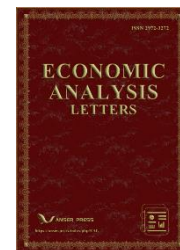




# Economic Analysis Letters

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## Modeling the Potential Impact of Government Regulation on Cryptocurrency Prices

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### ABSTRACT

Cryptocurrencies have gained popularity over the past five to six years. Most recently, events like the FTX bankruptcy fueled the interest in regulation. Moreover, it is possible that the FTX event disrupting the cryptocurrency market was a factor in Silicon Valley Bank's failure. While several countries consider regulation, from soft regulation, like Japan, to more rigid standards, like the total ban in China, we study the effect of other news or events on cryptocurrency prices. This paper looks at historical closing prices for Bitcoin, the largest of the cryptocurrencies, and how prices react to various events. Then we focus on modeling the time series considering an 'event,' China's ban on cryptocurrency exchanges, using intervention analysis. We find that intervention analysis provides a reliable approach to quantifying the impact regulation may have on cryptocurrency pricing.

### KEYWORDS

Time-series models; Intervention analysis; Government policy and regulation; Asset pricing

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## 1. Introduction

First conceptualized in late 2008, followed by its first transaction in January 2009, cryptocurrency has captured the attention of investors and regulators, alike. In this article, we consider the potential impact regulation might have on cryptocurrency pricing by using intervention analysis. Intervention analysis (Box and Tiao, 1975; Cryer and Chan, 2008) considers how 'events' affect the data in a time series. While generally unregulated there has been growing interest by several governments in enacting some form of regulation over the cryptocurrency market, including the US. Events such as the bankruptcy filing by FTX November 11, 2022, and November 14, 2022, has further fueled the call for regulation.

Perhaps not surprising, cryptocurrency price movements are often driven by the same fundamental catalysts as traditional markets: supply and demand, risk on vs. risk off, market events, news, and politics ("How Do Macroeconomic Events" n.d). Digital currencies are not physical, they only exist within the code of the blockchain. A blockchain stores information in a digital format, furthermore, it maintains a secure and decentralized record of transactions (Hughes 2018). Cryptocurrencies are tradable assets; therefore, the price is determined by the market.

This paper describes the historical price movements for Bitcoin. Then to assess the impact government intervention has on prices, we fit an autoregressive integrated moving average (ARIMA) model to the data with exogenous regressors and indicators of 'events.' This modeling approach is known as transfer function modeling or intervention analysis (Box and Tiao 1975; Brockwell and Davis 1991; Chen and Liu 1993). The events in which we are interested are government attempts to intervene or outright regulate the cryptocurrency markets.

The impact of regulatory events has been studied before. Chokor and Alfieri (2021) use event studies to find whether investors in cryptocurrencies view regulation as beneficial. Using daily returns, they measure the impact of potential regulation on cryptocurrency returns. They find that as the likelihood of regulation increases, the market experiences significant negative returns.

Event studies have broad applicability. Event studies consider events like announcements by companies, talk of or enactment of regulation, news either positive or negative, and measure the impact of the event on financial assets like stock prices, assets prices, and currency prices. The basis is market rationality and that the value of the financial assets immediately reflects the events (MacKinlay, 1997). Konchitchki and O'Leary (2011) study the application of event studies in information systems and accounting information systems.

Interestingly, Feinstein and Werbach (2021) studied the impact of regulatory actions or announcements on the trading volume of cryptocurrencies, not the impact on prices. In this regard, they found that under various modeling frameworks, trading volume is not affected by regulation.

