12-2021

The Volatility Implications of the Chinese Cryptocurrency Ban

Keaton Manwaring
Utah State University

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By

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Abstract:
In this paper, I examine the effect of the May 18th, 2021 Chinese ban of cryptocurrency transactions on the overall volatility of the cryptocurrency market. To do this, I analyze, in both univariate and multivariate settings, range-based volatility in various event windows surrounding the event. I find clear economic and statistical change in volatility in the five days after the ban. In the ten-day period after the ban, there is a moderate economic change in volatility. In the forty-day period after the ban, there is little economic change in volatility. I conclude that the Chinese ban had a clear short-term impact on the volatility of the cryptocurrency marketplace, but the effects wore off shortly thereafter.

1. Introduction

Cryptocurrencies (hereafter cryptos) have been in the news a lot lately as policy makers continue to debate their viability as a currency or if they are simply speculative investment vehicles. Although cryptos have been mostly used as investment vehicles (Hileman 2017), it is important to identify the value they might have over other more traditional currencies. Cryptos have a few advantages. First, the new technology that Bitcoin introduced in the blockchain. The blockchain is a series of ledgers that creates a system to keep track of payments using a "proof of work" method to broadcast the correct ledger. This creates the advantage of the ledger being decentralized, which means the holder of the crypto can mitigate the risk of destabilization in a country like you would with a regular currency. Second, cryptos have the ability to have an anonymous ledger, so that the holder can remain anonymous, which can be a real power in today's limited privacy environment. Lastly, there is a surge of advancements in the crypto field happening today. For example, Ethereum has developed a programming language that you can build apps on their platform and use Ether as the primary currency on the applications. This is just one example of progress that is taking the blockchain technology and providing further innovations. Perhaps this is why there are so many people interested in cryptos and why they get so much attention in the news.

However, this attention ends up being a double edge sword, with high profile figures, like Elon Musk, being able to affect the price of different cryptos just by sending out a tweet or a news release. A recent study built a supervised model to test cryptocurrency pricing using news and social media sentiment, which was able to correctly predict the biggest price fluctuations over a 67-day time period (Lamon, Nielsen, Redondo 2017). This correlation between news, social media and price – as well as the cryptos' speculative nature – creates a situation that makes cryptos a risky investment with extreme fluctuations that can create price instability. Therefore, big news events involving cryptos can be of intrigue for any investor, or holder, of the cryptocurrency.

The increase in news, size, and intrigue around cryptos has also caught the attention of world governments. Although China has been the biggest country in mining and trading cryptos (Hileman 2017), the country has also been the most stringent in terms of regulation. For instance, China recently banned public coin offerings (Zhang 2020). In addition, on May 18, 2021 China took an even further step in announcing the ban of cryptocurrency transactions altogether. While many can speculate on the reasons for the Chinese government to ban cryptocurrencies, the purpose of this paper is to look into the effects this ban had on the volatility of the overall crypto market. To measure volatility, I follow Alizadeh, Brandt, and Diebold (2002) and estimate a range-based measure of volatility, which has been shown to properly capture important properties of stochastic volatility. In particular, I calculate range volatility by taking the difference between the natural log of the daily high price minus the natural log of the daily low price (Alizadeh, Brandt, and Diebold 2002). I then examine this measure of volatility before and after the Chinese ban in an attempt to extrapolate whether this ban had any effect on the market as a whole.

To carry out this event study, I examine the prices (in USD) of 372 different cryptocurrencies, the corresponding volume in the number of coins traded, and the measure of volatility, discussed earlier. I also control for illiquidity, which is calculated using absolute continuously compounded return divided by daily dollar volume (Amihud 2002). I examine volatility around three different event windows: five days, ten days, and forty days before and after the ban of cryptocurrency transactions in China. This way I can test for the short-, medium-, and long-term effects of the news of the ban. I also estimate multivariate regressions that control for a number of important factors that might explain changes in volatility. I also provide a graphical analysis of volatility during the event days so I can observe an overall trend in order to can infer any information about the long-term effects of the event.

