Bitcoin and its Offspring: a Volatility Risk Approach

Walter Bazán-Palomino

School of Economics and Finance

Universidad del Pacífico
(University of the Pacific)

First Conference on Financial Stability and Sustainability

Lima 2020

Bitcoin and its Offspring

1. I provide a background on Bitcoin forks $\Rightarrow$ (aka **"split coins"**)

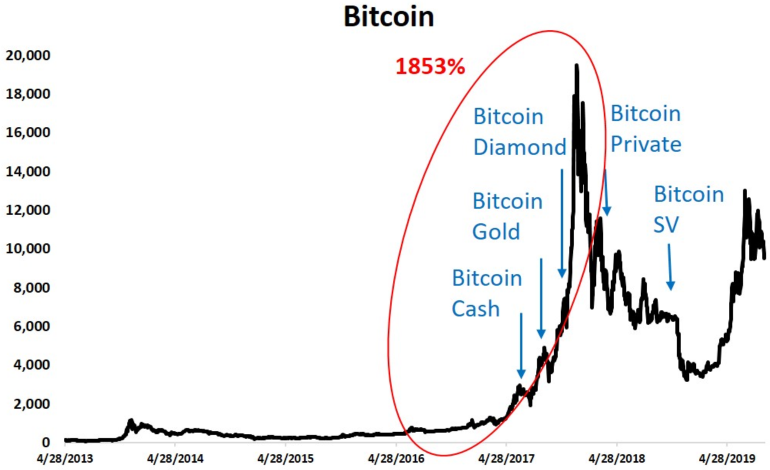
Bitcoin and its Offspring

1. I provide a background on Bitcoin forks $\Rightarrow$ (aka **"split coins"**)

2. I study the relationship between Bitcoin and Bitcoin forks
   - *Returns (r_t) and **Var-Covariance matrix** (Σ_t)*
   - *Does the 2017 bubble make a difference in the time-varying correlation (volatility transmission across tokens)?*

Motivation and Research Question

What are the return relationship and volatility risk transmission between Bitcoin and Bitcoin forks?



Key Takeaways / Contribution

- **Drivers behind Bitcoin forks**
  - Block size + high transaction fees + mining centralization $\Rightarrow$ splitting Bitcoin

Key Takeaways / Contribution

- **Drivers behind Bitcoin forks**
  - Block size + high transaction fees + mining centralization $\Rightarrow$ splitting Bitcoin
- **Volatility of Bitcoin forks and Bitcoin are dynamically related**
- **Time-varying correlation**
  - negative during times of high volatility and positive in low volatility periods

Related Literature

1. **Cryptography**
   - Narayanan et al. (2016), and Antonopoulos (2017)

2. **Volatility**
   - EGARCH and TGARCH: Bouoiyour and Selmi (2015), and Dyhrberg (2016)
   - Multiple Univariate GARCH: Katsiampa (2017), and Chu et al. (2017)

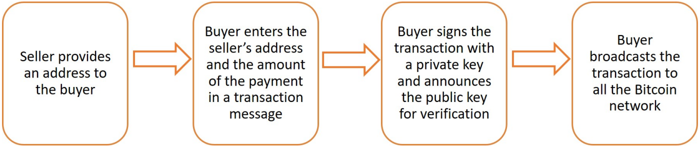
3. **Contagion or Interconnection**
   - Bouri et al.(2017) $\Rightarrow$ DCC-GARCH $\Rightarrow$ Bitcoin vs other assets
   - Corbet et al. (2018) $\Rightarrow$ Diebold and Yilmaz (2012) $\Rightarrow$ spillovers among markets
   - Beneki et al.(2019) $\Rightarrow$ BEKK-GARCH(1,1) $\Rightarrow$ Bitcoin vs Ethereum

What is Bitcoin?

- A peer-to-peer digital currency that allows decentralized transfers of value between individuals and businesses.
- A collection of Bitcoin transactions which is maintained by a network of users.
- Satoshi Nakamoto?

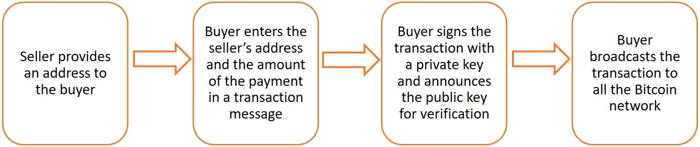
How does Bitcoin work?

