Essays on Cryptocurrencies

Doctoral thesis defense

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Thesis contents

Chapter I - Exploring the dynamics of Bitcoin Price: A Bayesian Structural Time Series Approach.

> Elicits cryptocurrencies in light of economic mindset. The approach includes a discussion about its "currency" vs "asset" conceptualization. Nonetheless, it is an exploratory study in general terms that aimed to find which are the factors that drive the price.

Chapter II - Investors' biases and herding behavior in the cryptocurrency market.

> Provide a conceptual framework to understand investing decision-making in cryptocurrency markets.

Chapter III - Attention, meta-information and behavioral convergence in cryptocurrency markets: A SVAR analysis

> Emphasize three traits that define decision making in crypto markets: attention-grabbing bias, behavioral convergence (herding) and response to uncertainty.

Chapter I - Exploring the dynamics of Bitcoin Price: A Bayesian Structural Time Series Approach.

Objectives

- Review the economic literature about cryptocurrencies.
- Explore the dynamics, and propose potential drivers of Bitcoin's price, that lets to:
  - Generate hypothesis.
  - Focus the attention on the relevant factors according to their prediction power.
  - Knowing the drivers, we can shed light on the scope and consequences for the economy.

Contribution

- Introduce an organized set of drivers, and how their relevancy is associated with different characteristics of Bitcoin.
- Employing the Bayesian State-Space modeling to:
  - A geographic and temporal perspective of interest on Bitcoin.
  - Perform variable selection to filter irrelevant variables.

Background

What is Bitcoin?

- Officially, Bitcoin is a decentralized digital currency, that allows users to send bitcoins on a peer to peer network without intermediaries.

However...

- *"...it can be defined as a protocol, platform, currency or payment method"* (Athey et al. 2016)
- *"...a commodity money without gold, fiat money without the state, and credit money without debt"* (Bjerg, 2016).
- Kristoufek (2015) opens the discussion of the duality property of Bitcoin (digital currency or speculative asset).
- In summary, its complexity makes it difficult to have a single definition that encompasses all uses.

Disagreements and consensus

- Bitcoin volatility is a great limitation to meet the store of value function of money.
  - Regarding its use as a currency, it is tightly linked to the credibility and acceptance of users and merchants (Luther 2016).
- It lacks intrinsic value.
- The low speed of transactions due to a long verification process is a disadvantage in front of typical mechanisms to change money.
- **Bitcoin is a speculative asset** (Baek & Elbeck, 2014; Bartos, 2015; Bouoiyour & Selmi, 2016ab; Bouri et al, 2017; Dyhrberg, 2016, among others)

Data

Dependent variable:

- Bitcoin price in levels

Independent variables:

- Internal factors
  - USD exchange trade volume
  - Median confirmation time for a block to be accepted
  - Hash rate that measures the power of miner's machines.
  - The number of transactions excluding the 100 most popular addresses.
- External factors
  - Attractiveness
    - Google trends: Weekly search queries the index for "bitcoin" from 27 different countries.
    - Varies across countries: Dynamic time warping dissimilarity algorithm
  - Macro-financial
  - S&P500 index: Indicator of the performance of a group of relevant stock market companies
  - Chicago Board Options Exchange (CBOE) Volatility Index (VIX)
  - The bearish sentiment from the AAII Investor Sentiment Survey
  - Gold's price
  - Exchanges rate of the euro with the dollar (EURO-USD), dollar with the yuan (USD-YUAN)

Methodology

- Spike and slab priors for variable selection
- Structural time series (state-space model) consists of two equations: a measurement equation which links the observed variables to unobserved state variables and a transition equation which describes the dynamics of the state variables

Observation/measurement equation:

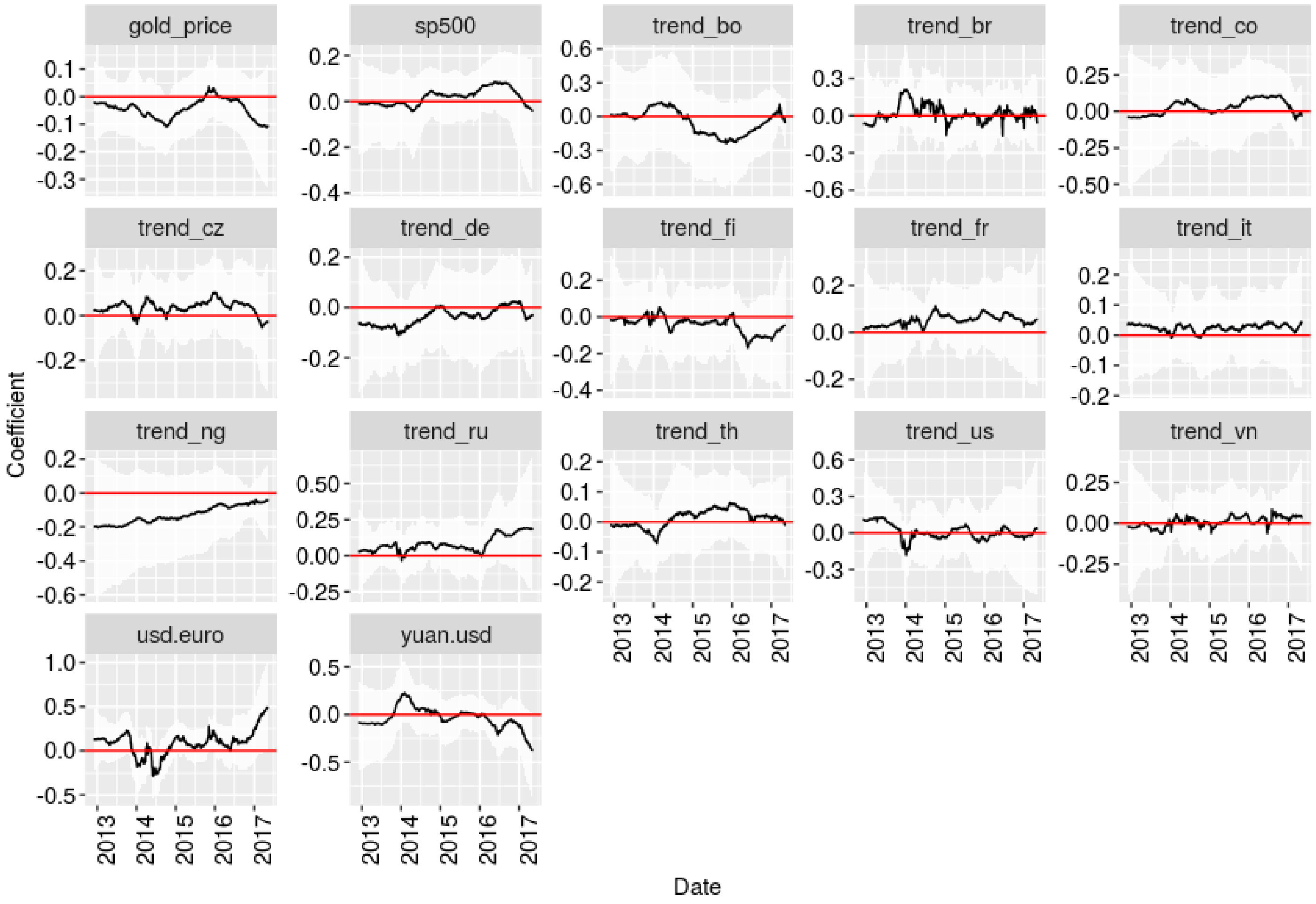
$$y_t = Z_t^T \alpha_t + \varepsilon_t \qquad \varepsilon_t \sim N(0, H_t)$$

Transition/state equation:

$$\alpha_{t+1} = T_t \alpha_t + R_t \eta_t \qquad \eta_t \sim N(0, Q_t)$$

- y_t: vector of observations
- α_t: unobserved state vector
- $Z_t,\ H_t,\ T_t,\ R_t, Q_t$: structural parameters' matrices
- $\varepsilon_t,\ \eta_t$: serially and mutually independent errors

Results | Time variant marginal posterior coefficient estimates



- Attractiveness was found to be the most relevant variables related to the Bitcoin price.
- Internal drivers (Blockchain statistics) found to have no significance to explain Bitcoin.
- Financial-related variables like gold price, S&P500 and bilateral exchange rates are related to Bitcoin price, nonetheless, the had little prediction power.
  - Bitcoin's relationship is reasonably stronger with exchange rates than any other price driver studied.