Results show that for all three event windows, volatility statistically increases. There is clearly a short-term economic effect from the event as the average five-day post-event volatility is 0.1685 more than the average five-day pre-event volatility. However, the long-term economic effect is questionable, as the 40-day post-event volatility is .0143 more than the 40-day pre-event volatility. While the post-minus-pre-period difference is still statistically significant in the longer window at the .01 significance level, there really does not appear to be much of an economic increase. When focusing on the multivariate analysis, I observe similar findings as the short-term economic effect of the event is statistically and economically significant, but the longer-term effect on overall volatility is too small to draw meaningful conclusions. The results from my analysis suggests that a country-wide ban on cryptocurrency transactions, like the one in China, has a dramatic, short-term effect on volatility. This information has practical importance to those using cryptos as an investment vehicle, or store of value, and to those using cryptos as a currency in a more traditional sense.

The rest of the paper follows. Section 2 presents a discussion of the data used throughout the analysis. Section 3 reports the empirical tests and results. Section 4 offers some concluding remarks.

2. Data Description

The data used in the analysis come from 372 different cryptocurrencies during an 80-day period (40 days before and 40 days after) surrounding the Chinese ban of crypto transactions on May 18th, 2021. I obtain daily pricing and volume data from the largest cryptos, like Bitcoin, as well as smaller coins in order to capture a broad crypto market trend. The data is obtained from *CoinMarketCap*. The daily price variable is the exchange rate between each coin and USD. Volume is the number of coins traded per day. *Rvolt* is a ranged based volatility, or the natural log of the daily high price minus the natural log of the daily low price following Alizadeh, Brandt, and Diebold (2002). *Illiq* is the absolute continuously compounded return divided by daily dollar volume following Amihud (2002). After obtaining this information, I clean the data by dropping any missing data cells and winsorizing at the 1st and 99th percentile levels. I note that winsorizing the data forces the maximum values, such as price, to be to be lower than expected. My final sample consists of 29,016 crypto-day observations.

In table 1, we report the summary statistics of the sample. The average price is $69.42 and the standard deviation is $410.46. The minimum price is $0.00, the maximum $3,587.51 and the median is $0.52. The price variable is highly right skewed as the median is lower than the mean, meaning that most of the cryptos exchange at a low price and there are some high outliers including the maximum, like Bitcoin. For this reason, I take the natural log of this variable in my multivariable regression analysis. The average of dollar volume is $438,318,185 and the standard deviation is $1,862,961,214. The minimum volume is $32, the maximum is $14,310,000,000, and the median is $3,184,751. Again, the volume is right skewed because most coins have little trade volume and there are the bigger coins have massive trade volume amounts. Again, I take the natural log of this variable in my multivariable regression analysis to account for this type of skewness. *Rvolt* has a mean of 0.1685 and a standard deviation of 0.1390. The minimum *Rvolt* is 0.0018, the maximum is 0.9086 and the median is 0.1313. This variable is pretty close to normally distributed and no adjustments need to be made. The *Illiq* variables mean is 0.4417, while the standard deviation 2.9596. The minimum volume is 0.0000, the max is 30.2439 and the median is 0.0001.

This variable is also right skewed, but since there are days with zero illiquidity (the absolute value of the daily return in the numerator is zero), we are unable to take the natural log of this variable.

3. Empirical Results

3.1. Correlation Matrix

To begin the analysis, I first look at a simple pooled correlation matrix of all the variables used in the study. Table 2 reports the pooled Pearson correlation coefficients between price, volume, volatility, and illiquidity. *Price* and *Volume* have a correlation coefficient of 0.3728, which is statistically significant. I expected price and volume to have a positive correlation because the lower priced coins are usually the less popular coins. *Price* and *Rvolt* have a correlation coefficient of -0.0674, which is also statistically significant. This is expected because as volatility increases, I expect that to have a negative impact on the price variable. *Price* and *Illiq* have a correlation coefficient of -0.0247 and is statistically significant. The likely reason they have a negative correlation coefficient is because an illiquid currency has a negative effect on price because of its' inefficiencies in trading. *Volume* and *Rvolt* have a correlation coefficient of -0.0374, which is statistically significant. I expect this negative correlation given that the more stable currencies usually trade more often. *Volume* and *Illiq* have a correlation coefficient of 0.2508 and is statistically significant. This is expected because more volume would suggest that the crypto is less illiquid. This unexpected result might be caused by the relationship between dollar volume and price. *Rvolt* and *Illiq* has a correlation coefficient of 0.2508 and is statistically significant. This is likely due to fact that the more volatile the coin, the less liquidity in the crypto.

