Economic Stability and Bitcoin Markets

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> *Do indicators of economic health such as inflation and employment help predict trends in Bitcoin markets?*

Bitcoin has been heralded as a safe haven for investors in markets experiencing political uncertainty or economic instability due to monetary policy, since its price is purely based on market discovery. Thus, when confidence in one's national (fiat) currency wavers, we might see an increase in investments in alternative stores of value such as cryptocurrencies. We seek to explore whether economic instability, measured by a combination of the **annual percentage of inflation** (CPI) and the **employment index**, corresponds to changes in market cap of Bitcoin. Formally, we evaluate relationships between the following variables:

Bitcoin (dependent):
- market capitalization

Economic Health Indicators (independent):
- inflation as measured by CPI (`LE_IX`)
- employment rates (`PCPI_IX`)
- exchange rates (`ENDE_XDC_USD_RATE`)

We choose to study the following four countries: the United States (`US`), Russia (`RU`), Japan (`JP`), and Korea (`KR`). These countries are known to be home to a significant population of both retail and institutional cryptocurrency investors.

To collect the requisite data, we begin by designing general methods to fetch data provided by the International Monetary Fund (IMF) in their API for the metrics mentioned above. The IMF has abbreviations for both countries and economic indicators, which have been noted above. We load the appropriate columns (datetime, country abbreviation, values of variable of interest) into a Pandas dataframe, which we will use as a starting point for EDA. To ensure that we are not dealing with IMF data that is corrupt, missing, or are status variables that are unimportant to our analysis, we cleanse the dataset.

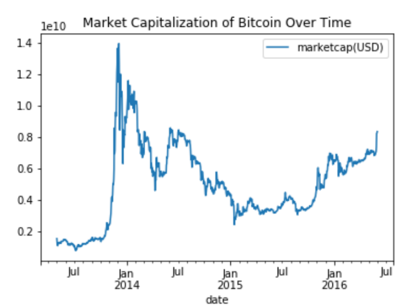
We then load a CSV file obtained from the CoinMetrics website containing market cap history for Bitcoin; we ensure that there are no `NaN` values, and extract the values into a Pandas dataframe with the appropriate datetime format. We then **left join** the Bitcoin market cap history dataframe with the economic health indicator dataframe, matching using the **datetime** column.

We interpolate economic data between months to obtain an adequate sample size for our data and to resolve the difference in observation frequency between the market cap and the economic data. It seems reasonable to assume that economic data is not extremely volatile within a month, so we linearly interpolate the data points to produce reasonable estimates for every day, instead of every month, of the year. This makes training and testing much more effective.

	date	marketcap(USD)	US.LE_IX	US.PCPI_IX	US.ENDE_XDC_USD_RATE	KR.LE_IX	KR.PCPI_IX	KR.ENDE_XDC_USD_RATE	JP.LE_IX	JP.PCPI_IX	JP.E
3	2013-05-01	1.543334e+09	103.860155	106.828307	1.0	106.564325	107.468047	1129.700000	100.886501	99.7669	
4	2013-05-02	1.292577e+09	103.869643	106.836577	1.0	106.574405	107.463831	1130.096774	100.883428	99.7669	
5	2013-05-03	1.180430e+09	103.879130	106.844847	1.0	106.584486	107.459615	1130.493548	100.880355	99.7669	
6	2013-05-04	1.090276e+09	103.888618	106.853116	1.0	106.594566	107.455399	1130.890323	100.877282	99.7669	
7	2013-05-05	1.255228e+09	103.898105	106.861386	1.0	106.604646	107.451183	1131.287097	100.874209	99.7669	

The Pandas dataframe containing our data.