Conclusions

1. Bitcoin is represented by an amalgam of features and uses, which makes it difficult to frame it into a precedent element in economic studies.
2. Its high volatility makes it an attractive product for speculators.
3. The results show that Bitcoin's price has a small relationship with gold (negative), Yuan and US Dollar exchange rate (negative), S&P500 (negative). And a significantly higher association with different countries' search trends.
4. The future of any cryptocurrency is directly related to the credibility people assign to it, this, concerning its use as a currency, payment method or asset.

Link to next chapter:

- Is Bitcoin a currency or an asset?
- Is the cryptocurrency market susceptible to a speculative bubble?

Chapter II - Investors’ biases and herding behavior in the cryptocurrency market.

Objectives

- Characterize the cryptocurrency markets from a behavioral economics perspective.
- Find commonalities with current evidence on investor's biases present in financial-like settings.
- Demonstrate that crypto-market suffers from fragility by testing herding behavior as a source of market instability.

Contribution

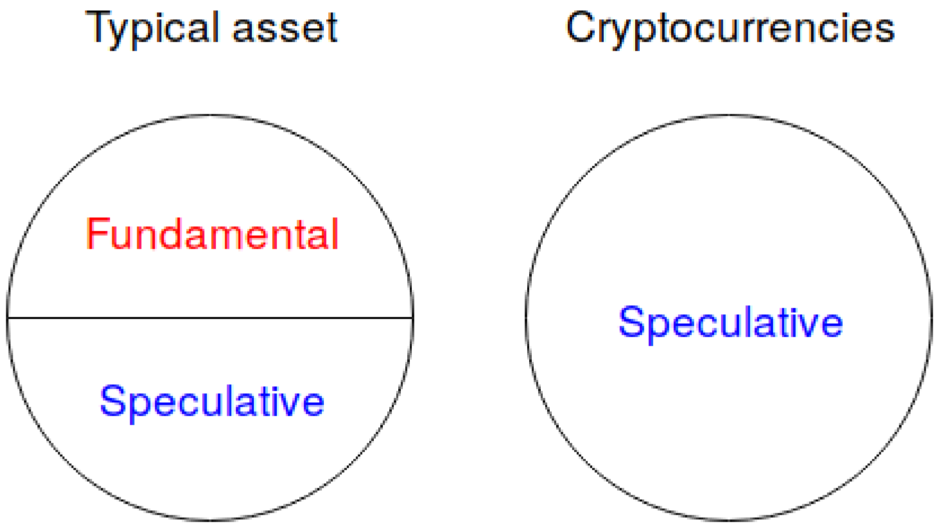
- Literature relating to behavioral economics and cryptocurrencies is barely existent yet.
- There **were** no herding behavior works on this topic (up to the time it was published).

Background

Currencies, investing or gambling?

- **Currency**:
  - Not used for transactions, besides:
    - Medium of exchange ✓
    - Unit of account ✓
    - Store of value ×

- **Asset**



Components of a typical asset vs cryptocurrencies

Background | Searching for the parallelism: Behavioral economics

Controversy:

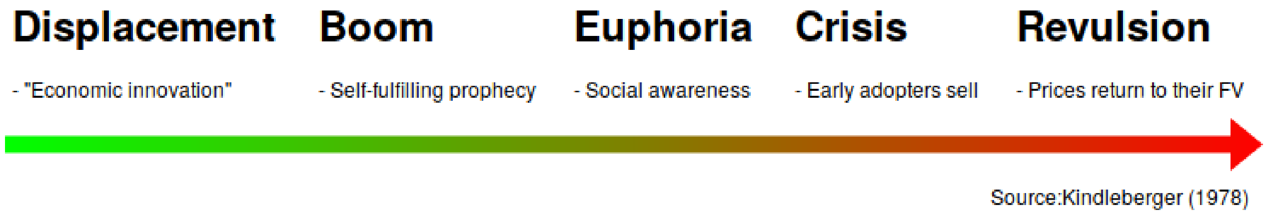
- By the late 1980s, there was a growing sense that some basic facts about financial markets were hard to reconcile with the traditional financial economics theory.
- Shiller (1981) demonstrated that fluctuations in stock market prices are unlikely a result of a rational forecast of firms' future cash flows.
  - Several cases of "anomalies" were found
  - Speculative bubbles: for instance, the Dot-com or Black Monday
- The existence of several speculative bubbles episodes stimulated the research on behavioral economics applications to finance.
- An important finding of recent years is that many of the patterns we observe in the stock market are also present in other asset classes.
  - Real state
  - Long-term bonds

Maybe cryptocurrencies?

Background | Behavioral economics: The cryptocurrency case

> Is a combination of two things people know the least: information technology and finance (not mine)

- Any disclosure evoking a "new economy" will always be an allure for people eager for profits.



Anatomy of bubbles

- Behavioral economists advocates insist on the argument that crashes are determined endogenously by investor's actions.
  - Unexpected reactions
  - "Gut feeling"
  - Momentum investor

Background | Behavioral economics: The cryptocurrency case

Can behavioral economics elucidate on the cryptocurrency puzzle?

Can we test for the existence of speculative bubbles in cryptocurrencies?

Problems:

- Most of the tests are designed to identify abnormal deviations from fundamentals.
- Fundamental valuation is arguably valid in cryptocurrencies.
- Speculative bubbles can only be determined *ex-post*.

Nonetheless, we can test if the system suffer from fragility

Background | Herding behavior

What is herding?

- A process that stems when someone **choose to ignore her private information and instead jump to the bandwagon by mimicking the actions of individuals who acted previously**[1]
- Herding or behavioral convergence entails the existence of a coordination mechanism (Devenow and Welch, 1996).
  - The coordination/transmission mechanism can be indirect or direct signals.
  - Word-of-mouth, news and social media exposition, in-place observation, etc.
  - **First degree: Observe other's decision-makers**
  - **Second degree: Price movements**

[1] See Banerjee, 1992; Bikhchandani; Kumar & Goyal, 2015; Hirshleifer and Welch, 1992; Graham, 1999.

Background | Herding behavior in crypto-markets

Characteristics:

- Social judgment is intrinsic to the cryptocurrency market since the valuation of any currency is contingent on the extension of the group that founds it valuable.
  - It is profitable to achieve the interest of a critical mass of users/investors that yield a higher market capitalization.
- Scharfstein and Stein (1990) stated that within individual investment environments, **managers usually disregard private information by adopting a follow-the-crowd strategy**.
- **Limits of attention** increase the probability of herding due to the difficulty to accurately process information (Hirshleifer and Hong Teoh, 2003).
- Welch (2000) found that **analysts herd in their stock recommendations**, exposing **significant positive correlation between adjacent analysts**.
- Bikhchandani, Hirshleifer and Welch (1992) proved that herding **explain conformity, fads, fashions, booms, and crashes**
  - De Long et al. (1990) **noise trader**[1] **misperceive expected returns** and **generate beliefs and heuristics to buy and sell following a simple feedback rule** -> **Volatility**

[1] Represents the irrational alter ego of sophisticated investors. Opposite of Information (Black, 1986)

[2] There are several works on investor trading, managerial investment, financing choices, analyst following and forecasts, market prices, market regulation, bank runs, bubbles, and welfare (see Hirshleifer and Hong Teoh, 2003; Brunnermeier and Oehmke, 2013, Grossman and Stiglitz; 1976)

Background | Herding

What is the relationship between herding and speculative bubbles?

- Herding solely could not explain the presence of speculative bubbles, but it provides information about **crypto-market conformity dynamics** that entails **fragility** and **bubble susceptible** behavior

Can herding be measured through prices?

R/ Test for empirical herding are by construction imperfect but some approximation can be done

Data

- The last cut showed that there were 1557 different cryptocurrencies available in the market
- This study dampens the sample to the first 100 leading ones which in aggregated terms account for nearly 96% of total cryptocurrency's (CC) market capitalization.
- Data was scraped from www.coinmarketcap.com website
- Range of date varies between cryptocurrencies From 2013-04-01 to 2018-04-15

$$R_{c,t} = \frac{CP_t - CP_{t-1}}{CP_{t-1}}$$

$R_{c,t}$: Market returns for the cryptocurrency c
CP_t: Closing prices for time t

Methodology | CSAD

Cross Sectional Absolute Deviation (CSAD) is calculated as:

$$CSAD_t = \frac{\sum_{i=1}^{n} \left|R_{c,t} - \bar{R}_{m,t}\right|}{N}$$

- $CSAD_t$: Cross-Sectional Absolute Deviations of Bitcoin' returns for time t
- $\bar{R}_{m,t}$: Cross-Sectional **Median** Return for crypto-market portfolio m across time t
- Basic idea: **if market participants tend to follow the consensus and ignore their priors during periods of large price movements, then the linear and increasing relation between dispersion and market return will no longer hold**.
  - The relation can become non-linearly increasing (adverse herding) or even decreasing (herding).

