the volatility of several currencies.

3. Test the data stationarity using the Augmented Dickey-Fuller (ADF) test. Stationarity test is a time series data that has an average value and the variance does not change systematically over the time studied or can be called the average and the variance is constant. The hypotheses of the Augmented Dickey-Fuller (ADF) test are:

H0: $p > 0.01$ (H0 is accepted) = data is not stationary

H1: $p < 0.01$ (H1 accepted) = stationary data

4. Perform ARMA model test. The ARMA model test is used to detect the ARCH effect in the data residues or to show the presence of autocorrelation in the data residues. The hypothesis of the ARMA test is as follows:

H0: $p > 0.01$ (H0 accepted) = data residue no autocorrelation

H1: $p < 0.01$ (H1 accepted) = residual data has autocorrelation

5. Using the Exponential GARCH or EGARCH method. The following EGARCH equation is used to test hypotheses 1,2, and 3:

$$\text{Return} = c + b1_{(\ln \text{ Volume of Trades}_{t-1})} * \ln \text{ Volume of Trades}_{t-1} + \varepsilon_t \quad (3)$$

$$\ln = \omega + \lambda \ln \text{ Volume of Trades}_{t-1} + \alpha(|Z_{t-1}| - E[|Z_{t-1}|]) + \gamma Z_{t-1} + \beta \ln(\sigma_{t-1}^2) \quad (4)$$

IV. RESULT/FINDING AND DISCUSSION

4.1 Descriptive Statistics

Table 1. Descriptive Statistics

	BTC	EURO	POUND	YUAN	YEN	RUBEL	FRANC
Mean	0.004261	3.54E-05	5.52E-05	0.000178	-9.86E-05	-0.00032	0.000122
Median	0.002687	0	0.000112	0	-0.000105	0	0
Maximum	0.195644	0.014355	0.026588	0.013578	0.02886	0.048689	0.014073
Minimum	-0.381776	-0.020434	-0.036266	-0.012483	-0.031122	-0.084362	-0.017821
Std. Dev.	0.044521	0.004157	0.005624	0.00244	0.004708	0.009568	0.004299
Observations	522	522	522	522	522	522	522

Source: Processed data (2022)

The number of data samples used in this study was 522 with the same time period. The time period used is 2 years starting from January 1, 2020 to December 31, 2021. The following is a description of Figure 4.1, namely:

1. Bitcoin has a mean value of 0.003981 with a maximum value of 0.195644 and a minimum value of -0.381776. Bitcoin has a standard deviation of 0.041945.
2. Euro has a mean value of 0.000278 with a maximum value of 0.014355 and a minimum value of -0.020434. The euro has a standard deviation of 0.004153.
3. Pound sterling has a mean value of 0.000502 with a maximum value of 0.026588 and a minimum value of -0.036266. Pound sterling has a standard deviation of 0.005623.
4. Yuan has a mean value of 0.000173 with a maximum value of 0.013578 and a minimum value of -0.012483. The yuan has a standard deviation of 0.002438.
5. Yen has a mean value of -0.000986 with a maximum value of 0.028860 and a minimum value of -0.031122. The yen has a standard deviation of 0.004708.
6. The ruble has a mean value of -0.000313 with a maximum value of 0.048689 and a minimum value of -0.084362. The ruble has a standard deviation of 0.009567.
7. Franc has a mean value of 0.000120 with a maximum value of 0.014073 and a minimum value of -0.017821. The franc has a standard deviation of 0.004299.

4.2 Bitcoin Volatility Comparison with Currencies

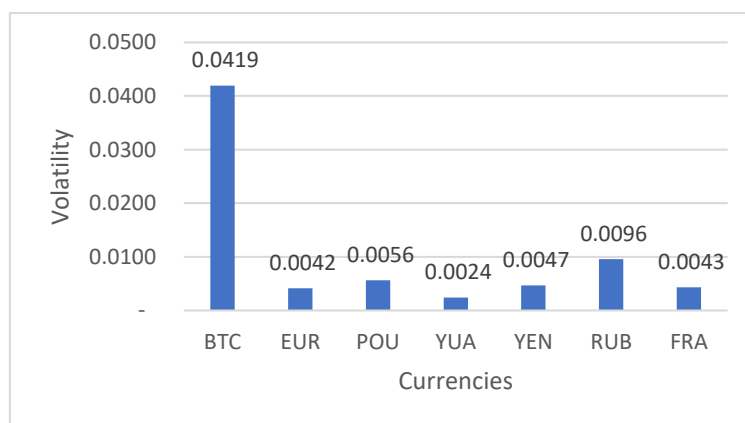


Fig 1. Volatility of Bitcoin and Multiple Currencies

Source: Processed data (2022)

Figure 1 shows that Bitcoin has the highest volatility compared to the Euro, Pound Sterling, Yuan, Yen, Ruble, and Franc. Bitcoin has a standard deviation of 0.0419, followed by the Ruble which has the second largest standard deviation of 0.0096. After that, the pound sterling has a standard deviation of 0.0056, the yen is 0.0047, the franc is 0.0043, the euro is 0.0042, and finally the yuan is 0.0024.