## 2. Data and Methodology

### 2.1. Bitcoin Historical Prices

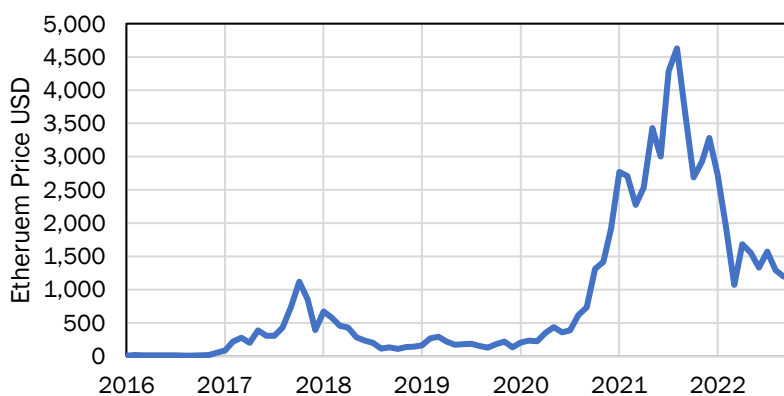
Bitcoin is known as the "father of all cryptocurrencies." Satoshi Nakamoto created Bitcoin in 2009, he designed it for use in daily transactions and to get around the traditional banking infrastructure after the 2008 financial collapse ("Bitcoin Historical Data," 2022). Since Bitcoin's start in 2009, Bitcoin's price has been known to be very volatile. Nonetheless, its price today is still significantly higher than when it was first conceptualized. Figure 1 shows the historical daily closing price for Bitcoin from January 2014 through December 2022.

Perhaps not surprising, examining the closing prices for Ethereum, the second most widely traded cryptocurrency, we note a similar path as the for Bitcoin. Other 'stablecoins' which are pegged to a fiat currency like the US dollar do not share the same degree of volatility.



Source: Bitcoin Historical Data, Investing.com.  
<https://www.investing.com/crypto/bitcoin/historical-data>

**Figure 1.** Average monthly Bitcoin closing Price Jan 2014 - Dec 2022.



Source: Ethereum Historical Data,  
<https://www.investing.com/crypto/ethereum/historical-data>

**Figure 2.** Average monthly Ethereum closing Price Jan 2016 - Dec 2022.

## 2.2. Outlier Analysis

Time series data are data that are observed over time. Most often, time series are recorded at regularly spaced intervals (e.g., daily, weekly, monthly) and display stable behavior. However, time series are subject to shocks from unexpected events that produce outliers. If left unaccounted for, outliers will lead to model misspecification. To deal with outliers, a typical approach is to use intervention analysis as described in Box and Tao (1975). Intervention analysis is a method for capturing changes in the process generating the time series that results in the series having different properties over different time intervals. We discuss intervention analysis in the next section.

There are four types of outliers that can influence the data. These are: additive outliers (AO), transient changes (TC), innovation outliers (IO), and level shifts (LS). An AO is when there is a one period spike (or dip) in the data series with an immediate correction, a TC is a spike (or dip) followed by a gradual recovery to the previous level, and a LS is a shift in the mean level of the series that persists, an IO is an outlier in the innovations (error term).

A LS outlier can be modeled by using a step function:

$$S_T(t) = \begin{cases} 0, & \text{if } t < T \\ 1, & \text{otherwise} \end{cases} \quad (1)$$

and is equivalent to a TC with  $\delta = 1$  (described below). An AO is modeled with a pulse function which is the difference of two successive step functions:

$$P_T(t) = S_T(t) - S_T(t - 1) \quad (2)$$

In the case of a LS outlier, we observe a shift in the mean of the time series, which is modeled by a level shift function. The magnitude of the shift is denoted by  $\omega$ , and the level shift function has the form:

$$m(t) = \omega S_T(t). \quad (3)$$

The transient change function (4) is a bit more complex as it is shaped by the magnitude of the initial change  $\omega$ , and the rate of decay  $\delta$ :

$$C(t) = \frac{\omega B}{1 - \delta B} P_T(t). \quad (4)$$

Varying  $\delta$  changes the rate of decay following the spike or growth if the initial shock is negative.

Identifying these change points and comparing them to events or interventions – news, political events, regulatory actions – we can estimate the effect of any such action. To study the outlier events, we used the "tsoutlier" package in R (Chen and Liu 1993) to identify the timing and type of events.