Methodology | Initial specification

$$\begin{aligned}
CSAD_{t,1} &= \gamma_{0,1} + \gamma_{1,1} D \times |R_{m,t}| + \gamma_{2,1}(1-D) \times |R_{m,t}| + \\
&\quad D \times \gamma_{3,1} R_{m,t}^2 + \gamma_{4,1}(1-D) \times R_{m,t}^2 + \gamma_{4+k,1} CSAD_{t-k,1} + \varepsilon_{t,1} \quad S_t = 1 \\
CSAD_{t,2} &= \gamma_{0,1} + \gamma_{1,2} D \times |R_{m,t}| + \gamma_{2,2}(1-D) \times |R_{m,t}| + \\
&\quad D \times \gamma_{3,2} R_{m,t}^2 + \gamma_{4,2}(1-D) \times R_{m,t}^2 + \gamma_{4+k,2} CSAD_{t-k,2} + \varepsilon_{t,2} \quad S_t = 2 \\
&\vdots \qquad\qquad\qquad\qquad \vdots \\
CSAD_{t,i} &= \gamma_{0,i} + \gamma_{1,i} D \times |R_{m,t}| + \gamma_{2,i}(1-D) \times |R_{m,t}| + \\
&\quad D \times \gamma_{3,i} R_{m,t}^2 + \gamma_{4,i}(1-D) \times R_{m,t}^2 + \gamma_{4+k,i} CSAD_{t-k,i} + \varepsilon_{t,i} \quad S_t = i
\end{aligned}$$

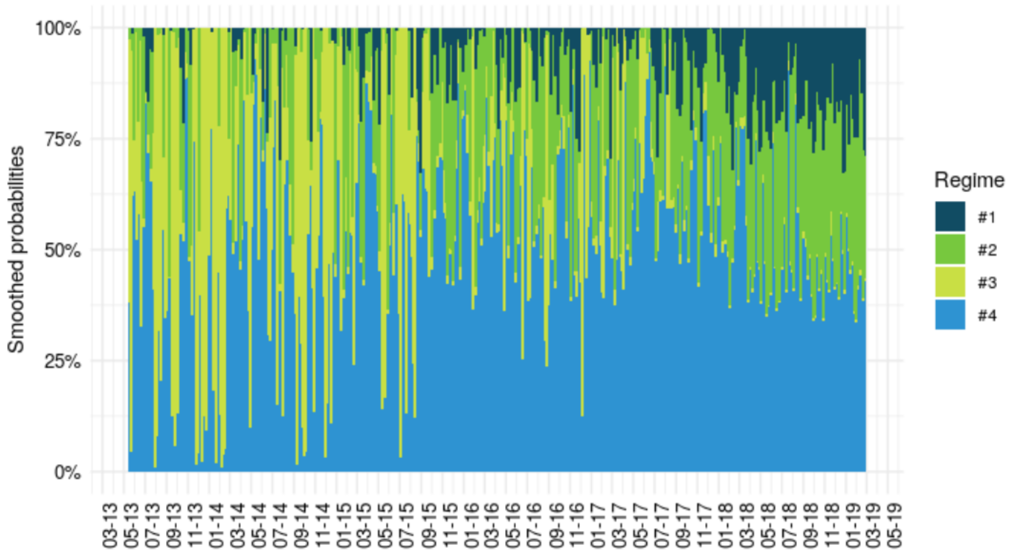
with: $\varepsilon_{t,i} \sim N(0, \sigma_i^2)\ for\ i = 1, \ldots, n$

- Parameters $\gamma_r \ \ for \ \ r = 1, \ldots, 4+k$ and σ_s^2 will be allowed to change.
- The model employed Newey and West (1987) variance estimator to produce consistent standard errors in the presence of autocorrelation and heteroscedasticity.
- The Markov Switching method captures shifts in behavior which are not observable.
  - High-frequency data exhibits structural changes in their behavior associated with observed and unobserved events.
  - **It is expected that herding display dynamics that are regime dependent, i.e. adverse herding (scattering) vs herding, and magnitude of herding-**
- The number of "regimes" is chosen given the Akaike Information Criteria (AIC).

Results | Herding under symmetric conditions

Term	OLS	OLS^{HAC}	Regime 1	Regime 2	Regime 3	Regime 4
γ_0	-0.007***	-0.007***	-0.006***	-0.005***	-0.016***	-0.001
	(-8.503)	(-7.517)	(-4.960)	(-11.692)	(-12.409)	(-0.792)
γ_1	0.203***	0.203***	0.024	0.142***	0.715***	0.191***
	(8.955)	(5.647)	(0.639)	(3.355)	(6.503)	(3.248)
γ_2	-0.212**	-0.212	0.416***	-0.540***	-1.615***	-0.545**
	(-2.361)	(-1.315)	(4.438)	(-2.779)	(-4.020)	(-2.048)
γ_3	-0.303***	-0.303***	-0.155	0.063	-0.290	-0.647***
	(-3.348)	(-2.787)	(-1.016)	(0.470)	(-0.698)	(-3.098)
γ_4	-0.566***	-0.566***	-0.682***	-0.486***	-0.761***	-0.125**
	(-26.533)	(-16.385)	(-18.596)	(-6.510)	(-35.233)	(-2.450)
γ_5	-0.373***	-0.373***	-0.708***	0.114***	-0.504***	-0.249***
	(-16.427)	(-10.554)	(-6.411)	(43.408)	(-6.589)	(-4.689)
γ_6	-0.208***	-0.208***	-0.667***	0.164***	-0.178**	-0.061
	(-10.167)	(-6.720)	(-9.435)	(3.383)	(-2.539)	(-1.482)
Multiple R^2	0.318		0.824	0.649	0.457	0.185
AIC	-9997.570		-10926.980			

This table presents estimates of $CSAD_{t,s} = \gamma_{0,1} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}R^2_{m,t} + \gamma_{3,s}Vol_t^{R_{m,t}} + \gamma_{3+k,s}CSAD_{t-k} + \varepsilon_{t,s}$ testing for the existence of herding behavior. Where OLS stands for Ordinary Least Square estimation and OLS^{HAC} shows the Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation, being both referred as static models. Alternatively, the columns referred as regimes 1-4 describe the Markov-Switching estimates of herding behavior where all variables are allow to change stochastically. The numbers in parenthesis are t-statistics, ***, ** and * stands for significance at 1%, 5% and 10% levels respectively, and finally, Multiple R^2 estimates and Akaike Information Criterion (AIC) are described for each model.

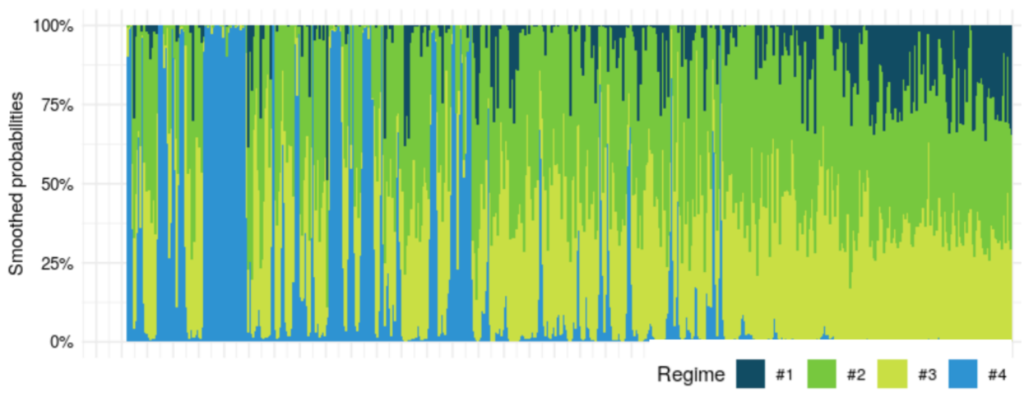


- The relevance of this result lies in the informational properties of crypto-markets. **Agents rely on current market conditions to define and shape the expected value of any cryptocurrency, prices are the coordination mechanism.**
- Crypto-investors behave in aggregate consensus in the existence of extreme market returns.
- **Herding is ubiquitous to crypto-markets, but there is a visible stronger tendency to follow the consensus in comparison to adverse herding.**