4.3 Stationary Test

Before conducting the EGARCH test, this study used the stationary Augmented Dickey-Fuller (ADF) test. The results of the Augmented Dickey-Fuller (ADF) test in table 2 show a probability of 0.0000. This shows that it is significant with a confidence level of = 10%, which means the null hypothesis (H0) is rejected, meaning that every data used is stationary. The following are the results of the stationarity test:

Table 2. ADF Test

Variable	Tests	Probability
Return Bitcoin	ADF	0.0000

Source: Processed data (2022)

4.4 ARMA Model Test

The ARMA model test is used to detect the ARCH effect or indicate the presence of an autocorrelation in the residual data. The results of the ARMA model test (1,1) in table 3 show that the probability is 0. This indicates a significant level of confidence = 10%, which means the null hypothesis (H0) is rejected, meaning that the residual data has autocorrelation. The following are the results of the ARMA model test:

Table 3. ARMA Model Test (1,1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003294	0.001468	2.243868	0.0251
AR(1)	-0.785916	0.10721	-7.330626	0
MA(1)	0.711341	0.124484	5.714315	0
SIGMASQ	0.001569	3.27E-05	47.93618	0
R-squared	0.014418	Mean dependent var	0.003295	
Adjusted R-squared	0.010351	S.D. dependent var	0.039929	
S.E. of regression	0.039722	Akaike info criterion	-3.608337	
Sum squared resid	1.147075	Schwarz criterion	-3.583197	
Log likelihood	1322.847	Hannan-Quinn criter.	-3.598639	
F-statistic	3.544999	Durbin-Watson stat	2.004757	
Prob(F-statistic)	0.014325			

Source: Processed data (2022)

4.5 EGARCH Test

The EGARCH test was conducted to find answers to hypothesis 1, namely the relationship between Bitcoin volatility and volume, hypothesis 2, namely the relationship between Bitcoin return, and volume, and to find answers to hypothesis 3, namely the relationship between Bitcoin return, and volatility. The following are the results of the EGARCH test:

Table 4. EGARCH Test (1,1)

Hypotheses 1 and 3				
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003324	1.93E-03	1.17E+00	0.0856
DLOG(VOLUME)	0.003302	0.006568	0.502817	0.6151
Variance Equation				
C(3)	-0.462162	0.119827	-3.856895	0.0001
C(4)	0.106074	0.027057	3.920377	0.0001
C(5)	-0.096749	0.013991	-6.915007	0
C(6)	0.939791	0.016811	55.90213	0
R-squared	-0.000936	Mean dependent var	0.002564	
Adjusted R-squared	-0.002319	S.D. dependent var	0.041203	
S.E. of regression	0.041251	Akaike info criterion	-3.615026	
Sum squared resid	1.231965	Schwarz criterion	-3.577112	

Log likelihood	1318.254	Hannan-Quinn criter.	-3.600395
Durbin-Watson stat	2.171649		
Hypotheses 2			
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))			
Variable	Coefficient	Std. Error	z-Statistic Prob.
C	0.00373	0.001504	2.479555 0.0132
DLOG(VOLUME)	0.007887	0.004629	1.703963 0.0884
Variance Equation			
C(3)	-0.395319	0.097263	-4.064429 0
C(4)	0.114446	0.025565	4.476699 0
C(5)	-0.073527	0.009587	-7.669273 0
C(6)	0.951617	0.012963	73.40963 0
R-squared	0.001798	Mean dependent var	0.003437
Adjusted R-squared	0.00042	S.D. dependent var	0.039973
S.E. of regression	0.039964	Akaike info criterion	-3.676016
Sum squared resid	1.15633	Schwarz criterion	-3.638102
Log likelihood	1340.394	Hannan-Quinn criter.	-3.661385
Durbin-Watson stat	2.179637		

Source: Processed data (2022)

To find the relationship between volatility and Bitcoin trading volume, it is shown in dlog(volume) table 4 hypotheses 1 and 3. Dlog (volume) has a coefficient value of 0.003302 and a probability of 0.6151, which can be concluded that the probability result is significant at the confidence level = 10 %. This shows that there is a positive and significant relationship at = 10% between volatility and Bitcoin trading volume.