What is a Bitcoin transaction?

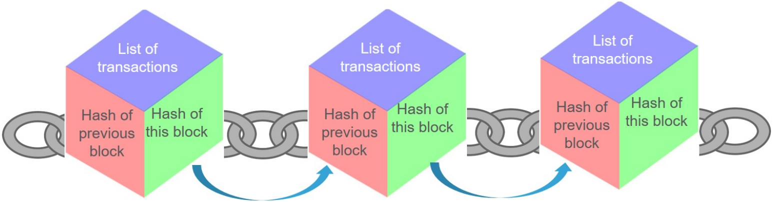


How does Bitcoin work?

What is a Bitcoin transaction?



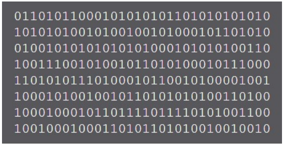
What is the Bitcoin blockchain?



How does Bitcoin work? A deeper look

Hash Function

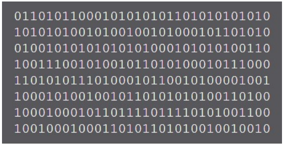
- $H(x, others) = hash$
- $H(x_1, others) \neq H(x_2, others)$

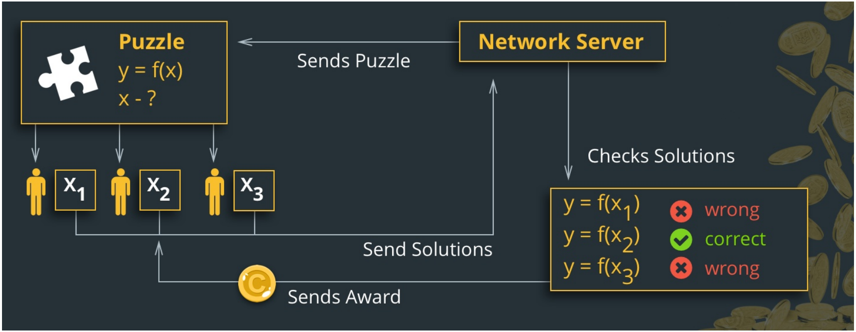


How does Bitcoin work? A deeper look

Hash Function

- $H(x, others) = hash$
- $H(x_1, others) \neq H(x_2, others)$



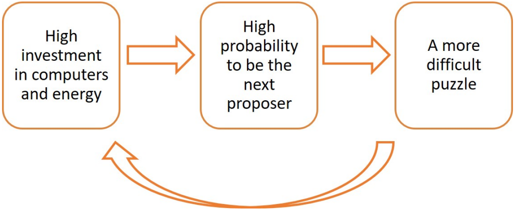


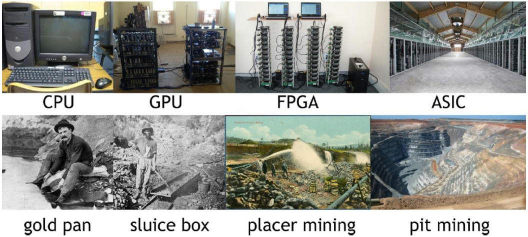
Drivers behind a fork

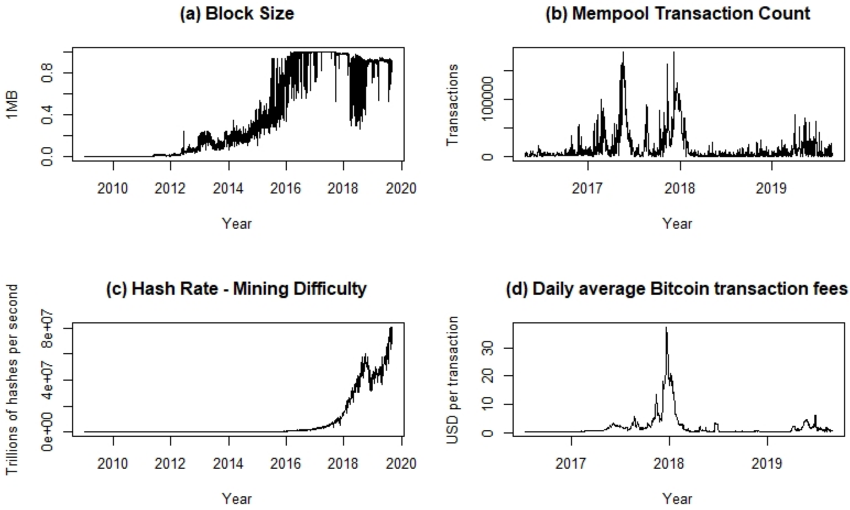
1. **Block size = 1MB**
2. **High Transaction Fees**