### 2.3. Intervention Analysis

Intervention analysis is a useful approach to estimate an intervention on a time series. The intervention may be from natural causes, a severe storm that impacts the yield from crops to manmade such as the 9-11 terrorist attacks' impact on air travel. Depending on the type of event several functions are useful for modeling interventions. For example, if the intervention results in an overall shift in the mean of the time series, a step-function would be the best option. In this case, we code the pre-intervention as zero and then one for the intervention time and later. If the intervention shows a shift with an immediate return to the current level, a pulse function is best suited to account for the event. For more details on modeling the various interventions, see Cryer and Chan (2008).

We explicitly model the effects of regulation, considering the event in May 2021 when China banned cryptocurrency exchanges. We fit an ARIMA model which captures any dependency or correlation across time periods, with exogenous regressors, and indicators for the change point events. This gives an indication of how interventions may affect cryptocurrency prices going forward. We apply intervention analysis (also known as transfer function modeling) to the monthly data with an indicator equal to zero pre-May 2021, and equal to one starting May 2021. We also included CPI as an exogenous variable. We fit the model using  $\log(\text{Price})$ . Modeling the data during the unperturbed period (pre-May 2021) results in an ARIMA (1,1,0) model. This tells us the  $\log(\text{Price})$  series is an AR(1) process after taking first differences. Having identified the model for the data before China's ban, we use the "arimax" function in the TSA R package. The arimax function allows one to specify the ARIMA model, the transfer function (in this case intervention), and allows inclusion of exogenous regressors, in our case, CPI.

The transfer function model has the general form

$$Y_t = m_t + N_t \quad (5)$$

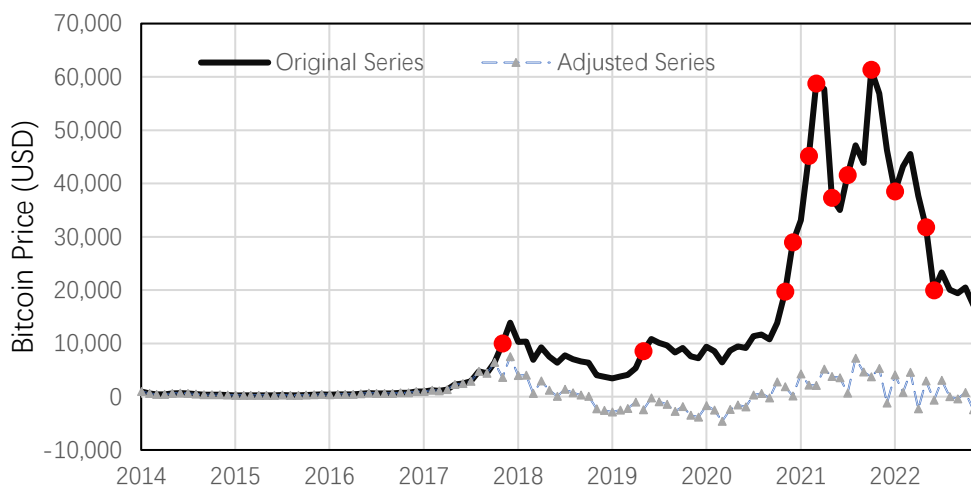
where  $m_t$  is the mean of the process and  $N_t$  is the unperturbed time series pre-intervention. The ARIMA (1,1,0) model fit to the pre-May 2021 data is the model specification for  $N_t$ .