Results | Herding under asymmetric conditions

Term	OLS	OLS^{HAC}	Regime 1	Regime 2	Regime 3	Regime 4
γ_0	-0.005***	-0.005***	-0.005***	0.002	-0.003*	-0.017***
	(-5.628)	(-5.526)	(-3.920)	(0.737)	(-1.908)	(-3.895)
γ_1	0.232***	0.232***	0.063**	0.094	0.114*	0.669***
	(9.652)	(6.849)	(1.971)	(1.577)	(1.851)	(7.188)
γ_2	-0.464***	-0.464***	-0.257	0.568*	-1.266***	-1.061***
	(-4.224)	(-3.000)	(-1.617)	(1.890)	(-3.009)	(-3.598)
γ_3	-0.168*	-0.168	0.163	-0.645	1.598***	-1.123***
	(-1.875)	(-1.191)	(0.771)	(-1.539)	(2.933)	(-4.646)
γ_4	-0.593***	-0.593***	-0.746***	-0.196***	-0.658***	-0.674***
	(-29.232)	(-17.754)	(-19.703)	(-3.578)	(-8.756)	(-13.248)
γ_5	-0.393***	-0.393***	-0.703***	-0.288***	0.065	-0.473***
	(-17.797)	(-10.972)	(-20.944)	(-4.272)	(1.061)	(-8.355)
γ_6	-0.217***	-0.217***	-0.632***	-0.080*	0.029	-0.236***
	(-10.731)	(-6.903)	(-23.417)	(-1.672)	(0.446)	(-4.425)
Multiple R^2	0.327		0.864	0.109	0.691	0.415
AIC	-10024.070		-10948.560			

This table presents the estimated coefficients of the specification $CSAD_{t,s} = \gamma_{0,s} + \gamma_{1,s}|R_{m,t}| + \gamma_{2,s}DR^2_{m,t} + \gamma_{3,s}(1-D)R^2_{m,t} + \gamma_{3+k,s}CSAD_{t-k} + \varepsilon_{t,s}$ testing for the existence of herding behavior, where OLS stands for Ordinary Least Square estimation and OLS^{HAC} shows the Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation, being both referred as static models. Alternatively, the columns referred as regimes 1-4 describe the Markov-Switching estimates of herding behavior where all variables are allow to change stochastically. The numbers in parenthesis are t-statistics, ***, ** and * stands for significance at 1%, 5% and 10% levels respectively, and finally, Multiple R^2 estimates and Akaike Information Criterion (AIC) are described for each model.



- Crypto-investors herd in both directions; nonetheless, the magnitude in which they react to declining conditions is almost three times greater than what could be seen in increasing conditions.
- Crypto-investors seem to be affected by the likelihood of losing money, henceforth, they shape outweigh "bad news," conveyed by a seemly declining evolution of the coordination mechanism.
  - Results that are consistent with the Prospect Theory

Conclusions

- Behavioral economics is a suitable framework to explain crypto-market price dynamics.
- The single most striking result of the research is that herding is not an unusual phenomenon or anomaly; instead, **herding is a regularity of the crypto-market**.
  - The boost of herding entails market fragility.
- Agents converge in their decisions 3 times higher in magnitude when the market shows median negative returns, in comparison to positive returns.
- A market as ambiguous as the cryptocurrencies is chaotic by construction, without any guide that determines an objective valuation that anchors informed expectations, it is impossible to coordinate a large sum of bias-prone individuals. **Trust may not be enough.**

Link to next chapter:

- Can we establish a causal relationship between herding behavior and market prices?

Chapter III - Attention, meta-information and behavioral convergence in cryptocurrency markets: A SVAR analysis

Objectives

- Integrate the insights from the 2 previous chapters.
- Propose a proxy to measure behavioral convergence in the cryptocurrency market.
- Approximate a causal interpretation of the relationship across the relevant elements of a crypto-market system.

Background

- Human beings have limited computational resources to undertake a decision-making task.
- Anomalies are far more common in crypto markets than in financial environments.
- Bitcoin plays a dual role, first, it is an amalgam of currency and an asset, and secondly as a meta-informational input to convey trust to the entire "crypto-market".
    - Trust is a proxy for loss-aversion.
- The market acts like a feedback loop cues $\rightarrow$ reaction $\rightarrow$ strategy $\rightarrow$ cues

Methodology | Measures and system variables

1. Measuring herding intensity:

$$\begin{aligned}CSAD_t =& \gamma_0 + \gamma_1 D \times |R_{m,t}| + \gamma_2(1-D) \times |R_{m,t}| + \\ & \gamma_3 D \times R_{m,t}^2 + \gamma_4(1-D) \times R_{m,t}^2 + \\ & \gamma_5 D \times Vol_t^{R_{m,t}} + \gamma_6(1-D) \times Vol_t^{R_{m,t}} + \\ & \gamma_7 CSAD_{t-1} + \gamma_8 CSAD_{t-2} + \gamma_9 CSAD_{t-3}\end{aligned}$$

$$\begin{aligned}CSAD_t =& \boldsymbol{Z_t}\alpha_t + \varepsilon_t \qquad & \varepsilon_t \sim N(0, H_t) \\ \alpha_t =& \boldsymbol{T_t}\alpha_{t-1} + \boldsymbol{R_t}\eta_t \qquad & \eta_t \sim N(0, Q_t)\end{aligned}$$

$$\begin{aligned}HIND &= \hat{\gamma_{3,t}}|\Omega_{t-1} \\ HINU &= \hat{\gamma_{4,t}}|\Omega_{t-1}\end{aligned}$$

2. Measuring uncertainty:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q}(\alpha_i \epsilon_{t-i}^2 + \gamma_i I_{t-i} \epsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where the I_t indicator variable describe the bias stemming from the less than average returns described as:

$$I_{t-i} = \begin{cases} 1 & if\ r_{t-i} < \mu \\ 0 & if\ r_{t-i} \geq \mu \end{cases}$$