Drivers behind a fork

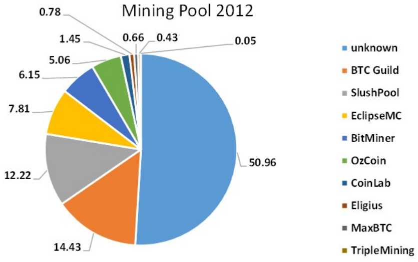
1. **Block size = 1MB**
2. **High Transaction Fees**
3. **Centralization!**

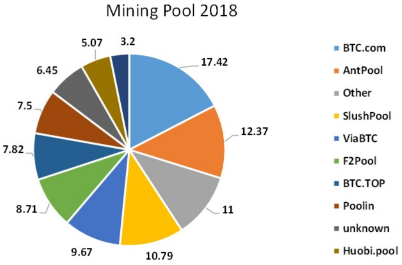





(a) Block Size
1MB
0.0
0.4
0.8
2010
2012
2014
2016
2018
2020
Year
(b) Mempool Transaction Count
Transactions
0
100000
2017
2018
2019
Year
(c) Hash Rate - Mining Difficulty
Trillions of hashes per second
0e+00
4e+07
8e+07
2010
2012
2014
2016
2018
2020
Year
(d) Daily average Bitcoin transaction fees
USD per transaction
0
10
20
30
2017
2018
2019
Year

Centralization





Data

1. Source: Coin Market Cap
2. Variables:
   2.1 Bitcoin (BTC): April 2013 - August 2019
   2.2 Litecoin (LTC): April 2013 - August 2019
   2.3 Bitcoin Cash (BCH): August 2017 - August 2019
   2.4 Bitcoin Gold (BTG): October 2017 - August 2019
   2.5 Bitcoin Diamond (BCD): November 2017 - August 2019
   2.6 Bitcoin Private (BTCP): February 2018 - August 2019
3. Notation
   3.1 $r_{i,t} = ln(P_t) - ln(P_{t-1})$ and $\sigma_{i,t}$
   3.2 $r_t = (r_{1,t}, r_{2,t})'$ and $\Sigma_t = \begin{bmatrix} \sigma_{11,t} & \sigma_{21,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{bmatrix}$

Recall: I want to measure the time-varying correlation among tokens

Univariate Models

Conditional Mean Equation

$$r_{i,t} = \mu_{i,t} + a_{i,t} \tag{1}$$

Conditional Volatility Equations

- GARCH(1,1) of Bollerslev (1986)

$$\sigma^2_{i,t} = \omega + \alpha a^2_{i,t-1} + \beta\sigma^2_{i,t-1} \tag{2}$$

- EGARCH(1,1) of Nelson(1991)

$$\ln(\sigma^2_{i,t}) = \omega + +\alpha\left(|\varepsilon_{i,t-1}| - E(|\varepsilon_{i,t-1}|\right) + \gamma\varepsilon_{i,t-1} + \beta\ln(\sigma^2_{i,t-1}) \tag{3}$$

- TGARCH(1,1) of Glosten et al. (1993)

$$\sigma^2_{i,t} = \omega + (\alpha + \gamma N_{i,t-1})a^2_{i,t-1} + \beta\sigma^2_{i,t-1} \tag{4}$$

$$Cov(x,y) = \frac{Var(x+y) - Var(x-y)}{4} \Rightarrow \rho(x,y) = \frac{Cov(x,y)}{\sqrt{Var(x)Var(y)}}$$

Multivariate Models

Conditional Mean Equation

$$r_t = \mu_t + a_t \tag{5}$$

Conditional Covariance Matrix

- Exponentially Weighted Moving Average (EWMA) of RiskMetrics

$$\Sigma_t = \lambda \Sigma_{t-1} + (1 - \lambda) a_{t-1} a'_{t-1} \tag{6}$$

- BEKK-GARCH(1,1) of Engel and Kroner (1995)

$$\Sigma_t = A_0 A'_0 + A_1 a_{t-1} a'_{t-1} A'_1 + B_1 \Sigma_{t-1} B'_1 \tag{7}$$

