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# Cryptocurrencies: Herding and the transfer currency

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ABSTRACT

We contribute to the ongoing debate on the existence of herding behavior in the crypto market and provide statistically significant evidence thereof. This finding is in contrast to existing empirical evidence in this field, which is primarily due to previous studies suffering from a sample bias. By introducing the concept of beta herding to the debate, we provide further robustness for our results. Moreover, we propose the concept of Bitcoin as a 'transfer currency' and empirically show that herding measures centered around such a transfer currency provide a more precise representation of dispersion in investors beliefs on the crypto market.

## 1. Introduction

This study is as a direct response to the ongoing debate on the existence of herding behavior on the cryptocurrency market. Specifically, we build on two recent research papers by Bouri et al. (2018a) and Vidal-Tomás and Farinós (2018) who provide empirical evidence on the behavioral finance aspect of herding among cryptocurrencies (CCs). Motivated by the so far mixed and inconclusive evidence on the existence of herding among CCs, we introduce the concept of Bitcoin as a 'transfer currency'. As a result, we document statistically significant evidence on the existence of herding behavior for a large cross-section of altcoins. This evidence is robust to alternative weighting schemes and various state-of-the-art methodologies.

The debate on herding behavior on the crypto market was initiated by Bouri et al. (2018a), who base their analysis on a fixed sample of 14 CCs between 04/2013-05/2018 and a market-capitalization weighted (cap-weighted) portfolio as the point of reference. Building on the methodology by Chang et al. (2000), namely cross-sectional absolute standard deviations (CSAD), they observe no evidence of herding based on a static approach, rather their findings suggest statistically significant anti-herding behavior. Due to several structural breaks in their sample they additionally apply a (250 day) rolling window approach, as suggested by Stavroyiannis and Babalos (2017), and find statistically significant herding mainly in the second half of 2016. On a theoretical basis, they reason the existence of herding in the crypto market by providing evidence that herding corresponds to periods of an increased economic policy uncertainty (EPU) index and as such is an indication of investors engaging in a flight to safety.

Vidal-Tomás and Farinós (2018) extend previously discussed findings by considering a larger cross-section, asymmetric herding behavior and an alternative measure of return dispersion. In detail, they consider a fixed sample of 65 CCs with data available across the full observation period from 01/2015-2/2017. They extend the previous analysis based on CSAD by using the cross-sectional standard deviation of returns (CSSD), as suggested by Christie and Huang (1995). Besides, they follow (Chiang and Zheng, 2010) and divide the sample into up and downturn phases, thereby accounting for asymmetric herding. Results provide no evidence of herding in the standard form of CSAD and CSSD. In fact, anti-herding is once more present when based on CSAD, which is consistent with (Bouri et al., 2018a). On the other hand, when testing for asymmetric herding based on CSAD the results are statistically significant with respect to periods of market downturns and as such herding is only present during bear markets. Besides, tests also show a

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tendency of small altcoins herding with the largest coins, which points towards a signaling effect of the largest coins with respect to the overall market. These findings are only robust for equally-weighted measures and do not hold for cap-weighted measures, which the authors reason with the dominance of Bitcoin in the latter approach.

In a broader picture, patterns of herding behavior in the cryptomarket can also be related to effects induced from trading volume (Bouri et al., 2018b), price explosivity (Bouri et al., 2018c) and connectedness (Ji et al., 2018). In this respect, Kristoufek (2015) provide implicit support of our 'transfer currency' concept by stating *"[... ] prices of bitcoins are driven by investors' interest in the crypto-currency"*, consequently Bitcoin acts as a transmission mechanism to the overall cryptomarket. In support of this notion, Bouri et al. (2018b) provide statistical evidence for a positive causality relation between trading volume and future returns, based on a quantile regression approach. Furthermore, Ji et al. (2018) show that return shocks to Bitcoin and Litecoin demonstrate strong knock-on effects on altcoins, with the effect being stronger for negative shocks. Accordingly, Bouri et al. (2018c) document the existence of explosivity among single cryptocurrencies as well as co-explosivity, which refers to the transmission of these dynamics among alternative cryptocurrencies. At the same time, Bitcoin is reported to be least dependent on explosivity of other crypto-currencies, whereas altcoins show higher levels of co-explosivity. Last, Baur and Dimpfl (2018) show, that the volatility of the largest cryptocurrencies reacts more strongly to positive price changes (in stark contrast to traditional stock markets), due to the herding of uninformed investors. The notable exceptions are bitcoin and (to some extent) Ethereum, which once more highlights their special role as 'transfer currency'.