3.2. Univariate Tests

To dig deeper into the variable of interest, *Rvolt*, I conduct a univariate analysis around three different time windows surrounding May 18, 2021 – the Chinese ban date. The results of this analysis are in Table 3. Here, I estimate the means and medians of crypto volatility during the periods before and after the event. I then examine the difference of the means and medians using t-statistics and Wilcoxon sum rank tests. The first event window consists of the five days before and after the ban. The difference in mean volatility during the pre- and post-event periods is 0.1685, which is statistically significant at the .01 level and has a t-statistic of 31.63. The difference in median during this same timeframe is 0.1759 and is also statistically significant at the .01 level. The implications of this result are clear. There seems to be a large short-term effect of the Chinese ban on the volatility of cryptocurrencies. In economic terms, these results suggest that volatility approximately doubled in response to the ban.

The question then shifts to whether or not the ban has a lasting impact on the volatility of cryptos. To test this possibility, I replicate my tests using the ten days before and after the event. The difference in means during this period is 0.0849, and the difference in medians is 0.0634. Again, the test statistics suggest that the differences are statistically significant at the 0.01 level. The results are muted quite a bit when adding only an extra five days to the event window. However, there is still an economic effect, and in a medium length time window, I can still say that the ban of crypto transactions in China had an effect on volatility on the crypto market as a whole. When looking at the 40 days before and after the ban, the difference in means for this event window is 0.0143, and the difference in the medians is 0.0038. These are also statistically significant at the .01 level. Although the 40-day time range has statistical significance it has severely less economic significance. What I can conclude from these univariate tests is that volatility increased dramatically during the time of the ban, but leveled out quickly after the event and went back to previous volatility levels.

I provide graphical representation of volatility surrounding the ban in Figure 1. The results from this simple analysis confirm what I have learned through the univariate tests discussed previously. This graph shows a huge spike in volatility on the day of the announcement. After the event, volatility stays unusually high for a few days then appears mean revert. In the second panel of Figure 1, I plot the price on the y-axis and event days on the x-axis. Price drops on the day of the event and appears to continue to decrease for the rest of the time period.

3.3. Multivariate Tests

To better understand the effect of the ban on crypto volatility, I conduct a multivariate analysis, which is reported in Table 4. More specifically, I estimate the following regression equation on a panel of crypto-day observations:

$$Rvolt_{i,t} = \alpha + \beta_1 Post_t + \beta_2 LN(Price_{i,t}) + \beta_3 LN(Volume_{i,t}) + \beta_4 Illiq_t + \varepsilon_{i,t} \,,$$

where *Rvolt* is the measure of range- based volatility. *Post* is an indicator variable equal to one on days after the announcement of the Chinese ban and zero otherwise. We include as control variables, the natural log of price and volume as well as Amihud's (2002) measure of illiquidity. We have taken the natural log of the price and volume variables to help normalize the distribution of both of these variables. This regression allows me to test whether the event has any effect on the volatility of cryptos while controlling for other important factors, such as price, volume, and illiquidity. To help with possible heteroskedasticity, I report heteroskedastic robust standard errors. I again look at the three different periods surrounding the ban.

First, I look at the five days before and after the event. The intercept for the regression is 0.064 with a 7.10 t-statistic and a .10 significance level. *Post* has a 0.1647 coefficient with a 32.49

t-statistic and a .01 significance level. This means that, on average, volatility is 0.1647 greater in the five days after the event then before the event. So even when controlling for price, volume and illiquidity, the event still effects the volatility of cryptos in the short term. Regarding the control variables, the *LN(price)* variable has a -.0079 coefficient with a corresponding t-statistic of -7.81, which is statistically significant at the .01 significance level. This coefficient suggests that if we increase price by one percent we expect volatility to decrease by .0079 units. This variable is not economically significant and does not give us any real insights. The *LN(volume)* variable produces a coefficient of 0.0052 with a t-statistic of 6.95. This result indicates that an increase in volume by one percent increases volatility by 0.0052 units. Like *LN(price)*, this variable is not economically significant either and does not provide us with important insights. The *Illiq* variable has a 0.0084 coefficient and a 7.93 t-statistic, which suggests that Illiq is statistically significant at the .01 level. This result indicates that a one unit increase in illiquidity has a 0.0084 unit increase in volatility. The findings for this coefficient is also economically insignificant as well. This model had 3,956 observations and had an adjusted R-squared as 0.2366 suggesting that the model explains 23.66% of the variation in volatility.