When conducting EDA, we notice that the market capitalization of Bitcoin skyrocketed at the end of 2013, then experienced instability trending downwards until 2015, at which point it began to rebound. This could be attributed to a couple of factors:

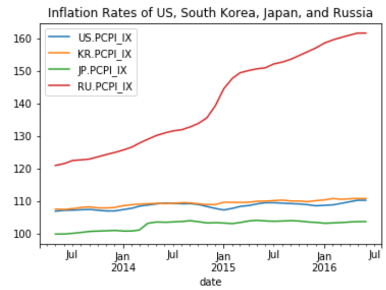


The market cap of Bitcoin from 2013 to 2015.

1. Bitcoin survives seizure of assets from the Silk Road bust, and proves itself to be resilient to government intervention.
2. Bitcoin becomes increasingly popular abroad (especially in Asian countries such as China,

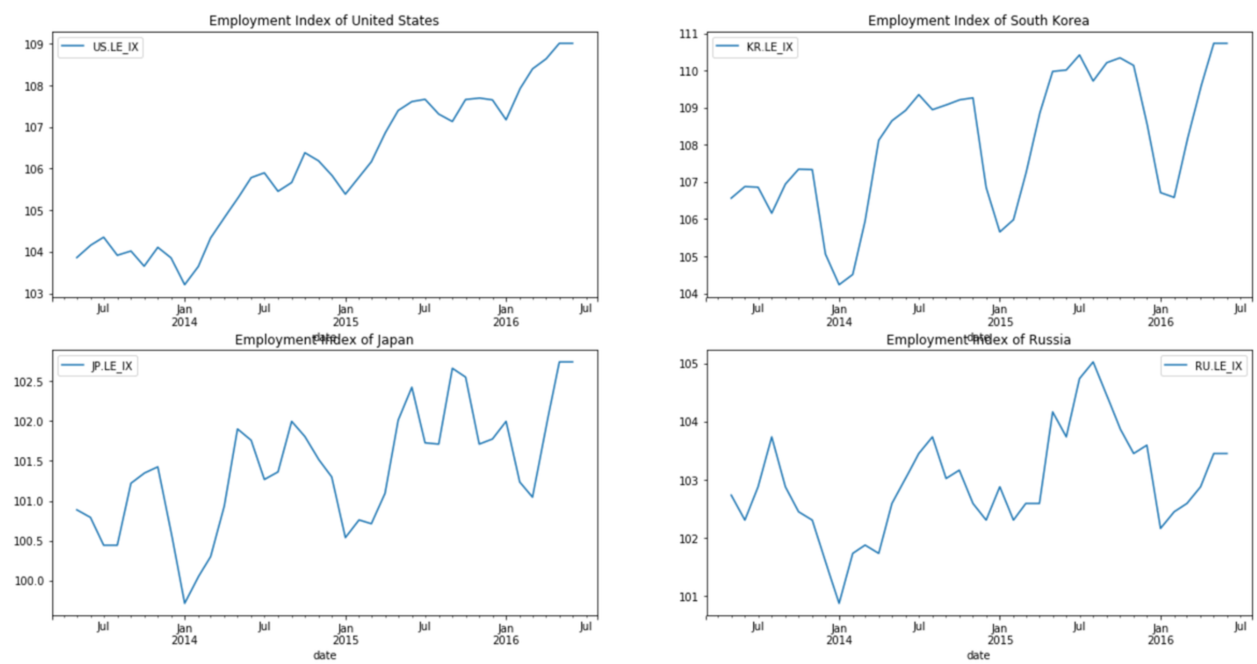
Japan, and Korea), with exchanges now providing liquidity to investors in those markets.

We now explore the data for inflation rates, and find that Russia experienced a rapid increase in inflation year over year between 2014 and 2016, while the other countries experienced only a moderate increase in inflation during that time period.