3. Measuring attention:

Adjusted Google Search Index

Methodology | Structural Vector Autoregressive system

$$
\begin{aligned}
trait_t^A = \gamma_{0,1} + \gamma_{1,1} trait_{t-1}^A + \cdots + \gamma_{n,1} trait_{t-n}^A + \\
\phi_{1,1} trait_{t-1}^B + \cdots + \phi_{n,1} trait_{t-n}^B + \\
\theta_{1,1} trait_{t-1}^C + \cdots + \theta_{n,1} trait_{t-n}^C + \cdots + \varepsilon_{1,t} \\
trait_t^B = \gamma_{0,2} + \gamma_{1,2} trait_{t-1}^A + \cdots + \gamma_{n,2} trait_{t-n}^A + \\
\phi_{1,2} trait_{t-1}^B + \cdots + \phi_{n,2} trait_{t-n}^B + \\
\theta_{1,2} trait_{t-1}^C + \cdots + \theta_{n,2} trait_{t-n}^C + \cdots + \varepsilon_{2,t} \\
\vdots
\end{aligned}
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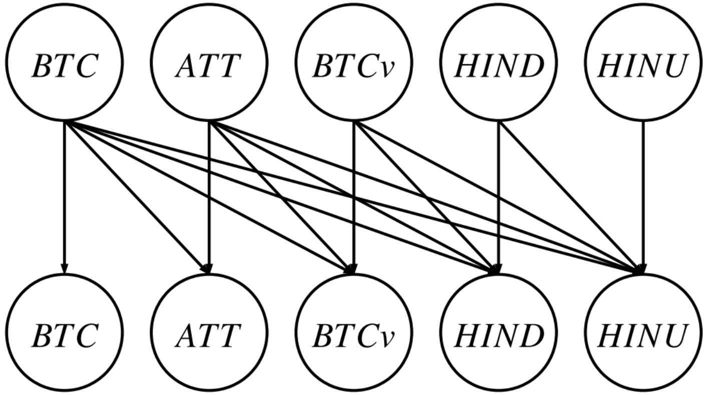
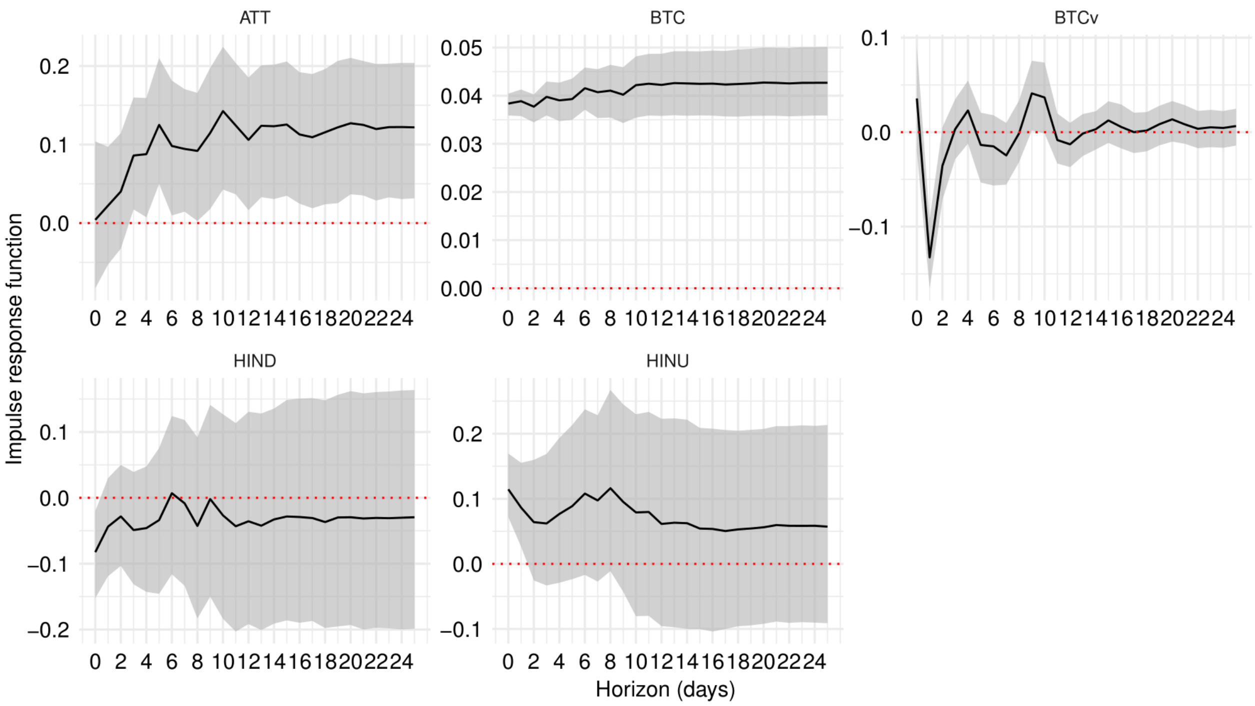


Ordering of the orthogonalized impulse-response function

- A Structural form of a VAR system based on the Cholesky Decomposition posits a causation chain of shocks.
- The order of the variables is defined by the speed of information flow.
- Assumptions:
  - Bitcoin's signal is the fastest trait that affects all the variables at time t.
  - Behavioral variables are "sticky", therefore they respond to the lastest.

Results | Shock from Bitcoin

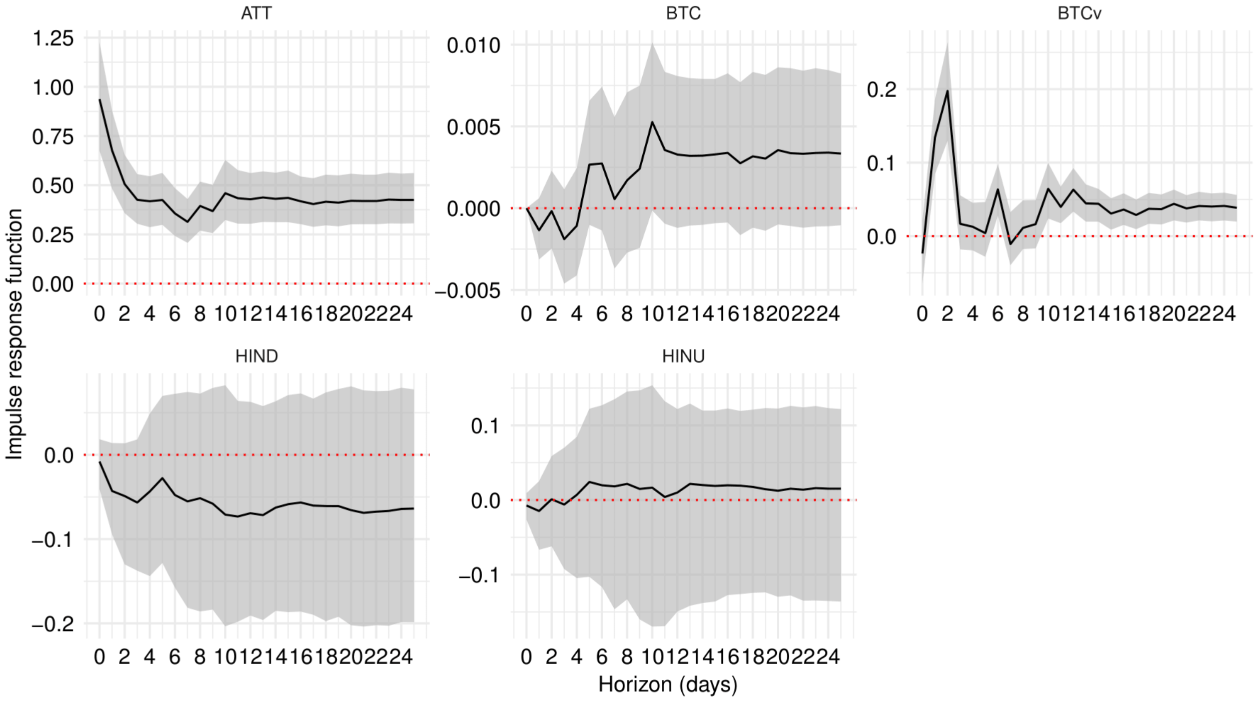


Cumulative IRF effect from Bitcoin's returns (BTC) to the rest of the variables in the system

- One shock from Bitcoin's returns generates a short-term effect on the level of attention, which remains for several days, prices indeed react faster than revealed attention.
- A positive shock in BTC returns is associated with a decrease in dispersion, but the effect cancels out quickly.
- BTC returns sends a signal to the participants, then they react by following the consensus by demanding more of the any of the cryptocurrencies used to generate the index.

- Bitcoin is more than an asset/currency, it also conveys trust on the whole market, i.e. if Bitcoin is doing good, that market is going well.
- It defines strategy to follow, for instance, momentum trading.