Next, I examine the ten days before and after the Chinese ban to see if controlling for these variables has any differing effect on volatility in the medium term. The intercept coefficient is 0.1136 and has a t-statistic of 13.44, which is statistically significant at the .01 significance level. Again, the *Post* variable has a coefficient of 0.0819 and a t-statistic of 22.67, which is significant at the .01 significance level. This result suggests that the time after the event has a 0.0819 higher volatility, on average, when compared to the pre-event period. Again, I find that after controlling for price, volume and illiquidity, there is a moderate economic effect on the volatility due to the event. I will not review the coefficients of the control variables here as they had no significant change when I examined the different time period. This model had 7,554 observations and an adjusted R-squared of 0.1159.

Given the univariate analysis – conducted in the previous subsection – I next determine whether controlling for price, volume and illiquidity variables had any change in the post-event variable in the long-term of forty days before and after the event. The intercept for this model is 0.1657 and has a t-statistic of 39.86. The *Post* variable has a coefficient of .0083 and has a t-statistic of 4.85 and is statistically significant at the .01 significant level. This result indicates that, relative to the pre-event window, volatility is .0083 greater after the event, which is not very economically significant. I find that as the longer the event window is, the less economically significant the *Post* variable becomes. This confirms what I learned in the univariate analysis as the event impacted the volatility in the short term, but as time went on, the volatility returned to pre-event levels. The intercept follows the opposite trend as we might predict because all the other variables are very similar. The intercept starts to explain the volatility instead of the post variable, this simply means that volatility is explained more by a constant as time goes on or another explanatory variable we have not included in our model. I note that there are 29,016 observations used in this analysis and the adjusted R-squared is 0.0711. The R-squared has also decreased significantly which means the model is explaining less when looking longer term.

4. Concluding Remarks

In this study, I examine whether or not the Chinese ban of cryptocurrency transactions affected the overall volatility of the crypto market in the short-, medium, and long-term. To do this, I use both univariate and multivariate analyses that capture changes in volatility during the period immediately surrounding the ban. My findings show that in the five days before and after the ban, there is a clear economic and statistical impact on crypto volatility. When I increase the event window to the 10 days before and after the ban, the inferences change slightly. I find that there is only a moderate economic change in volatility in the medium term. Finally, to examine the longer-term effects of the ban, I explore the 40 days before and after the event. Here, I find that the effect on volatility decreases so low that there is little to no economic significance in the long-term. My conclusion is that while the news of the Chinese government banning crypto affected the stability of prices, the ban did not affect the long-term volatility of the marketplace.

Perhaps future studies might examine the effect of the ban on overall prices. As I show in Figure 1, the average crypto price decreases dramatically after the event and stays at this decreased level for at least 40 days. I would say that this requires further attention to see if I can find a causal relationship between this event and the price of cryptos when China announced the ban. This type of research might provide evidence of a longer-term price effect even though the change in volatility is transitory.

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Table 1. Summary Statistics

This table displays summary statistics that describe the sample of 372 cryptocurrencies in the 40 days prior to May 18, 2021 when China announced it would ban cryptocurrency transactions. We obtain daily pricing and volume data from CoinMarketCap. *Price* is the exchange rate between the cryptocurrency and USD. *Volume* is the number of coins traded in USD. *Rvolt* is range based volatility of Alizadeh, Brandt, and Diebold (2002), or the natural log of the daily high price minus the natural log of the daily low price. *Illiq* is Amihud (2002) illiquidity, or absolute continuously compounded return divided by volume (scaled by 10^4).