Building on these existing studies, we make four central contributions: (i) we consider the full cross-section of the coin market in order to derive a fair representation of the crypto market portfolio, (ii) we account for a survivorship bias, (iii) we incorporate the concept of Bitcoin as a transfer currency and (iv) we incorporate a measure of systematic/beta herding. First, existing literature has in large provided evidence on the efficiency of Bitcoin and the crypto market – as well as specific aspects like herding behavior – based on single coins or few ($<10$) very large coins. In this respect, we utilize the full cross-section of coins available from www.coinmarketcap.com with only a few restrictions necessary from a statistical point of view. A preferably complete representation of the crypto market is also crucial on a theoretical basis, given that the traditional herding measures are derived from Black's (1972) zero-beta CAPM and as such a fair approximation of the market portfolio is required.

Secondly, all previous studies are subject to a selection bias, given that the samples are comprised of a fixed number of coins with data available across the full sample and characteristics (e.g. size, trading volume, etc.) above a certain threshold. In this respect, the sample and survivorship bias are likely going to have the strongest impact and even more so as the crypto market matures and more coins are starting to decease. Our use of the entire cross-section of crypto coins remedies these issues.

Thirdly, we build on the concept of Bitcoin as a transfer currency, which refers to the fact that the majority of coins are not tradable on fiat exchanges, meaning one cannot exchange USD for any altcoin directly. As such, investors have to buy Bitcoin first (or few alternatives) in order to subsequently buy/sell altcoins. At the same time, the crypto market has been - and probably still is - dominated by private investors with an increasingly more short-term speculative trading behavior, commonly represented by a binary decision making process of being in the crypto market or out-of-the market, rather than shifting between alternative coins as is the case for other asset classes (e.g. stocks). This notion is consistent with the EPU-based observation by Bouri et al. (2018a), according to which the crypto market acts as a safe haven during periods of economic uncertainty. In this respect, transfer currencies like Bitcoin which allow for an exchange to fiat currency are acting like a gateway to the crypto market and are implicitly reflecting investors' overall bullish and bearish beliefs on crypto coins. Thereon, we propose a CSAD measure in reference to Bitcoin rather than a weighted-average market portfolio as a more precise representation of the level of dispersion of investor beliefs on the crypto market.

Finally, we provide additional insight on herding among cryptocurrencies by considering a standardized beta herding measure proposed by Hwang and Salmon (2009). Beta herding is a relevant alternative measure to consider, given that we are additionally interested in herding towards Bitcoin which acts as our transfer currency. Based on Hwang and Salmon (2009), beta herding can also increase when the general market outlook is positive rather than significant herding only taking place during market downturns as commonly reported for CSAD. Consequently, beta herding may yield particularly meaningful insight for the case of the crypto market, which has experienced extraordinary growth over many years.

The remainder of this letter is organized as follows: Section 2 discusses the underlying data and methodology; in Section 3 we report our empirical findings and Section 4 concludes.

## 2. Data & methodology

### 2.1. Data

For comparability we utilize closing price and market capitalization data from www.coinmarketcap.com, which is consistent with multiple previous studies like (Bouri et al., 2018a; Vidal-Tomás and Farinós, 2018) and (Kaiser, 2018). In contrast to previous studies we include all coins available at every point in time. Consequently, our sample is not subject to any selection bias and the number of assets $N$ changes over time, thereby accounting for any new and deceased coins. The sample period is from 2015-01-01 to 2019-03-25, with a total number of 1'478'267 daily observations. The minimum number of coins at any given time is 395 and the maximum 2'026. Table A.1 reports the cross-CC statistics on the statistics of each CC (e.g. the mean of all individual CC average returns). Table A.2 reports individual statistics for the entire as well as sub-sample periods on the cap-weighted market portfolio as well as Bitcoin.