Results | Shock from attention

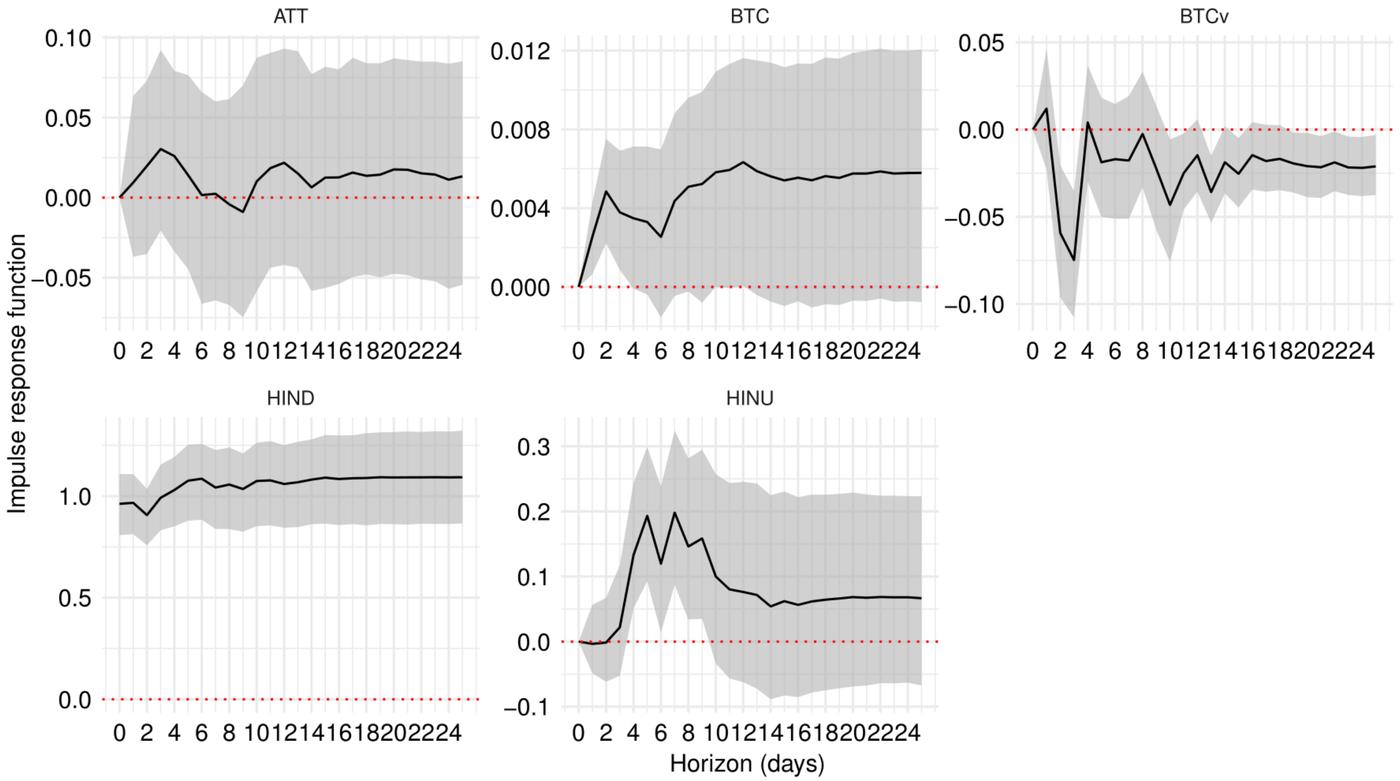


Cumulative IRF effect from attention (ATT) to the rest of the variables in the system

- A shock from the attention-grabbing index does not affect BTC returns. Meaning that this relationship is uni- directional.
- Attention does affect the dispersion of the BTC horizon of 2 days, then it is adjusted quickly and shows a positive long-lasting response.

- H: attention-grabbing events induce price pressure since investors respond to such shocks demanding more of a small set of stock that “glitter” among all.
- Revealed attention is an approximation to the decision mechanism used by the newswatchers (Holt and Stein, 1999)

Results | Shock from herding index under decreasing states

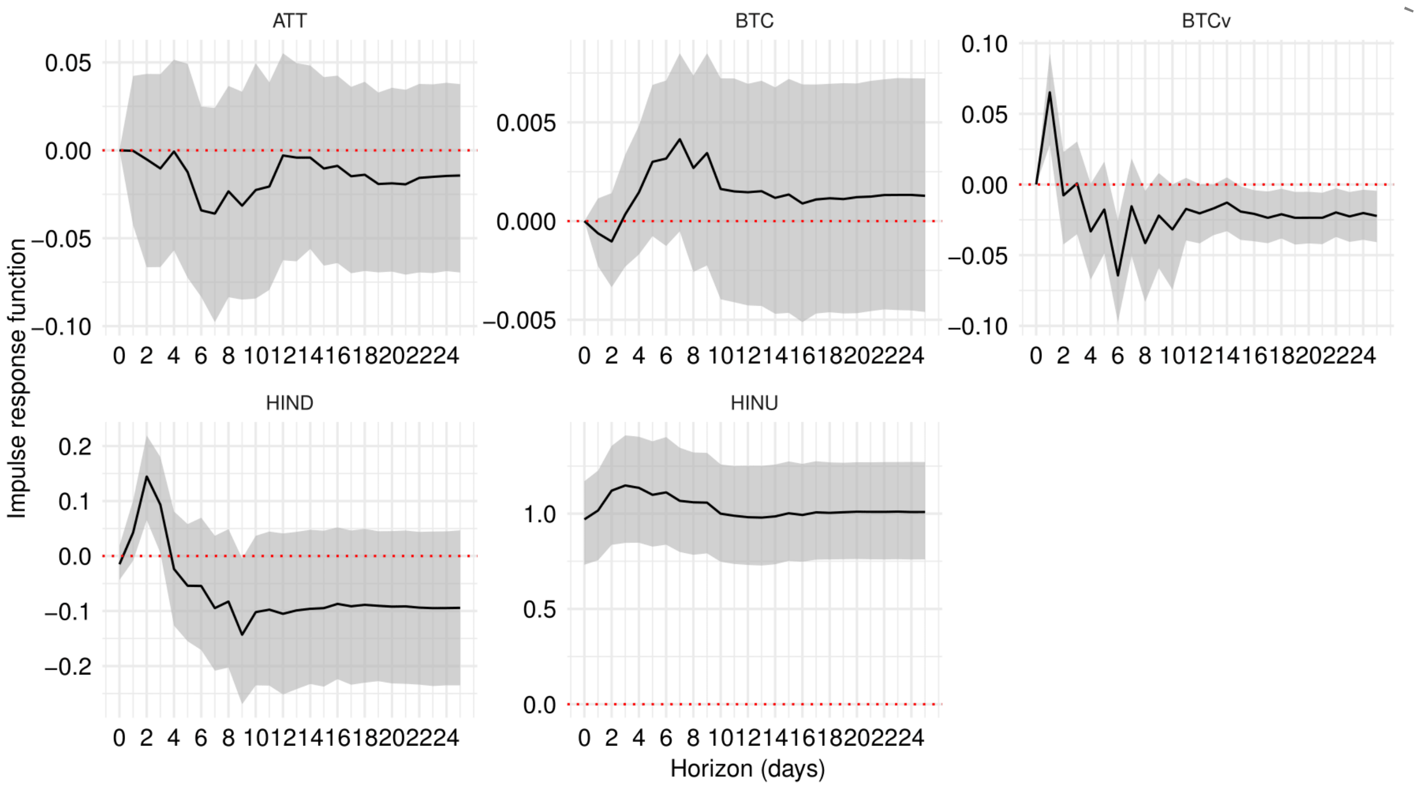


Cumulative IRF effect from herding index under decreasing states (HIND) to the rest of the variables in the system

- Attention either manifested from cues-seekers and momentum traders' agents, serve as drivers to decision-making, either to play a contrarian or herding role, and not the other way around.
- An impulse in herding under decreasing market states does not affect ATT, however, it does have a significant (but small one) response on Bitcoins' returns.

- Herding is not explicitly observable by investors.

Results | Shock from herding index under increasing states



Cumulative IRF effect from herding index under decreasing states (HINU) to the rest of the variables in the system

- HINU and HIND are underlying market behavior, hence there are not expected to affect the cues-seekers actions.
- The more the market coordinates their behavior, the less dispersion around the BTC price. The transmission of market-wide uncertainty is passed to price returns.

Conclusions

- The absence of reliable signals, there is strong evidence of crypto-investors to resort to ignore their private information and follow the consensus.
- Revelead attention does not have an effect on BTC, but BTC does have a short effect on attention.
- Bitcoin is a reference to take decisions in the whole market. If Bitcoin is doing good, the market is doing good, however, this mechanism creates fragility and foster uncertainty.
- In the absence of cues on fundamentals, BTC returns guides crypto-investors, therefore, there is little chance for the market to correct itself by the active participation of individuals if all of them form beliefs according to the positive feedback valuation only.

