Time-Frequency Analysis of Cryptocurrency Attention

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Motivation

- cryptocurrencies attract a lot of retail investors who do not trust traditional financial products and traditional brokerage companies and use the Internet to look for new investments opportunities, higher yields, lower transaction costs or greater autonomy which sometimes leads to overconfidence (Barber and Odean, 2001)
- retail investors often apply technical trading based on online data and produce cyclical behavior and excessive volatility
- Bitcoin market follows underlying yearly cycles and is driven by macroeconomic factors in the long run (Kristoufek, 2014)
- cryptocurrencies have no underlying macroeconomic price fundamentals and rather show the behaviour of a speculative bubble (Selmi, 2015; Garcia et. al., 2014)
- we study the cyclical behavior of cryptocurrency returns and retail investor attention using a wavelet analysis

Cryptocurrency as a diversifier or safe-haven?

- cryptocurrencies cannot be treated as regular currencies, and their prices often resemble speculative bubbles (Garcia et al., 2014; Bouoiyour and Selmi, 2015)
- while the Bitcoin is now commonly believed to be the ‘New Gold’, this view is largely rejected by academic research
- Bitcoin acts mainly as a diversifier but not as a hedge tool or a safe-haven currency, i.e. as an alternative asset (Bouri et al., 2017a)
- Bitcoin serves as a hedge only in times of extreme uncertainty, however, it holds only at shorter investment horizons (Bouri et al., 2017b)

- cryptocurrencies may serve mainly for diversification purposes for investors with short investment horizons (Corbet et al., 2018)
- Bitcoin prices are disconnected from gold and the main international currencies (Yermack, 2015)
- the value of cryptocurrencies primarily derived by its relation to other cryptocurrencies, not its underlying economic values (Halaburda and Gandal, 2014)

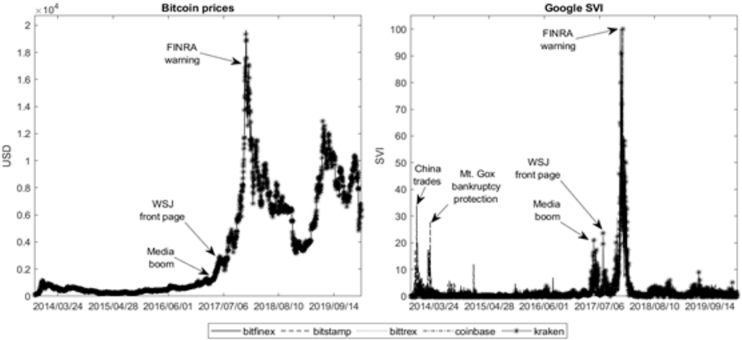
Contribution

- we identify time-varying cyclical behavior and comovements of the selected cryptocurrencies at different frequency scales
  - we separate short-term behaviour (isolation, bubbles, shocks etc.) from long-run cycles (investment horizons)
  - we introduce wavelet analysis as a form of technical analysis that looks for recurrent long-term price patterns
- we use daily data set on Google Trends (compare to Kristoufek (2015) who uses weekly data)
  - daily data is more appropriate for the analysis of cryptocurrency returns due to low liquidity of these markets
  - daily data allows us to perform a deep analysis of investment horizons
- we analyze lead/lag behaviour between retail market attention and cryptocurrency returns

Data

- daily data, from 2013-10-06 to 2020-03-31 (more than 2300 observations)
  - log returns (log differences)
  - Cryptocurrencies: Bitcoin, Ethereum, Litecoin
  - Exchchanges: Bitfinex, Bitstamp, Bittrex, Coinbase, Kraken
- Google Trends data (SVI)
  - keywords: selected cryptocurrencies and crypto-exchanges
  - Abnormal Search Volume Index (robustness checks)

Bitcoin


Bitcoin prices
×10^4
USD
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
FINRA warning
WSJ front page
Media boom
2014/03/24 2015/04/28 2016/06/01 2017/07/06 2018/08/10 2019/09/14
Google SVI
SVI
100
90
80
70
60
50
40
30
20
10
0
FINRA warning
China trades
Mt. Gox bankruptcy protection
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bitfinex
bitstamp
bittrex
coinbase
kraken