- DCC-GARCH(1,1) of Engel(2002)

$$\rho_t = D_t^{-1} \Sigma_t D_t^{-1} \tag{8}$$

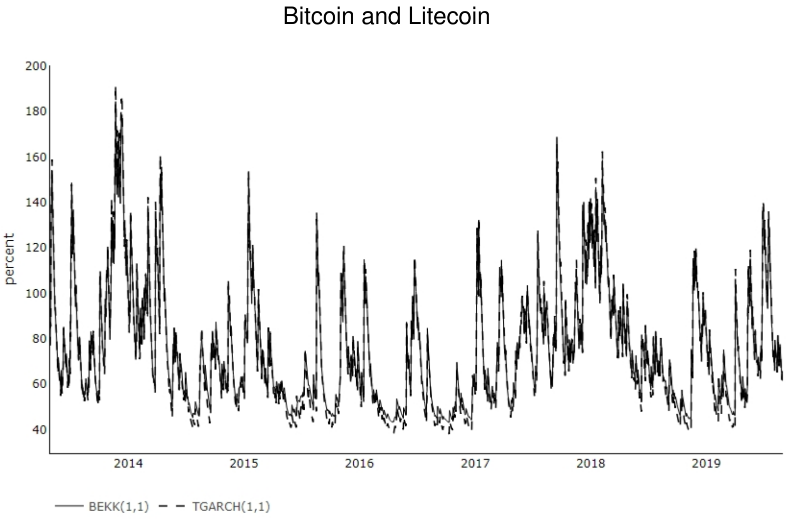
AR(p)-GARCH(1,1)

Table 2: Estimation results of GARCH-type models for crypto-currency returns.

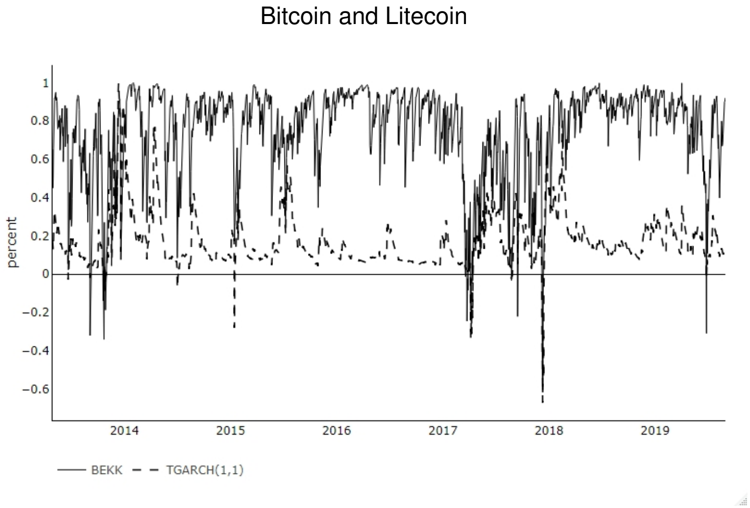
	BTC	LTC	BCH	BCD	BTCP	BTG
GARCH(1,1)						
$Const(\mu)$	0.112*	-0.072	-0.160	-0.371	-0.953**	-0.394*
$AR(1)(\phi)$	-	-	-	-0.110***	-0.0118	-
$Const(\omega)$	0.538***	1.054***	7.268	1.280***	0.898*	0.227***
$ARCH(\alpha)$	0.111***	0.084***	0.100***	0.057***	0.069***	0.021**
$GARCH(\beta)$	0.862***	0.885***	0.754***	0.926***	0.930***	0.971***
LL	-6289.97	-7068.24	-2572.63	-2291.8	-2090.72	-2162.81
AIC	5.435	6.107	6.701	7.122	7.776	6.410
EGARCH(1,1)						
$Const(\mu)$	0.131*	-0.024	-0.068	-0.330	-1.577***	-0.346
$AR(1)(\phi)$	-	-	-	-0.103***	-0.019	-
$Const(\omega)$	0.191***	0.188***	0.342***	0.230***	0.877*	0.009
$ARCH(\alpha)$	0.250***	0.174***	0.138***	0.245***	0.195***	0.039***
$GARCH(\beta)$	0.939***	0.951***	0.914***	0.954***	0.986***	0.990***
$Leverage(\gamma)$	-0.001	0.020***	0.041***	0.045***	-0.082***	0.017***
LL	-6276.14	-7071.43	-2573.31	-2286.71	-2083.19	-2163.79
AIC	5.424	6.111	6.704	7.110	7.752	6.4163
TGARCH(1,1)						
$Const(\mu)$	0.122*	0.057	-0.122	-0.363	-1.164***	-0.381*
$AR(1)(\phi)$	-	-	-	-0.108**	-0.021	-
$Const(\omega)$	0.530***	1.054***	5.463	1.395**	0.929*	0.063
$ARCH(\alpha)$	0.117***	0.090***	0.100***	0.066***	0.023***	0.02***
$GARCH(\beta)$	0.863***	0.885***	0.807***	0.921***	0.928***	0.983***
$Leverage(\gamma)$	-0.012	-0.014	-0.037	-0.010	0.097***	-0.017
LL	-6289.72	-7067.72	-2571.98	-2291.72	-2081.29	-2161.42
AIC	5.536	6.108	6.702	7.124	7.745	6.410