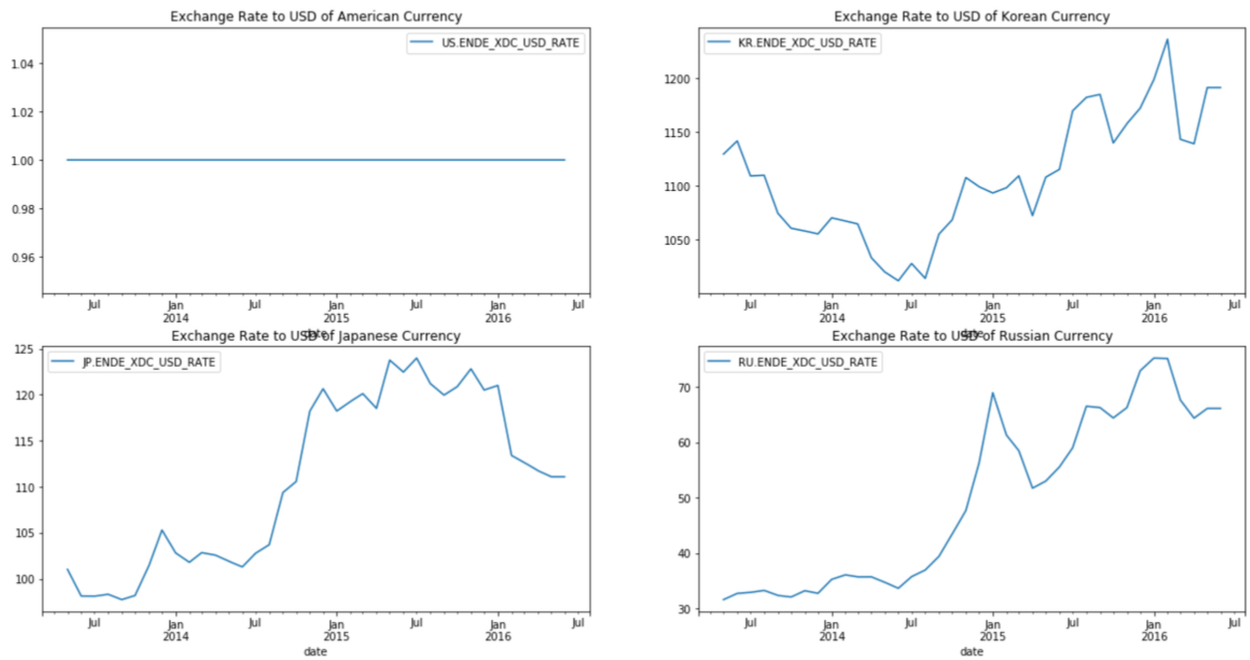
Inflation rates, plotted.

Similarly, we plot the employment indexes for the respective countries, and notice cyclical (trending upwards) patterns in Japan, South Korea, and Russia, whereas we see a less unstable trend upwards in the United States. We also notice that all four countries had noticeably low unemployment indices in January 2014. Russia's volatility is clear, but the employment index is not upwards trending.



Employment indices, plotted.

We also explore foreign exchange rates (US dollar vs. local currency), and notice that all of the other (non-US) currencies have been devalued relative to the dollar consistently from 2013 to 2016, though the Yen (Japanese currency) has increased in value post-January 2016.



Exchange rates, plotted.

We use Facebook Prophet to build our model for forecasting. From the official Prophet website:

> *Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is robust to missing data and shifts in the trend, and typically handles outliers well. It is open-source software, used extensively at Facebook.*

We begin building our model to determine which variables of interest are to be included, and how the settings of Prophet could be adjusted (i.e. exogenous vs. no exogenous variables) to result in the best forecast.