Furthermore, to find the relationship between return and Bitcoin trading volume, it is shown in dlog(volume) table 4 hypothesis 2. Dlog (volume) has a coefficient value of 0.007887 and a probability of 0.0884, which can be concluded that the probability result is significant at the confidence level = 10%. This shows that there is a positive and significant relationship at = 10% between return and Bitcoin trading volume.

Then to find the relationship between Bitcoin return and volatility, it is shown in C(5) table 4 hypotheses 1 and 3. C(5) has a coefficient of -0.096749 and a probability of 0.0000, which can be concluded that the probability result is significant at the confidence level = 1%. This shows that there is a negative and significant relationship at = 1% between Bitcoin return and volatility.

4.6 Discussion

1. Bitcoin Volatility Comparison with Currencies

Compared to other currencies namely Euro, Pound sterling, Yuan, Yen, Ruble, and Franc. This is in accordance with previous research which argues that Bitcoin has a high volatility compared to currencies used in general (Baur & Dimpfl, 2018; Kasper, 2017; Yermack, 2015). Bitcoin has the nature of speculative investment and investors prefer to invest in Bitcoin in the short term (Yermack, 2015). In addition, it is very difficult to predict Bitcoin price movements. There are no variables that can be used to predict Bitcoin returns (Aalborg et al., 2019).

2. Relationship Between Volatility and Bitcoin Trading Volume

Based on the EGARCH test in table 2, the volatility and trading volume of Bitcoin has a positive and significant relationship at =10%. These results indicate that the higher the volatility, the higher the trading volume of Bitcoin. This is in accordance with previous research which states that volatility and Bitcoin trading volume have a positive and significant relationship over three time periods (Sapuric et al., 2020). First, in 2013-2014 when there was a loss of public confidence in the banking system which made investors invest in Bitcoin, even though investors knew that Bitcoin had a very high risk. Second, in 2014-2017 when the Mt. Gox in Tokyo resulted in a loss of \$500 million which made investors hesitant to invest in Bitcoin. Mt. Gox itself is a cryptocurrency exchange located in Tokyo and has handled 80% of Bitcoin trades in the world (Frankenfield, 2022). Third, in 2017 when there was the introduction of the law regarding Bitcoin in Japan.

3. Relationship Between Return and Bitcoin Trading Volume

Based on the results of the EGARCH test in table 3, the return and trading volume of Bitcoin have a positive and significant relationship at = 10%. These results indicate that the higher the return, the higher the Bitcoin trading volume. This result is in accordance with previous research which states that the return and trading volume of Bitcoin have a positive and significant relationship in four time periods (Sapuric et al., 2020). First, in 2011-2012 when things were normal. Second, in 2013-2014 when there was a loss of public confidence in the banking system. Third, in 2014-2017 when the Mt. Gox in Tokyo resulting in a loss of \$500 million. Fourth, in 2017 when there was the introduction of laws regarding Bitcoin in Japan. The introduction of this law made Japan legalize all the selling, buying, and exchanging of crypto assets. In addition, Japan legalizes payments using Bitcoin which makes investors interested in investing in Bitcoin.

4. Relationship Between Return and Bitcoin Volatility

Based on the results of the EGARCH test in table 2, the return and volatility of Bitcoin have a negative and significant relationship at = 1%. These results indicate that the higher the return, the lower the volatility of Bitcoin. This is in accordance with previous research which states that Bitcoin returns and volatility have a negative and significant relationship in one period of time, namely 2017, but in contrast to the other three time periods, which have a positive and significant relationship (Sapuric et al., 2020). In 2017, when Japan legalized all selling, buying, and exchanging of crypto assets, the Japanese government imposed a tax on any profits made on crypto assets that make high returns but low volatility.

The results of the discussion that have been described previously can be concluded that during the Covid-19 pandemic in 2020-2021, volatility with Bitcoin trading volume has a positive and significant relationship, the same as return with Bitcoin trading volume which has a positive and significant relationship but return with Bitcoin volatility there is a negative and significant relationship. This is because during the Covid-19 pandemic, Bitcoin was not affected by government policies and other global policies. As previously explained, Bitcoin works without a central bank, and transactions occur between users directly without intermediaries/third parties. Therefore, more investors choose and are interested in investing their funds in Bitcoin during the Covid-19 pandemic.

V. CONCLUSION AND RECOMMENDATION

Based on the results of the discussions that have been carried out, the following conclusions can be drawn that volatility with Bitcoin trading volume has a positive and significant relationship. Return with Bitcoin trading volume has a positive and significant relationship. Return with Bitcoin volatility has a negative and significant relationship. This

research can be used as a reference and learning information for further researchers. The following are suggestions that are expected to be carried out by further researchers by using different crypto currency assets like Ethereum, Litecoin, Tether, Cardano, Ripple, Solana, etc and using different time periods, because in the financial market each time period has different events, so that similar events are unlikely to happen again.

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