(*) Represents the significance at the 10% level, (**) represents the significance at the 5% level, and (***) represents the significance at the 1% level.

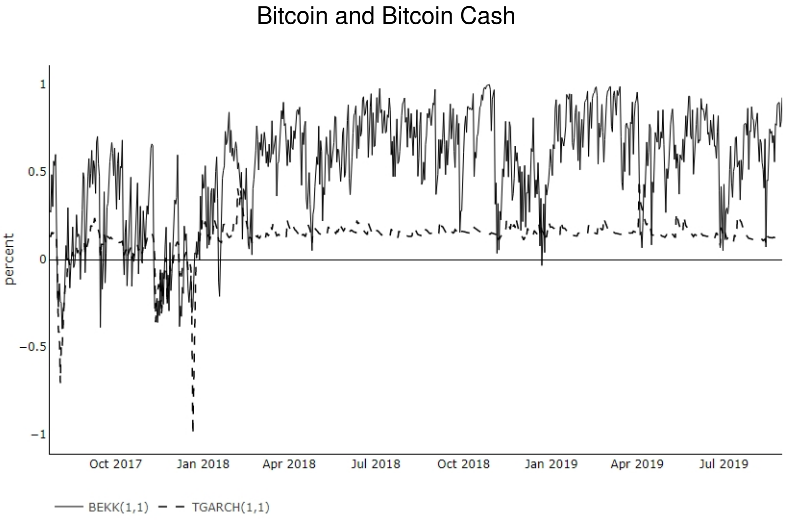
Volatility: BEKK vs TGARCH



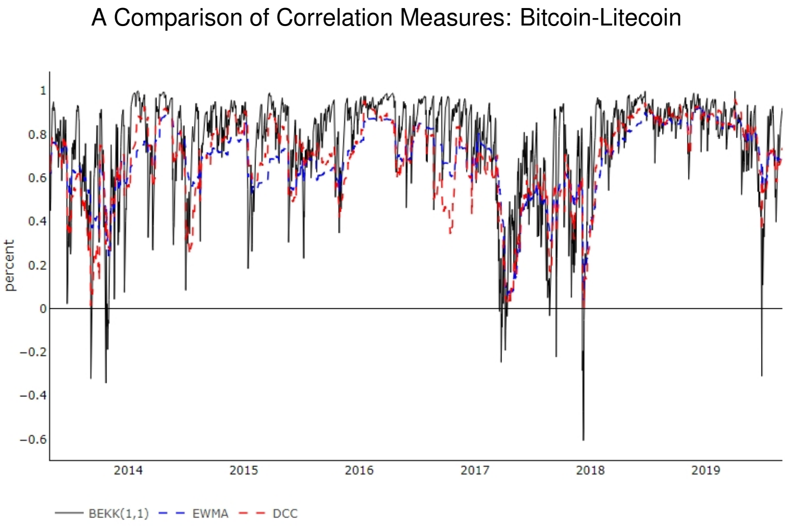
Time-varying correlation: BEKK vs TGARCH