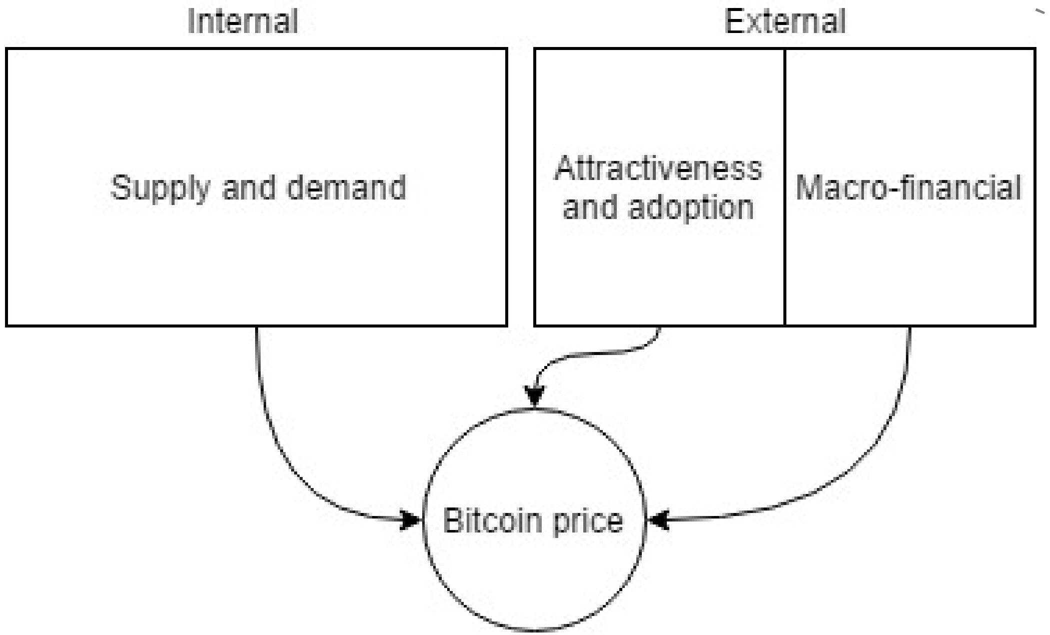
Insights' summary

1. In a constantly changing environment that cryptocurrency exposes, it is highly important to introduce a dynamic analysis to understand and differentiate between perennial and long-lasting relationships. In that sense, this thesis emphasized into adopting such perspective.
2. Cryptocurrencies are practically isolated from the economy outside, namely financial and macroeconomic conditions. If so, any impact that might affect here will have little effect on the economy.
3. Crypto-inversors behave in a collective decision-making process in which prices “as is” are the coordination mechanism to invest.
   1. This can trigger the formation of speculative bubbles.
   2. The current behavioral setting within the cryptocurrency market posits doubts about their use as a currency since volatility is a persistent trait.
4. Once the state is herding there is a high likelihood that the next state will be strong herding as well..
   1. This means that once there is evidence of people to ignore their own priors substantially, herding propagates in the market, which is unlikely to be corrected back to the “normal” state.
5. The evidence suggests that it is unlikely that cryptocurrencies have a future to trade for goods and services. However, as many inventions of the information technology environment, they can evolve to solve other needs.

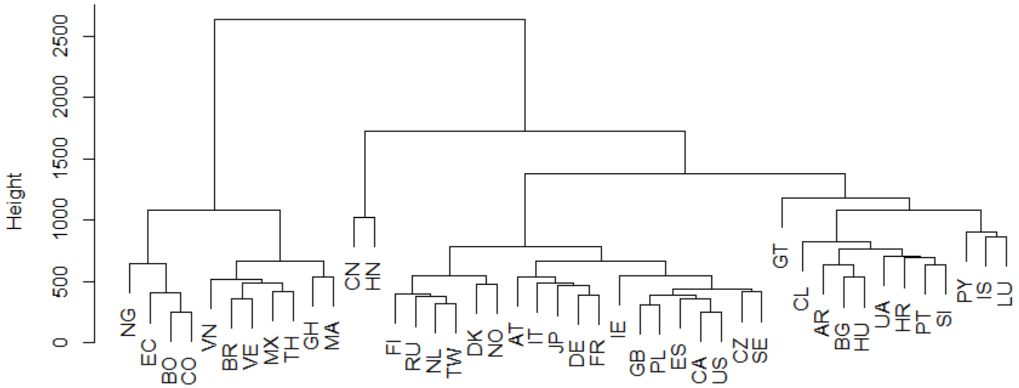
Thanks!

Appendix

Chapter I



Group of drivers



Clustered GSI by country

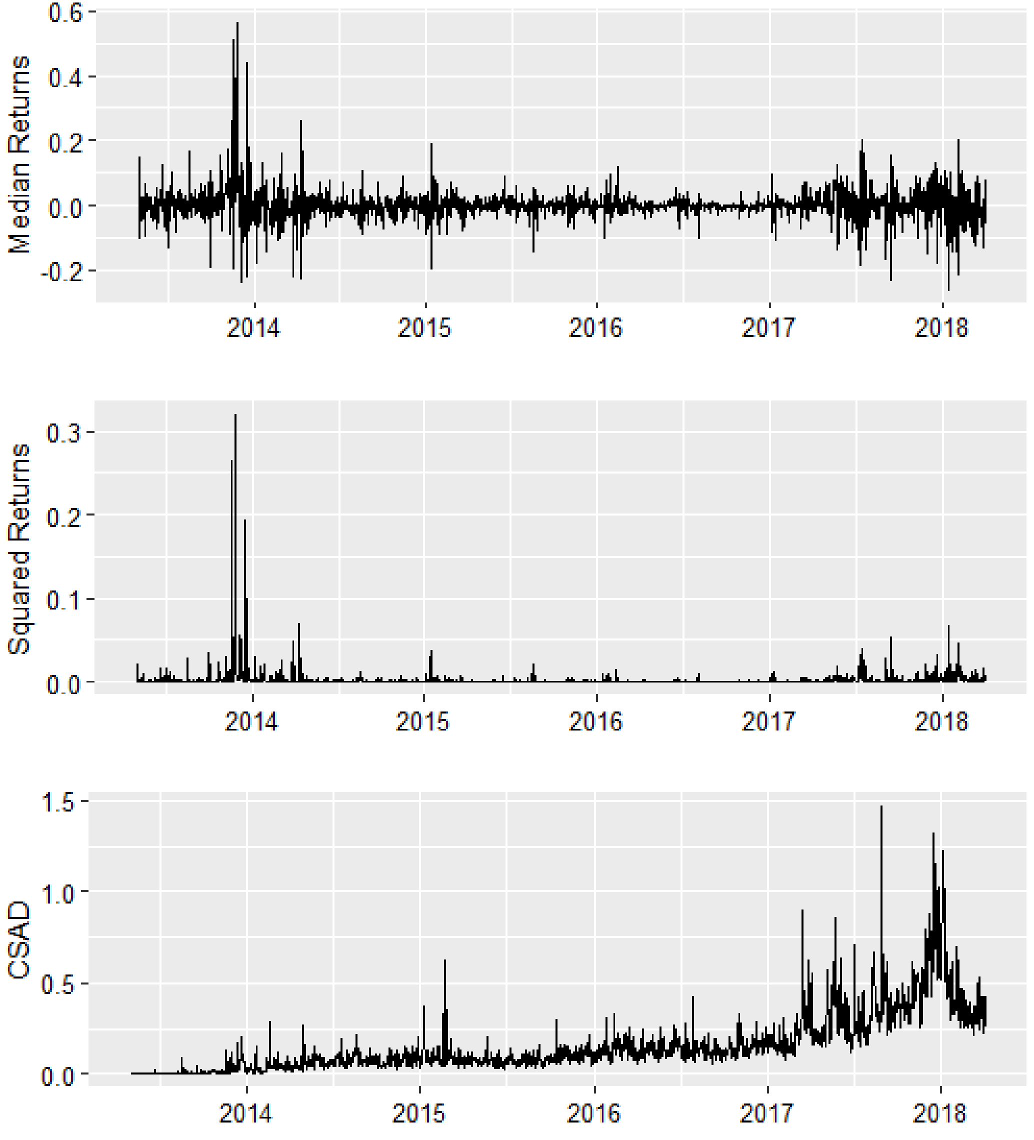
Chapter II

Searching for the parallelism: Efficient markets

- Current theoretical framework on financial economics assumes markets function **efficiently** [1]
- An efficient market is characterized by:
    - *Large numbers of rational, profit-maximizers and, actively competing individuals*
    - Current information is almost freely available to all participants
    - Actual prices reflect the effects of salient announcements
    - The actual price is a good estimate of assets' intrinsic value[2]
- EMH had an unprecedented impact on the economic theory and practice of modern financial economics

[1] Contemporaneous modern finance theory is based on the contribution of Eugene Fama, Stephen Ross, Robert Merton, Myron Scholes, William Sharpe, among others.

[2] Fundamental or intrinsic value is the true value of a stock-based business measured by the discounted cash flows of a firm.