## 3. Results

### 3.1. Outlier Analysis

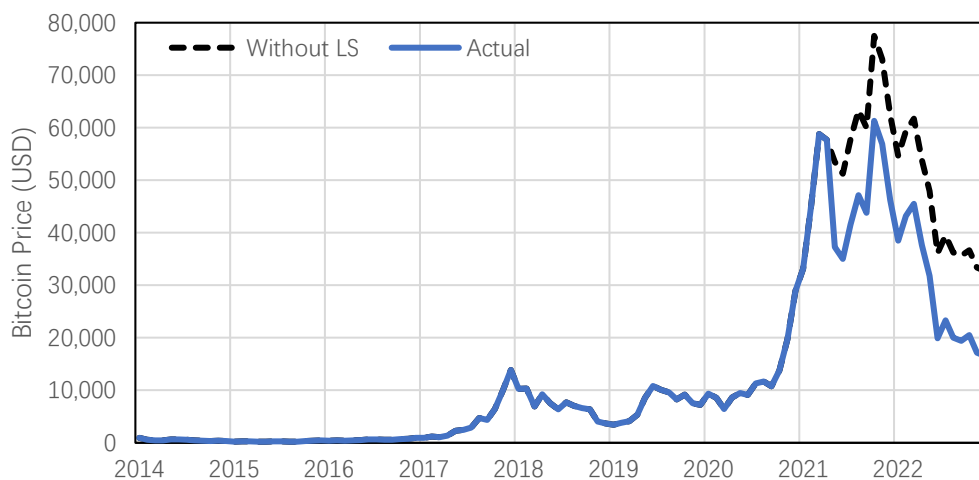
The outlier analysis identifies 12 events including three AO, seven LS, and two TC. Figure 3 shows the results of the outlier analysis, with the events identified as points on the graph. The heavy black line is the original series, and the dashed lighter line is the series adjusted for the outliers. While some data points in the adjusted series are negative, we don't intend to suggest that Bitcoin prices would be negative. Rather the adjusted series represents the underlying ARIMA process after accounting for the outlier events.

The earliest event in late 2017 associates with Japan's government passing the bill to recognize Bitcoin as a legal payment method and legal tender. Bitcoin's price, already rising, saw a jump in price with a gradual leveling off towards earlier levels. Another example of government intervention, in 2021 China banned the use of all cryptocurrency exchanges. This aligns with the seventh event in Figure 2, which shows a steep decline in Bitcoin's price.



**Figure 3.** Average monthly Bitcoin closing prices Jan 2014 - Dec 2022, with outlier events plotted as points. The adjusted series is plotted with filled triangle markers.

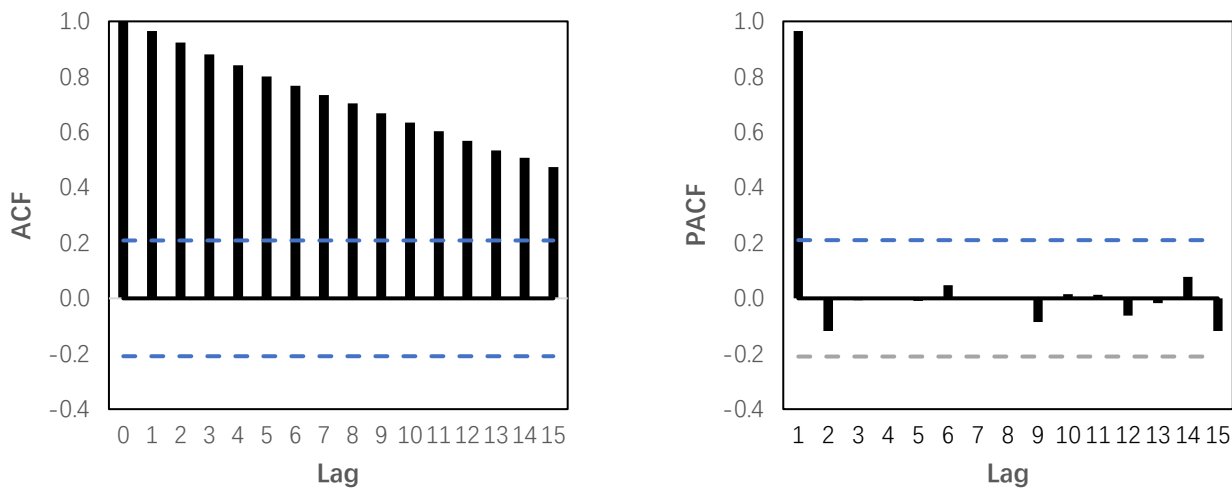
We can isolate the effects of the ban imposed by China and see how the event cause a LS outlier. Figure 4 shows the original Bitcoin price series plotted along with the LS effect removed. From the plot we note a downward shift in the overall level of prices persisting following the event.