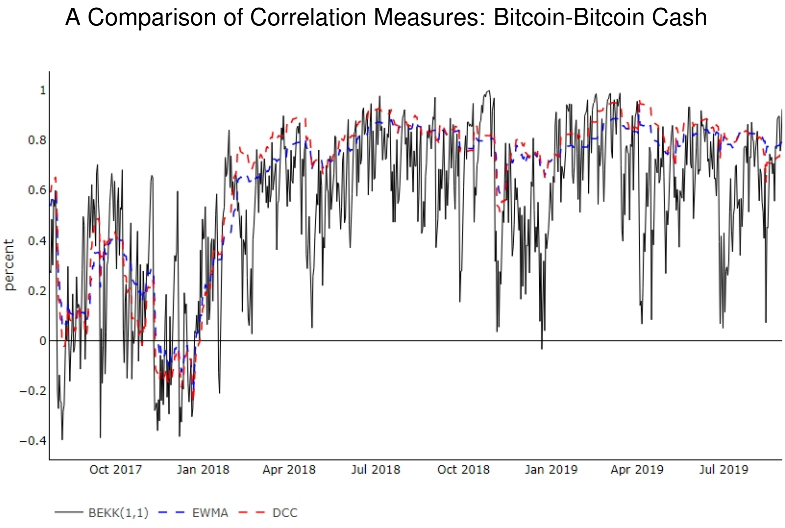
Time-varying correlation: BEKK vs TGARCH



The Superiority of BEKK model



The Superiority of BEKK model



Model checking of EWMA, BEKK, and DCC models

Table 5: Model checking of the multivariate volatility models - The p-values of the multivariate Ljung-Box and the multivariate Lagrange Multiplier tests.

	BTC-LTC	BTC-BCH	BTC-BCD	BTC-BTCP	BTC-BTG
EWMA					
$Q(5)$	0.002	0.007	0.000	0.004	0.000
$Q(10)$	0.046	0.000	0.006	0.000	0.000
$LM(5)$	0.001	0.000	0.001	0.000	0.000
$LM(10)$	0.007	0.000	0.020	0.000	0.000
BEKK-GARCH(1,1)					
$Q(5)$	0.983	-	-	0.000	-
$Q(10)$	0.995	-	-	0.000	-
$LM(5)$	0.828	0.207	0.986	0.000	0.085
$LM(10)$	0.798	0.430	0.643	0.000	0.069
DCC-GARCH(1,1)					
$Q(5)$	0.534	0.003	0.497	0.488	0.000
$Q(10)$	0.621	0.080	0.841	0.011	0.000
$LM(5)$	0.338	0.001	0.329	0.633	0.050
$LM(10)$	0.436	0.001	0.644	0.432	0.084

Q(m) and LM(m) denote the Weighted Ljung-Box Test and the Weighted ARCH LM Test on standardized squared residuals at lag m, respectively.

Volatility Spillovers

The BEKK Model

$$\Sigma_t = A_0 A_0' + A_1 (a_{t-1} a_{t-1}') A_1' + B_1 \Sigma_{t-1} B_1'$$

Volatility Spillovers

The BEKK Model

$$\Sigma_t = A_0 A_0' + A_1 (a_{t-1} a_{t-1}') A_1' + B_1 \Sigma_{t-1} B_1'$$

$$\begin{bmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{bmatrix} = \begin{bmatrix} A_{11,0} & \\ A_{21,0} & A_{22,0} \end{bmatrix} \begin{bmatrix} A_{11,0} & A_{21,0} \\ & A_{22,0} \end{bmatrix}$$
$$+ \begin{bmatrix} A_{11,1} & A_{12,1} \\ A_{21,1} & A_{22,1} \end{bmatrix} \begin{bmatrix} a_{1,t-1}^2 & a_{1,t-1} a_{2,t-1} \\ a_{2,t-1} a_{1,t-1} & a_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} A_{11,1} & A_{21,1} \\ A_{12,1} & A_{22,1} \end{bmatrix}$$
$$+ \begin{bmatrix} B_{11,1} & B_{12,1} \\ B_{21,1} & B_{22,1} \end{bmatrix} \begin{bmatrix} \sigma_{11,t-1} & \sigma_{12,t-1} \\ \sigma_{21,t-1} & \sigma_{22,t-1} \end{bmatrix} \begin{bmatrix} B_{11,1} & B_{21,1} \\ B_{12,1} & B_{22,1} \end{bmatrix}$$

The off-diagonal elements are statistically significant!