Cryto-market: Median, Squared CSAD returns

Optimism and overconfidence [1]

- People exhibit exacerbated trust on their own ability, knowledge, and skills
- Self-reliance on personal judgments entails
  - miscalibration
  - over-precision
  - optimism
  - and overreaction to random events

- Examples:
  - **90% of Swedish car drivers considered themselves better than the median driver** (Svenson, 1981).
  - People fail to assign probabilities and calibrate unexpected events.
    - When asked for 1% and 99% tails for inflation and exchange rates, the results found experts had **20% rate of "surprise" instead of the expected 2%** (Alpert & Raiffa, 1982)

[1] See Barber and Odean 2013; Kahneman and Riepe, 1998; Barberis and Thaler, 2002; Alpert and Raiffa, 1982

Optimism and overconfidence

- Crypto-investors can easily be overconfident of their capacity to invest in a market characterized by increasing trend and high returns
- Random events in one cryptocurrency are interpreted and extrapolated to other altcoins, **this might be the reason several cryptocurrencies are correlated**

Interpretation to random events

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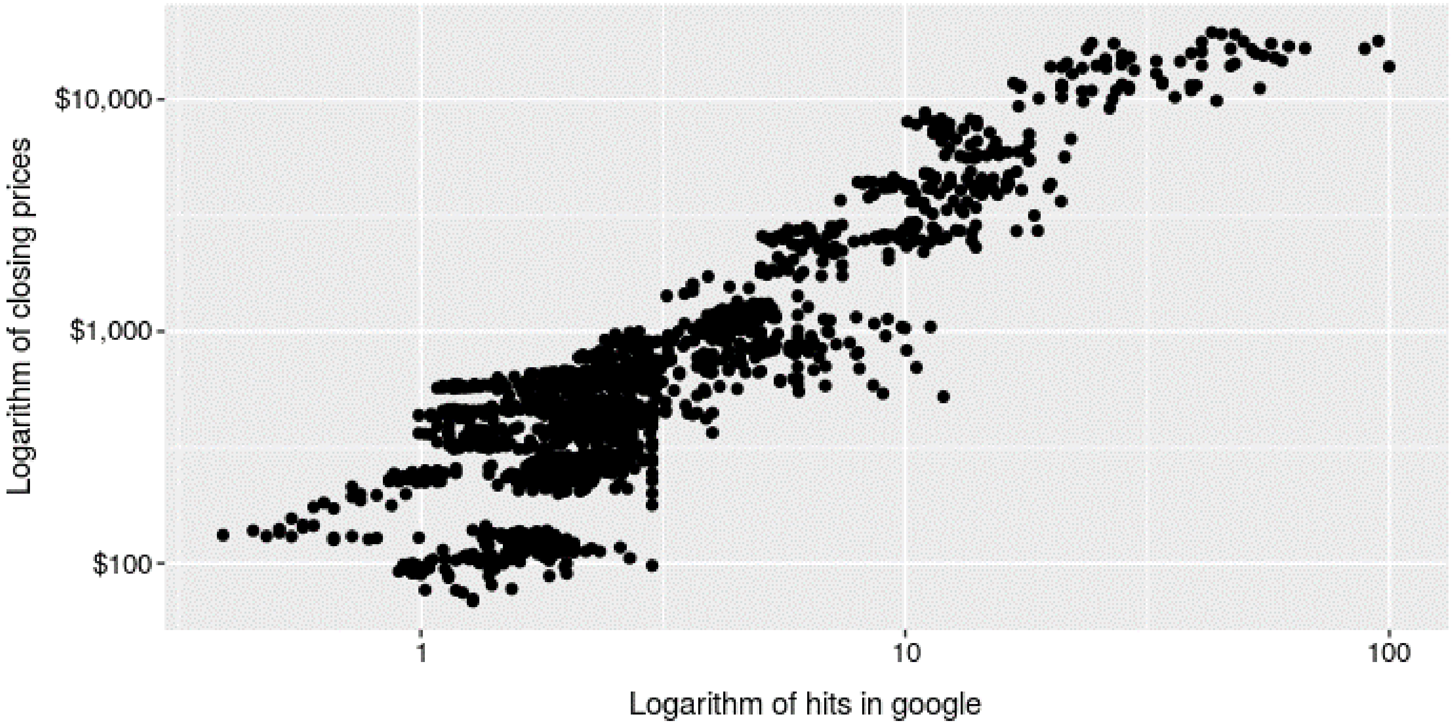
Information, interest, and social wisdom

> "A wealth of information creates a poverty of attention" (H. Simon)



Bitcoin price vs Google Search Index for "Bitcoin" interest

Information, public interest, and social wisdom

Characteristics:

- In the information era, there is an **overload of data** that demands the creation of mechanisms to discern **which information is relevant and which is not.**
- Humans have **limited computational capabilities** hence, the formation of **rules of thumb** usually takes place instead of coherent/rational reasoning according to each problem (see Bounded Rationality)
- Cryptocurrencies' information is based on fairly diversified sources
  - Whitepapers
  - News, project websites, blogs, and social media.
  - Presumed cryptocurrency's experts declare higher prices predictions (anchoring prospects)
- Reddit: Online forums
  - The largest community on the Internet, with more than 600.000 subscribers
  - Advice to buy and sell
  - Investment in new altcoins
  - Price pattern recognition

Information, public interest, and social wisdom

- News media have incentives to broadcast hypes to capture the reader’s attention towards different issues, being crypto-markets one of many of them.
- Specialized websites offer "social investing", that is, a system that automatically copies trades done by **experienced, professional and successful investors.**
  - Paying a "success fee" as a reward
  - Following others’ actions is precisely a clear contradiction to what EMH states about random investors’ decisions.

Information, public interest, and social wisdom

Hypothesis?

- An active agent in the crypto marketplace may face:
  - Uncertainty and inability to assess probabilities of events
  - Problems to decide accurately
  - Limitations to assess the degree of quality of announcements
- **Is it possible to catch up with 2K+ cryptocurrencies and ~40 new ones per month?**[1]
  - In my opinion: **hardly**. Especially in the task of distinguishing between fake and true potential projects.

> Once people receive information, they have to discern if it is accurate or not, **but prices often react faster**, then, it is strategically convenient to **follow what others do**, but because it is unobserved, there are incentives to rely only on **price dynamics**.

[1] Almost 2100 by the first week of December 2018.

"The less information you have, the stronger is your incentive to follow the consensus." (Graham, 1999)

Model: Herding behavior

An empirical test based on absolute dispersion:

$$CSAD_t = \gamma_0 + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \gamma_{2+k} CSAD_{t-k} + \varepsilon_t$$

with:
$\varepsilon_t \sim N(0, \sigma^2)$

- γ_1 captures the linear relationship between dispersion and market returns
- γ_2 captures herding with $\gamma_2 < 0$ and adverse herding for $\gamma_2 > 0$

- k: AR(k) to dismiss lagged effects

- The baseline in this model will be a rational model of asset returns, that is, a scenario in which crypto-investors do not follow the consensus.

Model: Herding behavior under asymmetric market states

An empirical test based on absolute dispersion:

$$CSAD_t = \gamma_0 + \gamma_1 D \times |R_{m,t}| + \gamma_2(1 - D) \times |R_{m,t}| + D \times \gamma_3 R_{m,t}^2 + \gamma_4(1 - D) \times R_{m,t}^2 + \gamma_{4+k} CSAD_{t-k} + \varepsilon_t$$

with:
$\varepsilon_t \sim N(0, \sigma^2)$

- $D = 1$: if $R_{m,t} < 0$
- $D = 0$: if $R_{m,t} >= 0$
- k: AR(k) to dismiss lagged effects

Model: Markov Regime-Switching model for herding behavior

A two-state MC can be described as:

$$P(S_t = j|S_{t-1} = i, S_{t-2} = b, \ldots, \Omega_{t-l}) = P(S_t = j|S_{t-1} = i) = P_{ij}$$

where: p_{ij} transition probability of being at j will only depend on the previous state i, S_t is not observed, but it can be inferred from observed data. And, Ω represent all the parameters necessary to describe the Data Generating Process (DGP)

- MS captures shifts in behavior which are not observable for instance the appearance of interventions or forcing variables.
- High-frequency data exhibits structural changes in their behavior associated with observed and unobserved events.
- It is expected that herding display dynamics that are regime dependent
  - 1. Adverse herding vs herding 2. Intensity of herding- Herding behavior states are (likely):
  - Unobserved
  - Probabilistic