### 2.2. Methodology

We follow the methodology by Chen (2013) and consider the following two empirical models to test for herding behavior in the crypto market: (i) cross-sectional absolute deviation method (CSAD) by Chang et al. (2000), and (ii) the beta-herding state-space method by Hwang and Salmon (2004). The first approach is also in-line with the previous evidence on herding among cryptocurrencies by Bouri et al. (2018a) and Vidal-Tomás and Farinós (2018), whereas the latter has not previously been applied to cryptocurrencies. In order to account for the previously elaborated concept of Bitcoin as a transfer currency, we modify the standard approaches and reference all three measures against Bitcoin as well as the cap-weighted market portfolio, whilst weighting individual CCs according to their market value.[1]

Specifically, we follow (Chang et al., 2000) and calculate CSAD based on all $N_t$ available CCs at any point in time as

$$CSAD_t(x) = \sum_{i=1}^{N_t} w_{i,t}|R_{i,t} - R_{x,t}| \text{ with } \sum_{i=1}^{N_t} w_{i,t} = 1, \tag{1}$$

where $R_{i,t}$ denotes the return of the $i$th CC on day $t$, $w_{i,\ t}$ its market-cap weight $w_{i,t} = \frac{MW_{i,t}}{\sum_{i=1}^{N_t} MW_{i,t}}$ and $R_{x,t}$ is either the return of a cap-weighted portfolios across all available CCs ($x = m$) at time $t$ or the return of Bitcoin on that day $t$ ($x = bc$). According to Chang et al. (2000), in times of market stress (e.g. bear markets), more herding is equivalent to a lower value of $CSAD_t$. Fig. A.1 shows both measures of $CSAD_t$, together with a moving average. We find that herding is on average less pronounced when measured against the entire market-cap weighted market portfolio versus an application of Bitcoin as the benchmark. Furthermore, in times of distress (e.g. the end of 2017), we report larger changes in herding towards Bitcoin, which is in line with our concept of Bitcoin as a transfer currency.

Consistent with previous research on herding, we follow (Chen, 2013) and Bouri et al. (2018a) and run regressions of the form

$$CSAD_t(x) = \gamma_0 + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2, \tag{2}$$

where, $R_{m,t}$ is the return of a market-cap weighted average of all available CCs. In the absence of herding in (2), we would find $\gamma_1 > 0$ and $\gamma_2 = 0$. If either $\gamma_2$ is significantly larger (smaller) than zero, we would find statistical evidence for herding (anti-herding). Extensions of this model are presented by Chiang and Zheng (2010) and Vidal-Tomás and Farinós (2018) as:

$$CSAD_t(x) = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2|R_{m,t}| + \gamma_3 R_{m,t}^2, \tag{3}$$

which incorporates the linear relationship between $CSAD$ and the market implied by any asset pricing model. To test, whether herding takes place in bull or bear markets, we run a similar regression including a dummy variable $D$ that is equal to one when $R_{m,t} < 0$ and zero otherwise (cf. Chiang and Zheng, 2010; Vidal-Tomás and Farinós, 2018):

$$CSAD_t(x) = \gamma_0 + \gamma_1(1 - D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1 - D)R_{m,t}^2 + \gamma_4 DR_{m,t}^2. \tag{4}$$

Finally, we introduce the concept of beta herding to the cryptocurrency literature by applying the methodology proposed by Hwang and Salmon (2004) and Hwang and Salmon (2009). Their measure of beta herding is based on the notion, that rolling betas of herding CCs should be much closer to one (the beta of the reference currency) and therefore should have a cross-sectional standard deviation that is decreasing in the level of herding taking place. Following (Chen, 2013), we conduct rolling monthly regressions of all CCs that have at least 15 daily observations on the respective market index (Bitcoin $x = bc$, cap-weighted market $x = m$) to derive their monthly betas:

$$R_{i,t} = \alpha_{i,x} + \beta_{i,x}R_{x,t} + \varepsilon_{i,x,t} \tag{5}$$

Next, we calculate the logarithm of the cap-weighted cross-sectional standard deviation of the betas (henceforth: *log-beta dispersion*) within each month:

$$ln(Std(\beta_{x,t})) = ln\left(\sum_{i=1}^{N_t} w_{i,t}\beta_{i,x,t}\right) \text{ with } \sum_{i=1}^{N_t} w_{i,t} = 1. \tag{6}$$