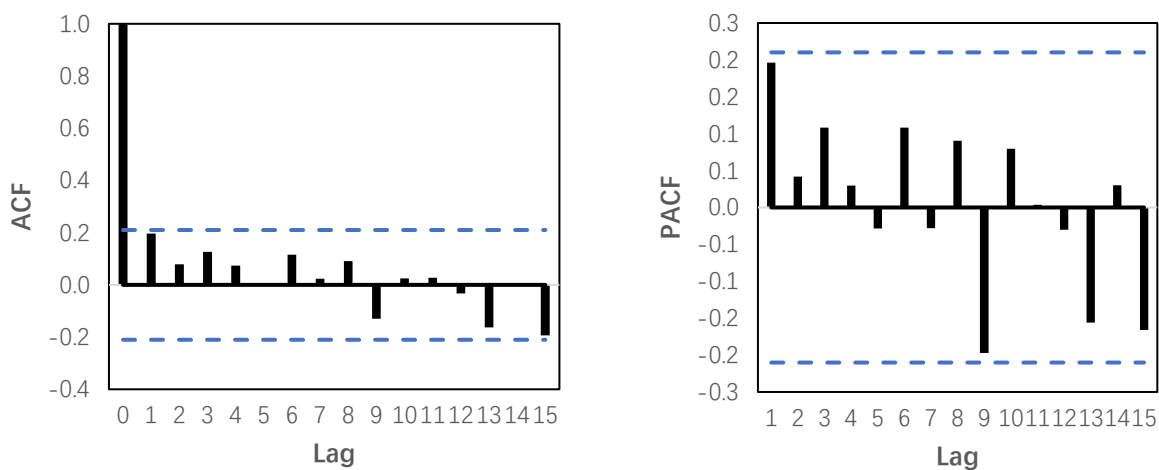
**Figure 4.** Average monthly Bitcoin closing prices Jan 2014 - Dec 2022 (solid line), and the series adjusted for the LS outlier occurring in May 2021 (dashed line). The event caused a downward shift in the price data.

### 3.2. Intervention Analysis

Before fitting the ARIMA model with intervention, we fit an ARIMA model to the data prior to China's ban in May 2021, the intervention. Using the log (Price) as the time series, results in an ARIMA (1,1,0) model with drift; the AR parameter  $\phi = 0.209$  with standard error 0.108. We determined the order of the ARIMA model by examining the plots for the autocorrelation function (ACF) and partial autocorrelation function (PACF), for the log(Price) in Figure 5, and for the first differenced log series in Figure 6. These plots suggest the ARIMA (1,1,0) model is appropriate.



**Figure 5.** ACF (left) and PACF (right) plots for the log (Price) time series clearly showing and AR(1) process.



**Figure 6.** ACF (left) and PACF (right) plots for the first differenced log (Price) time series.

The ARIMA (1,1,0) is further supported by the modeling results, with ARIMA (1,1,0) producing the lowest AICC and BIC statistics among competing models, and the residual plots and tests of randomness supporting the assumption of *iid* normally distributed residuals.

We use this model in the ARIMA with intervention. In the first pass of the modeling process, we included CPI as an exogenous variable, but it was not statistically significant. Table 1 lists the model coefficients and standard errors for the ARIMA (1,1,0) with intervention.

**Table 1.** ARIMA Model Parameters with Intervention.

Items	$\hat{\phi}$	$\omega_0$
ARIMA (1,1,0) model	0.216 (0.096)	
Intervention parameter		-0.42 (0.204)

We interpret the ARIMA model results as follows: The AR parameter  $\hat{\phi}$ , governs the dependency of the time series at time  $t$ , on the value at  $t - 1$ , while  $\omega_0$ , is the effect of the intervention. Quantifying the intervention effect gives

$$1 - e^{-0.42} = 0.3429 \quad (6)$$

or roughly a 34.3% decline in Bitcoin price due to the regulatory event. The actual observed decline from April 2021 to May 2021 was about 35.4%, so the intervention model estimate compares favorably with the observed decline.