	Mean	Std. Dev.	Min	Median	Max
Price	$69.42	$410.46	$0.00	$0.52	$3,587.51
Volume	$438,318,185	$1,862,961,214	$32	$3,184,751	$14,310,000,000
Rvolt	0.1685	0.1390	0.0018	0.1313	0.9086
Illiq	0.4417	2.9596	0.0000	0.0001	30.2439

Table 2. Pooled Correlation Matrix

This table shows the Pearson pooled correlation coefficients between various cryptocurrency measures in the 40 days prior to May 18, 2021 when China announced it would ban cryptocurrency transactions. *Price* is the exchange rate between the cryptocurrency and USD. *Volume* is the number of coins traded in USD. *Rvolt* is range based volatility of Alizadeh, Brandt, and Diebold (2002), or the natural log of the daily high price minus the natural log of the daily low price. *Illiq* is Amihud (2002) illiquidity, or absolute continuously compounded return divided by volume (scaled by 10^{4}). P-values are in brackets.

	Price	Volume	Rvolt	Illiq
Price	1.0000			
Volume	0.3728	1.0000		
	[<.0001]			
Rvolt	-0.0674	-0.0374	1.0000	
	[<.0001]	[<.0001]		
Illiq	-0.0247	-0.0351	0.2508	1.0000
	[0.0031]	[<.0001]	[<.0001]	

Table 3. Volatility of Cryptocurrencies around Chinese Ban – Univariate Analysis

This table displays average daily volatility for 372 cryptocurrencies in various event windows surrounding May 18, 2021 when China announced it would ban cryptocurrency transactions. *Rvolt* is range based volatility of Alizadeh, Brandt, and Diebold (2002), or the natural log of the daily high price minus the natural log of the daily low price. T-statistics are in parentheses and p-values are in brackets. *** and ** represent statistical significance at the 0.01 and 0.05 levels, respectively.

	[-5, +5]		[-10, +10]		[-40, +40]	
	Mean	Median	Mean	Median	Mean	Median
Pre	0.1721	0.1389	0.1802	0.1465	0.1685	0.1313
Post	0.3406	0.3148	0.2651	0.2100	0.1829	0.1351
Different	0.1685***	0.1759***	0.0849***	0.0634***	0.0143***	0.0038***
	(31.63)	[0.0001]	(22.70)	[0.0001]	(8.18)	[0.0001]

Table 4. Volatility of Cryptocurrencies around Chinese Ban – Multivariate Analysis

This table reports the results from estimating the following regression equation on a sample of crypto-daily observations:

Rvolti,t=α+1Postt+2LN(Pricei,t)+3LN(Volumei,t)+4Illiqt+i,t

where the dependent variable is range-based volatility, *Rvolt*, or the natural log of the daily high price minus the natural log of the daily low price. *Post* is an indicator variable equal to one if the crypto-day observation is on or after May 18, 2021 when China announced it would ban cryptocurrency transactions; zero otherwise. *Price* is the exchange rate between the cryptocurrency and USD. *Volume* is the number of coins traded in USD. *Illiq* is Amihud (2002) illiquidity, or absolute continuously compounded return divided by volume (scaled by 10^{4}). T-statistics are in parentheses obtained from robust standard errors. *** represents statistical significance at the 0.10 level.

	[-5, +5]	[-10, +10]	[-40, +40]
Intercept	0.0864***	0.1136***	0.1657***
	(7.10)	(13.44)	(39.86)
Post	0.1647***	0.0819***	0.0083***
	(32.49)	(22.67)	(4.85)
LN(Price)	-0.0079***	-0.0077***	-0.0068***
	(-7.81)	(-10.83)	(-20.21)
LN(Volume)	0.0052***	0.0039***	-0.0003
	(6.95)	(7.43)	(-1.27)
Illiq	0.0084***	0.0094***	0.0080***
	(7.93)	(10.66)	(16.31)
N	3,956	7,554	29,016
Adj. R^2	0.2366	0.1159	0.0712

Figure 1. Volatility and Price of Cryptocurrency Market around Chinese Ban

This table plots average range-based volatility and prices across the 372 cryptocurrencies in the months surrounding May 18, 2021 when China announced it would ban cryptocurrency transactions. *Rvolt* is range based volatility of Alizadeh, Brandt, and Diebold (2002), or the natural log of the daily high price minus the natural log of the daily low price.