A low value of $ln(Std(\beta_{i,x,t}))$ however, is not sufficient evidence for herding according to Hwang and Salmon (2009). The authors argue, that the existence of true herding can only be proven through a state space model:

$$ln(Std(\beta_{x,t})) = \mu_x + H_{x,t} + \nu_{x,t} \text{ with } \nu_{x,t} \sim iid(0, \sigma_{\nu,x}^2) \tag{7}$$

$$H_{x,t} = \phi_{x,t}H_{x,t-1} + \eta_{x,t} \text{ with } \eta_{x,t} \sim iid(0, \sigma_{\eta,x}^2), \tag{8}$$

where a significant $\sigma_x^2$ would prove the existence of herding in the presence of a zero-mean AR(1)-structure of the herding component $H_{x,t}$. If $\sigma_x^2 = 0$, Eq. (7) would collapse to $ln(Std(\beta_{i,x,t})) = \mu_x + \nu_{x,t}$ indicating no herding at all. We estimate this model using a Kalman

[1] Thereon, we avoid overweighing the very small CCs that have been prone to extreme movements throughout the entire sample period. To analyze herding for the entire cross-section, weighting CCs by volume is another possibility. As for robustness, we check for a volume-weighted approach and find qualitatively similar results. Nevertheless, we apply the market value in our baseline approach, due to volume being driven by single large trades that occur only from time to time and therefore 'blur' the overall picture.

filter and present the results in A.5. Additionally, we present bootstrapped 95% and 99% confidence intervals for alle estimates.

## 3. Empirical findings

Tables A.3 and A.4 present the results for models (2)–(4) (columns (1)–(3)) in terms of the cap-weighted market return ($x = m$) and Bitcoin ($x = bc$) as the reference currency for the construction of the CSAD measure ($CSAD(x)$), respectively. In line with the contribution of this paper, we make four central observations.

First, in Table A.3 we report statistically significant negative coefficients for squared market returns ($R^2_{m,t}$) in models (2) and (3) – with CSAD measured against the market portfolio ($CSAD(m)$) – and as such confirm the existence of herding in the crypto market. This is in contrast to Bouri et al. (2018a) and Vidal-Tomás and Farinós (2018) and as such confirms our hypothesis of previous studies suffering from a small sample and survivorship bias, which we account for by constructing our measures of dispersion based on the full cross-section of available coins at every point in time *t*. This emphasizes the importance of a (i) fair representation of the theoretically routed market portfolio, also for the case of the crypto market, and (ii) the need for a dynamic adjustment of the constituents (coins) subject to new coins entering the market and existing ones deceasing.

Next, we find statistically and economically strong evidence of herding when deriving CSAD on the basis of Bitcoin ($CSAD(bc)$) and thereby account for the 'transfer currency' concept. Results presented in Table A.4 report statistically significant negative coefficients for the generalized form ($R^2_{m,t}$) and when accounting for asymmetric herding by considering bull ($(1 - D)R^2_{m,t}$) and bear ($DR^2_{m,t}$) markets separately. This finding is in sharp contrast to Vidal-Tomás and Farinós (2018), who, as part of their robustness checks, report no evidence of herding for the case of a cap-weighted portfolio of 64 coins, which they reason on the basis of the large proportion of Bitcoin (approx. 88%) in the portfolio. Thereon they conclude, that *"Bitcoin has lost its influence in the cryptocurrency market"*. By introducing the concept of Bitcoin as a transfer currency and methodologically accounting for this as part of the construction of the CSAD measure, we provide statistically and economically strong evidence for herding in the crypto market. The evidence on herding is present for both the generalized form – coefficients of $-2.238$ (model (2)) and $-1.92$ (model (3)) – and in model (4) during both market upturns ($-2.16$) and market downturns ($-1.527$). In relation to the findings of Baur and Dimpfl (2018) who claim herding by uninformed investors to be the reason for larger volatility increases in response to positive market shocks (except for Bitcoin and Ethereum), we show that properly taking into account bitcoin as 'transfer currency', their puzzling results evaporate and we find statistically significant herding in both market phases, albeit being about 41% larger in negative markets. This observation is consistent with existing literature on equity markets.