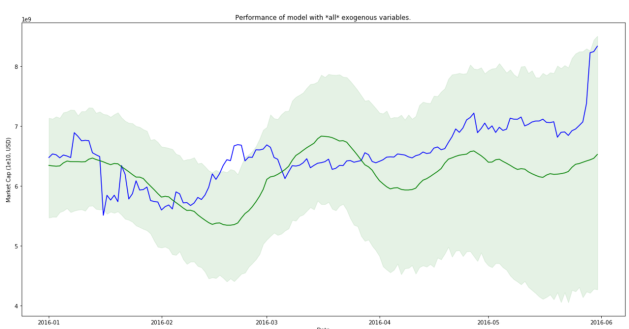
We attempted to build SARIMAX (Seasonal AutoRegressive Integrated Moving Average with Exogenous Regressors) models as well. The price data was stationary after second-order differencing. However, these models performed very poorly experimentally as they were unable to effectively handle the long-term seasonality present in our data. There is significant yearly seasonality in our daily data, which would require an extremely large number of parameters in the model that to be tuned. This process would be extremely time-intensive and therefore impractical.

Initial models with exogenous regressors performed very poorly and gave nonsensical results, such as predicting a negative market capitalization within two months. As it would have taken a very long time to tune the SARIMAX models and our Prophet models were extremely good, we did not pursue SARIMAX models for our final results.

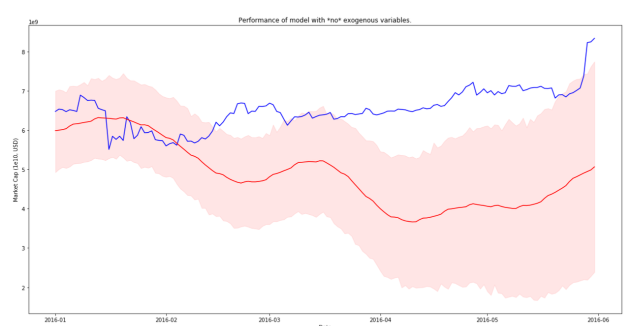
We split the dataset into training and testing sets. We will train on data before 2016 (from 2013 to 2015), and predict the first five months of 2016. This time period was after the initial boom of Bitcoin prices, but before the unpredictable media craze that led to a dramatic increase in prices in mid- to late-2017. We note that global markets experienced fluctuations during this time (specifically Korea and Japan), and we hope to find a relationship between employment rates and the CPI as it relates to investment in cryptocurrencies.

We determine our best model includes data from the United States, Korea, and Japan — three countries with some of the largest populations of active retail and institutional crypto investors. For metrics of economic activity caused by lack of confidence in domestic markets, we measure employment rates and the consumer price index (an excellent indicator of inflation/deflation). We exclude Russian metric and Exchange Rate data as both experimentally hinder our model's performance.

We are producing two Prophet models: one containing exogenous variables and one not containing exogenous variables. We would like to see that the model containing economic data as a regressor performs better than the one without.



all *exogenous variables*



no *exogenous variables*

Clearly, the model with exogenous regressors is often much closer to the actual market cap of Bitcoin. Additionally, almost every point in the first six months of forecasting is in the prediction interval for the model with exogenous regressors, but roughly half of the time, the true value falls outside the prediction interval for the model with no exogenous regressors. We measure the RMSE of the two models, and notice that the values look quite high — this is because of the scale of the market cap (it's in the tens of billions of dollars). In fact, our model with exogenous regressors gives us predictions that are on average within 7% of the true value. This is much better than the model without exogenous regressors, which predicts within 25% of the true value on average.

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RMSE of no Exogenous Variables Model: 2004137573.1770084
RMSE of all Exogenous Variables Model: 594966108.1281198