Final Comments

- First paper to study the volatility spillovers within Proof-of-Work

Final Comments

- First paper to study the volatility spillovers within Proof-of-Work

- Drivers behind Bitcoin forks: Block size + high transaction fees + mining centralization

Final Comments

- First paper to study the volatility spillovers within Proof-of-Work

- Drivers behind Bitcoin forks: Block size + high transaction fees + mining centralization

- **Volatility of Bitcoin forks and Bitcoin are dynamically related**
  - The Superiority of BEKK: volatility spillovers

Final Comments

- First paper to study the volatility spillovers within Proof-of-Work
- Drivers behind Bitcoin forks: Block size + high transaction fees + mining centralization
- **Volatility of Bitcoin forks and Bitcoin are dynamically related**
  - The Superiority of BEKK: volatility spillovers
- **Time-varying correlation**
  - estimates based on TGARCH(1,1) have to be taken carefully
  - negative during times of high volatility and positive in low volatility episodes

Final Comments

- First paper to study the volatility spillovers within Proof-of-Work
- Drivers behind Bitcoin forks: Block size + high transaction fees + mining centralization
- **Volatility of Bitcoin forks and Bitcoin are dynamically related**
  - The Superiority of BEKK: volatility spillovers
- **Time-varying correlation**
  - estimates based on TGARCH(1,1) have to be taken carefully
  - negative during times of high volatility and positive in low volatility episodes

The Road Ahead

- Probability model for Bitcoin forks, Principal Volatility Components, Contagion

Comments on "Bitcoin and its offspring: a volatility risk approach" by Walter Bazan-Palomino

Ricardo Mayer

Universidad Diego Portales

January 21, 2020

Summary

- Very nice paper: there is indeed a need for better understanding price dynamics of BTCs, including volatility
- Focus on a very specific set of coins: Bitcoin and five of its forks, which shares the same consensus protocol (others, like ethereum, monero and libra are not BTCs forks).
- Forks create volatility but this paper also founds volatility from BTC to its forks.
- This choice makes it easy to understand why and when they appear. The fact that they work very similarly to BTC should make them very close substitutes to BTC, so in priciple we know what to expect. However the papers founds that they not always work like substitutes, but particularly since th end of 2017 thay have not.
- December 2017 and the BTC bubble seem to be a watershed for correlation behaviour

Comments

- I'm going to make one observation, suggest an easy-to-follow addition and a couple of suggestions to build on the empirical findings of this paper

Positive correlation and hedging

- "After the bubble period, Bitcoin and its forks are strongly positive correlated indicating that investors cannot reduce Bitcoin risk by taking opposite positions in Bitcoin forks"
- I am bit puzzled by this: why short selling a positive correlated fork can not help to hedge your bets on BTC or vice versa?

Building upon your findings (I)

- Maybe a quantification of the total volatily induced by and suffered by a particular coin could illuminate more facts
- Gamba-Santamaría et al 2017 and 2017: "Stock Market Volatility Spillovers: Evidence for Latin America" and later for global markets.
- Constructs a spillover index that allows you to identify a unit's contribution to total volatility in a group and how much volatility receive it recieves
- A sample of claims: "Regarding directional spillovers, we encounter that Brazil is a net volatility transmitter for most of the sample period, while Chile, Colombia and Mexico are net receivers"
- "(..) around the Lehman Brothers' episode, shock transmission from the United States to the other four countries increases significantly. Even Brazil becomes a net receiver for that period of time.
- GS et al. implementation requires the output of DCC multivariate GARCH estimation, that your paper already have, so it is a low hanging fruit

Building upong your findings (II)

- "Forks often create price volatility and increase uncertainty in the market, but its implications are not fully understood". I agree . . . and market participants do too!
- In this paper's environment, learning seems particularly (Timmerman 1993 and following literature)
- Adam, Marcet y Nicolini (2016, JF) use a consumption-based asset pricing model where learning about the growth rate of returns goes a long way into explaining stock price volatility, among other things

Building upong your findings (II)

- AMN: "We relax the standard assumption that agents have perfect knowledge about the pricing function that maps each history of fundamental shocks to a market outcome for the stock price."
- Standard, time-separable preferences (not, say, E-Z preferences as in the long-run risk literature):

$$E_0^{\mathcal{P}} \sum_{t=0}^{\infty} \delta^t \frac{C_t^{1-\gamma}}{1-\gamma}$$

- It would be really interesting to see the empirical performance of this in your settings and if it is capable to reproduce the stylized facts you found in term of correlations between BTC and forks.
- Thinking out loud: could episodes like the bubble bursting of December 2017, in a newly established market as BTCs, warrant a sort of "reset" of initial beliefs ("Look guys, we thought we knew more, but we really didnt")