#### 4. Discussion

Regulatory actions are not the only cause of outliers in the Bitcoin price series. During the period of study in this paper there are several events that created outliers in the time series. A positive LS outlier occurred around May 2019 as institutional investors became optimistic about Bitcoin. Similarly, in the fall of 2020 we observe a positive AO and LS outlier corresponding to the US government printing millions of dollars to help the economy during COVID. Tesla's purchase of Bitcoin in February 2021 produced another positive LS. Through 2021 prices recovered noting a positive LS in July and a positive TC in October as investors found workarounds following the Chinese ban in May 2021. We observe a negative AO in May 2022 as Bitcoin miner Core Scientific began a sell-off, and Luna/UST, Celsius, Voyager, and 3AC suffered financial collapse. This one-time negative shock was followed by a negative LS in June as Tesla sold off 75% of its Bitcoin holdings. Market dynamics influence Bitcoin prices as they do any other assets.

#### 5. Conclusion

This paper studies the impact regulation has on the cryptocurrency market and attempts to quantify the impact by looking at the effect of news and events on cryptocurrency prices. Specifically, we analyze outlier events and associate them with regulatory or other events in time. Then focus on an extreme regulatory event in China in 2021 to better understand the impact of regulation. We fit an ARIMA model with an intervention marking the ban on cryptocurrency exchanges by the Chinese government in May 2021. The model results estimate a 34.3% drop in Bitcoin price because of the event. This compares favorably with the observed drop of 35.4%. Intervention analysis is a viable approach to quantifying and forecasting the regulatory impact on cryptocurrency prices.

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#### Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

#### References

Bitcoin Historical Data. (2022). Investing.Com. <https://www.investing.com/crypto/bitcoin/historical-data>

- Box, G. E. P. and Tiao, G. C. (1975). Intervention Analysis with Applications to Economic and Environmental Problems. *Journal of the American Statistical Association*, 70 (349), 70–79. <https://doi.org/10.2307/2285379>
- Brockwell, P. J. and Davis, R. A. (1991). *Time Series Theory and Methods* 2nd ed., Springer. <https://doi.org/10.1007/978-1-4419-0320-4>
- Chen, C. and Liu, L-M., (1993). Joint Estimation of Model Parameters and Outlier Effects in Time Series. *Journal of the American Statistical Association*, 88, (421) 284-297. <http://dx.doi.org/10.2307/2290724>
- Chokor, A. and Alfieri, E. (2021). Long And Short-Term Impacts of Regulation in The Cryptocurrency Market. *The Quarterly Review of Economics and Finance*, 81, 157–173. <https://doi.org/10.1016/j.qref.2021.05.005>
- Cryer, J. D. and Chan, K-S. (2008). *Time Series Analysis with Applications in R*, 2nd ed., Springer. <https://doi.org/10.1007/978-0-387-75959-3>
- Feinstein, B. D. and Werbach, K. (2021). The Impact of Cryptocurrency Regulation on Trading Markets. *Journal of Financial Regulation*, 7(1), 48–99. <http://dx.doi.org/10.2139/ssrn.3649475>
- How Do Macroeconomic Events Affect Bitcoin? (n.d.). *River Financial*. <https://river.com/learn/how-do-macro-events-affect-bitcoin/>
- Hughes, T. M. (2018). The Global Financial Services Industry and the Blockchain. *The Journal of Structured Finance*, 3 (4) 36-40. <https://doi.org/10.3905/jsf.2018.23.4.036>
- Konchitchki, Y. and O’Leary, D. E. (2011). Event Study Methodologies in Information Systems Research. *International Journal of Accounting Information Systems*, 12, 99–115. <https://doi.org/10.1016/j.accinf.2011.01.002>
- MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, 35(1), 13–39. <https://www.jstor.org/stable/2729691>