Average Mean Relative Error for no Exogenous Variables Model:
0.25492608879911066
Average Mean Relative Error for all Exogenous Variables Model:
0.07293850517492426
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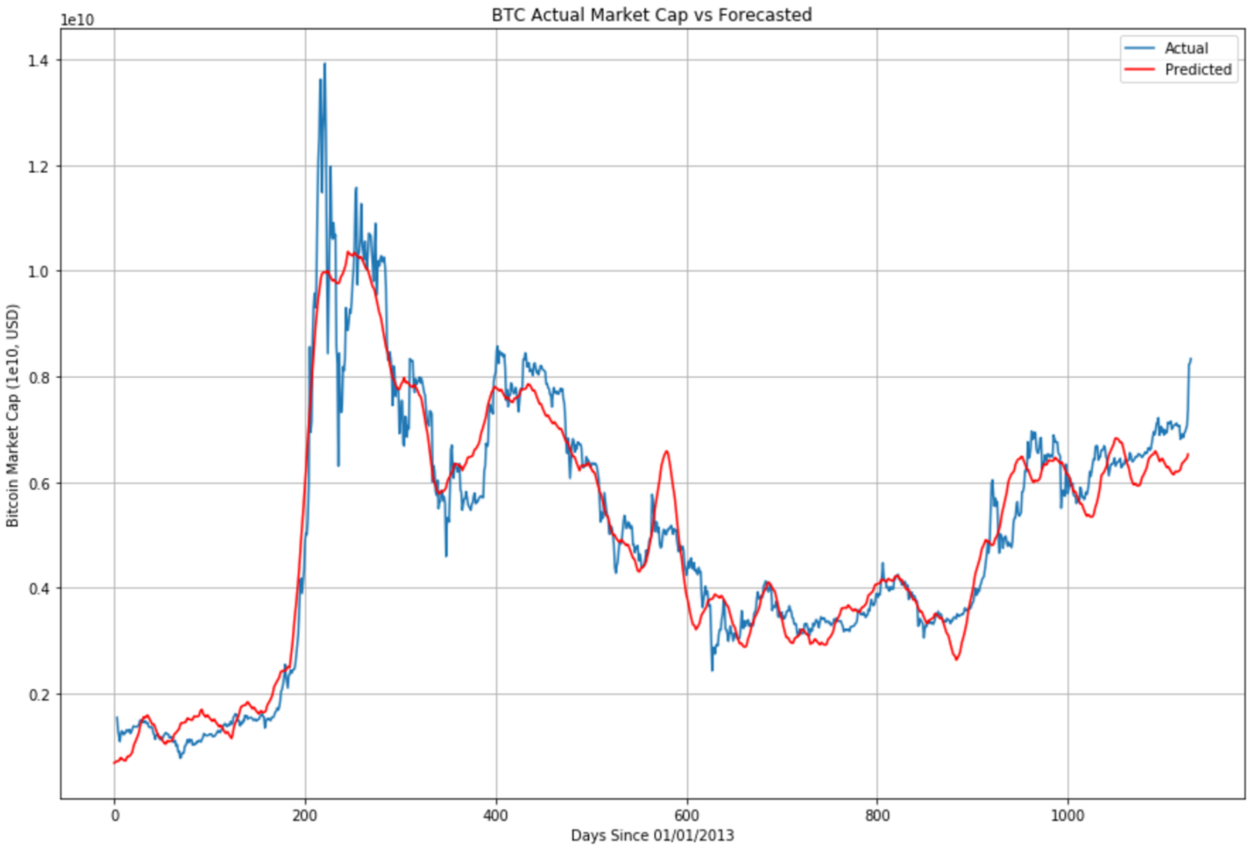
We can see that the Prophet model fairly accurately predicts BTC's market capitalization for the entire 3-year duration of the data set, although it is less sensitive to sudden changes in prices, possibly caused by one-time events (i.e. it is not accurate at a level of granularity). The performance can be viewed below:

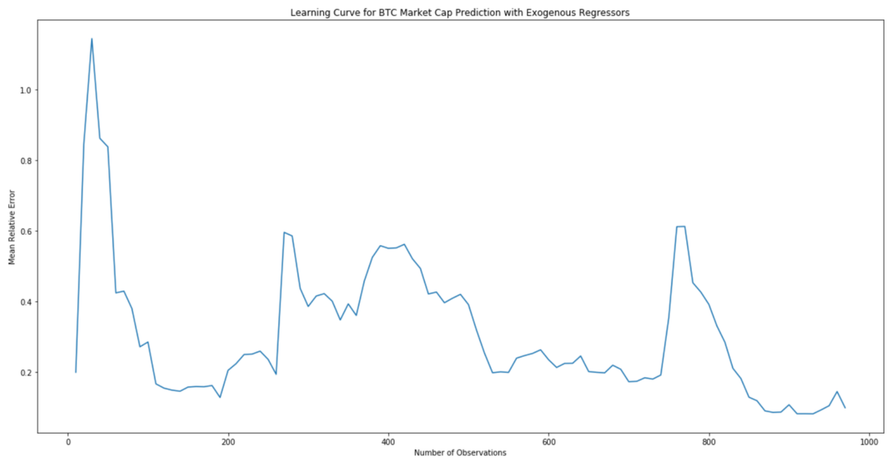


Performance of our model is indicated by the line in red.

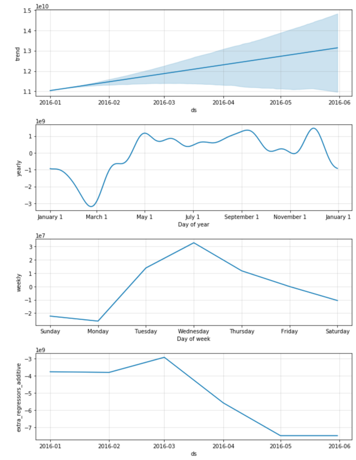
There seems to be a fair bit of yearly and weekly seasonality in Bitcoin's market cap, which is definitely surprising. Also, we notice that the role of the exogenous regressors seems to fall noticeably between March and May of 2016.

We notice that the MRE does decrease as observations increase, but we see some increases due to volatility in market cap due to variables not factored into our model, including changing legal landscapes and government regulation.

We do not attempt to predict the price of Bitcoin beyond mid-2016, since the market experiences an unprecedented amount of investment due to media (hype cycles), shifting regulations (bans or lack thereof on ICO's as a means of raising funds), securitization of tokens, etc.



Learning curve for our model.



Components of the Prophet model.

Future Work

After building our model and verifying that exogenous variables significantly aid prediction of Bitcoin market capitalization, we would be interested in exploring other hypothesized factors affecting Bitcoin price. Notably, Bitcoin is used in black markets for drugs and weapons, so if any data exists quantifying the volume of trading in these markets, this could be added as an explanatory variable as well. Further, we could use Google Trends data to explore whether media attention would allow us to predict the dramatic rise and fall of Bitcoin market capitalization between 2016 and 2018.

Additionally, we would like to investigate some unexpected conclusions of our model. We were surprised to see a degree of weekly seasonality in Bitcoin market capitalization. Our hypothesis was that there would be no significant differences between days of the week, as all exogenous regressors in our analysis did not change significantly day-to-day, and in fact we did not even have economic data at this granularity before interpolation. Also counterintuitive is that the effect of the exogenous regressors sharply declined midway through our testing interval, indicating that they were no longer as important. We do not fully understand this shift and would like to investigate it further, which could perhaps take the form of adding additional regressors, as mentioned above.

Sources

- Coinmetrics (https://coinmetrics.io/data-downloads) for retrieving daily data regarding transaction count, on-chain transaction volume, value of created coins, price, market cap, and exchange volume since December of 2013.
- IMF (data.imf.org) for data regarding inflation metrics that are more specific (as measured by the CPI, down to monthly), in case we see that inflation measures from the previous source are inadequate.
- IMF (data.imf.org) for data regarding exchange rates, which are a straightforward indicator of the value of a currency (given some other, more stable currency to which a delta can be pegged).
- IMF (data.imf.org) for the employment indices of countries of interest.

Further Reading

This is an excellent resource regarding capital flight to Bitcoin markets in the face of economic and political uncertainties:
https://cointelegraph.com/news/hyperbitcoinization-how-currency-crises-are-driving-nations-to-crypto.