Time-frequency transformation

- we apply Continuous Wavelet Transform (CWT) as a band pass filter to time series ($x_n, n = 1, ..., N$) with uniform time steps δt, where the time step is defined as the convolution of x_n with the scaled and normalized wavelet
- wavelet power is defined as $|W_n^X(S)|^2$ (Grinsted, 2004) and:

$$W_n^X(x) = \sqrt{\frac{\delta t}{S}} \sum_{n'=1}^{N} x_n' \Psi_0 \left[(n' - n) \frac{\delta t}{s} \right]$$

  where s represents scale in time
- to localize a function in frequency and time we use Morlet wavelet Ψ_0 which provides an optimal tradeoff between both time and frequency localization (Teolis, 1998):

$$\Psi_0(\eta) = \pi^{-1/4} e^{i\omega\eta} e^{-1/2\eta^2}$$

  where $\omega_0 = 6$ is dimensionless frequency and $\eta = x \times t$ is dimensionelss time by varying its scale s

Comovement

- to identify common time-localized oscillations in nonstationary time series (comovement/correlation) we apply Wavelet Coherence (WTC) of time series x_n and y_n as:

$$R^2(s) = \frac{|S\left(s^{-1}W_n^{XY}(s)\right)|^2}{S\left(s^{-1}|W_n^X(s)|^2\right) \times S\left(s^{-1}|W_n^Y(s)|^2\right)}$$

  where smoothing operator S is defined as $S(W) = S_{scale}(S_{time}(W_n(s)))$. S_{scale} and S_{time} represent smoothing operators along the wavelet scale axis and in time.

- to identify shocks in co-movements between the analysed time series x_n and y_n we apply the Cross Wavelet Transform (XWT):

$$W^{XY}(s,t) = W^X(s,t)W^{Y*}(s,t)$$

  where $*$ denotes complex conjugation (Grinsted, 2004)

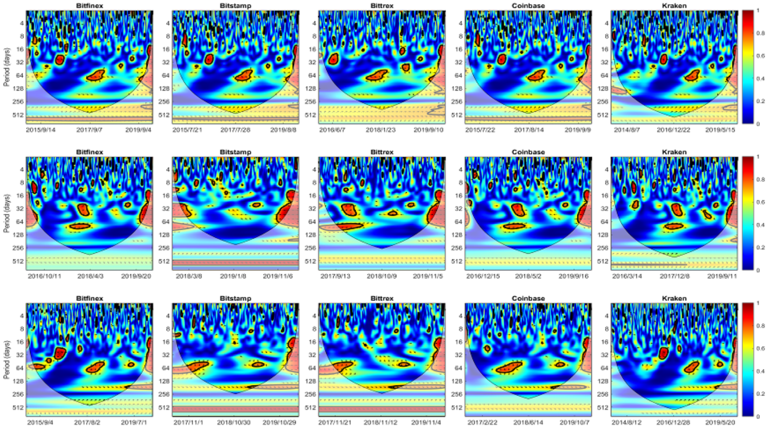
Leading/lagging indicators

- we applied phase shift to identify a time offset between the reflection and the maximum value on the waveform
- we interpret phase shift as a lead or a lag between time series
- following Grinsted (2004) we estimate the mean and confidence interval of the phase difference. The mean phase calculation is based on the circular mean of a set of angles $(a_i, i = 1, ..., n)$:

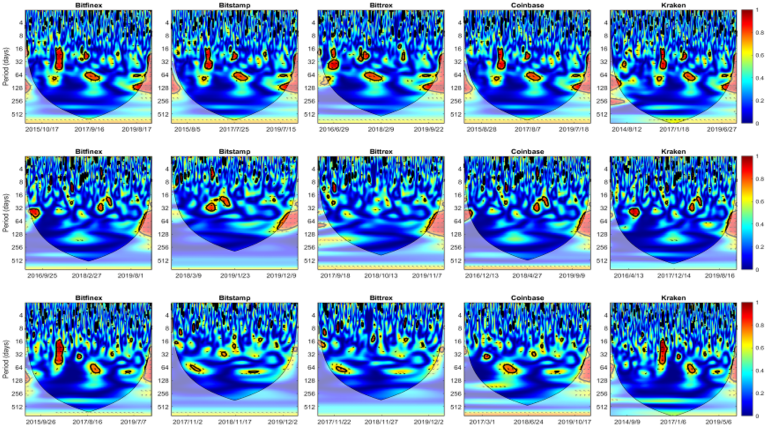
$$a_m = arg(X, Y)$$

  where $X = \sum_{i=1}^{n} cos(a_i)$ and $Y = \sum_{i=1}^{n} sin(a_i)$
- we estimated statistical significance against an autocorrelation model with lag 1 and error term represented as white noise (Torrence and Compo, 1998)