Finally, we provide a new perspective on herding among cryptocurrencies by introducing the concept of beta dispersion. In Fig. A.2, we depict betas, in line with model (6), based on the cap-weighted market portfolio (left-hand side) and Bitcoin (right-hand side). Whilst we observe a mean reversion pattern in both cases, we document stronger sudden shifts in beta dispersion based on Bitcoin compared to a fairly smooth time series pattern when considering the cap-weighted market portfolio. Again, this observation suggests stronger herding when CSAD is derived with respect to Bitcoin and, as such, underpins our transfer currency concept. Table A.5 supports our graphical interpretation, by documenting (i) statistically significant beta herding coefficients for the cap-weighted and Bitcoin derived measures at the 99% level, and (ii) a higher herding coefficient for Bitcoin of 0.30 compared to the cap-weighted market measure of 0.15. Adding to this, we regress our measure of beta dispersion on the absolute change in Bitcoin trading volume. If the transfer currency concept holds, we should find a significantly positive coefficient. Indeed, we observe a statistically significant coefficient of -0.1, at the 99% level and, consequently provide further evidence in the direction of Bitcoin as a transfer currency.[2]

## 4. Conclusion

Building on the previously mixed evidence of herding behavior on the cryptocurrency market, we contribute to the literature by specifically accounting for a sample and survivorship bias, extending the methodological framework by including beta herding as an additional measure and introducing the concept of 'transfer currencies' in the crypto market.

We attribute the identified significant herding behavior to irrational individual (non-professional) investors. In this respect, the crypto market is dominated by non-institutional investors whose investment decisions are likely characterized by market sentiment, fad and informational cascades, as well as positive-feedback trading, resulting in irrational herding. This is also in-line with previously documented stronger herding behavior among individual investors than for fund managers in the U.S. equity market (Barber et al., 2009).

Additionally, this is further amplified through the non-existence of a fundamental value for cryptocurrencies, which generally provides a point of reference in periods of market bubbles. As such, the return chasing behavior of irrational individual investors, subject to informational cascades and no fundamental anchor, results in market return shocks and high levels of volatility – a feature well observed for the cryptocurrency market. Similarly, this also results in higher degrees of co-explosiveness among crypto-currencies, as previously discussed by Bouri et al. (2018c). In this respect, investors jointly shift from one coin to the next after former has experienced exponential price appreciation resulting in lower future expected returns.

[2] We regress $ln(Std(\beta_{x,t}))$ on the logarithm of Bitcoin trading volume. We take the logarithm of trading volume to overcome the differences in scaling between the two variables. Findings are also statistiicially significant without any transformation, but result in extremely small regression coefficients.

Overall, the existence of herding in the cryptomarket should leave investors cautious on the fair valuation of single coins and the market overall, as the non-existence of a fundamental value anchor makes it harder to identify overvaluation and excessive optimism in the market. Consequently, bubble-like price appreciation can occur faster and stronger with a higher likelihood of a subsequent sudden and stark collapse thereof, which is further amplified by the dominant force of weakly informed private investors subject to irrational herd behavior due to social pressure and fashion.