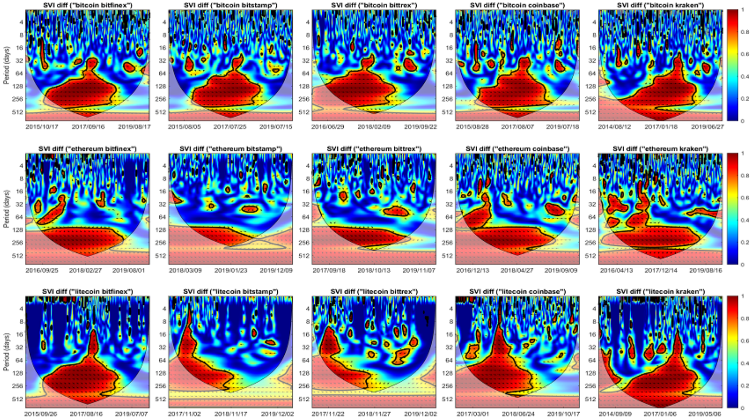
Wavelet Coherence of Stocks (S&P500) and Cryptocurrency Returns



Wavelet Coherence of Economic Policy Uncertainty and Cryptocurrency Returns



Wavelet Coherence of Search Volume Index (Investor Attention) and Cryptocurrency Returns



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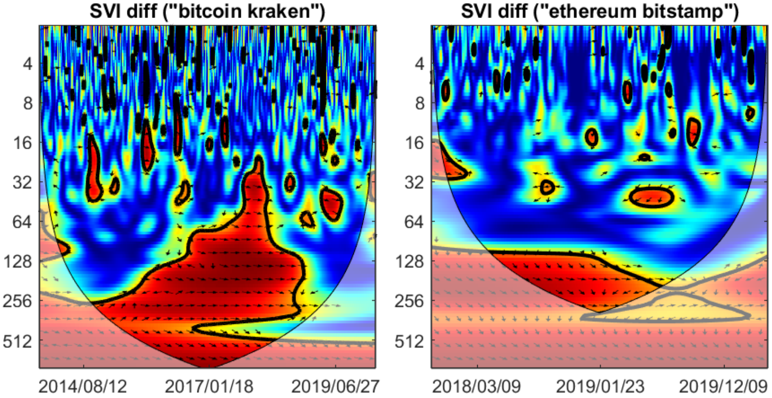
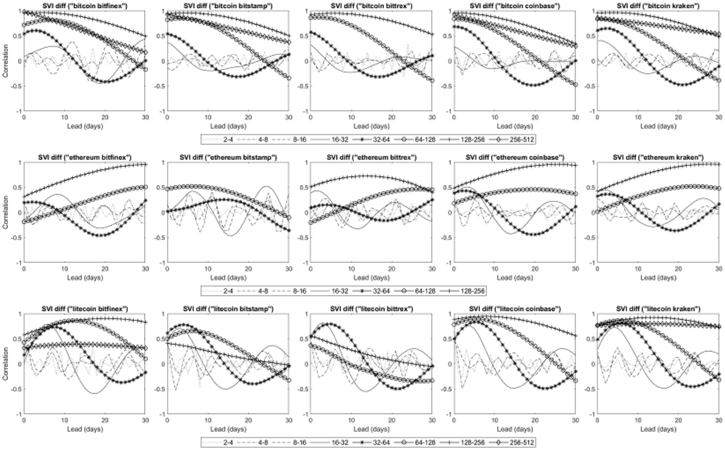
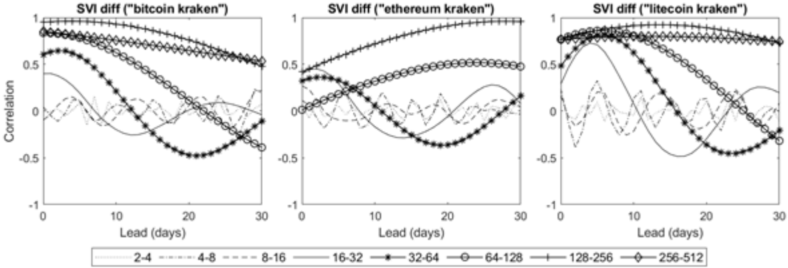


Wavelet Cross-Correlation of Search Volume Index (Investor Attention) and Cryptorurrency Returns



Wavelet Cross-Correlation of Search Volume Index (Investor Attention) and Cryptorurrency Returns



Discussion and Conclusions

- we offer alternative empirical approaches to analyze cyclical pattern of cryptocurrency returns
  - to evaluate efficient market hypothesis
  - to distinguish investment horizons employing different frequency scales
  - to identify leading/lagging indicators
- we compare selected major crypto-exchanges and their interaction across three major cryptocurrencies (Bitcoin, Ethereum and Litecoin) during a highly dynamic period, October 2013 to March 2020

Discussion and Conclusions

- we confirm low correlation to stocks and EPU
- we show comovements with retail market attention at frequencies below 64 days
- we identify retail market attention as leading indicator for two-month investment horizon

Thank you for your attention . . .

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