## Appendix A

### *A1. Figures*

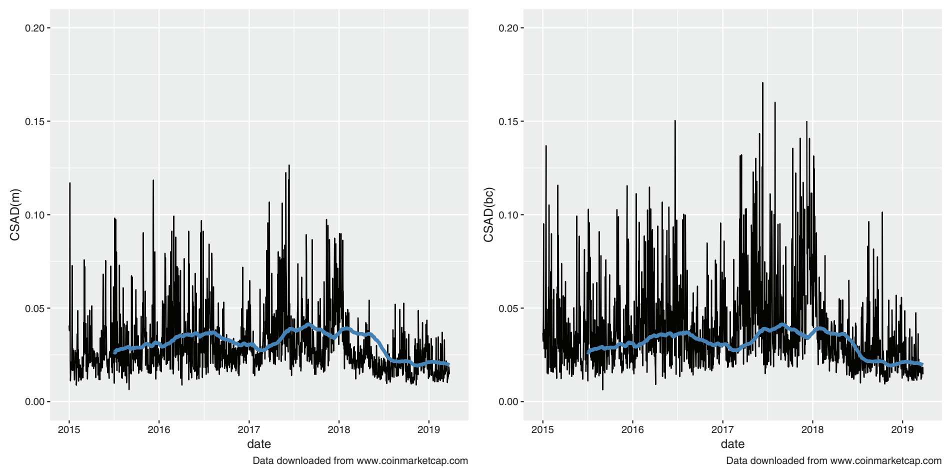


**Fig. A.1.** Evolution of value weighted cross-sectional absolut deviation CSAD in relation to two market proxies (value weighted market portfolio and bitcoin).

### *A2. Tables*

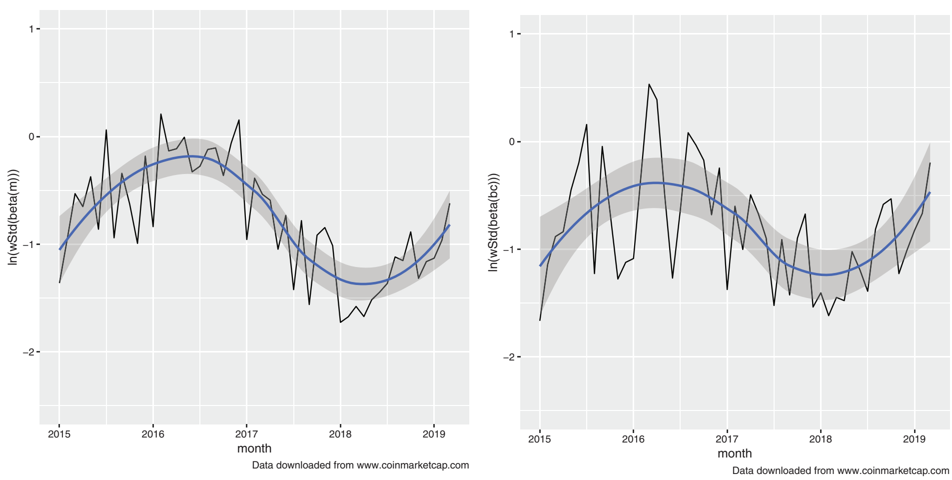


**Fig. A.2.** Evolution of value weighted cross-sectional beta dispersion in relation to two market proxies (value weighted market portfolio and bitcoin).

**Table A.1**
This table presents cross-CC statistics for all individual CC statistics (e.g. the mean of all individual CC average returns or the median of all individual CC skewnesses). All data was gathered from www.coinmarketcap.com.

| rownames | CC mean | CC standard deviation | CC skewness | CC kurtosis |
|---|---|---|---|---|
| min of | −0.9860 | 0.0006 | −29.8984 | −2.7500 |
| $q(0.01)$ of | −0.1240 | 0.0452 | −4.8688 | −0.6172 |
| $q(0.25)$ of | −0.0107 | 0.1103 | −0.1695 | 3.0777 |
| median of | −0.0049 | 0.1815 | 0.2808 | 6.0381 |
| mean of | −0.0079 | 0.2324 | 0.3238 | 14.5038 |
| $q(0.75)$ of | 0.0001 | 0.2886 | 0.8515 | 13.5411 |
| $q(0.99)$ of | 0.0323 | 0.8523 | 5.2923 | 134.5181 |
| max of | 6.0315 | 8.5298 | 20.2807 | 1044.9633 |
| standard deviation of | 0.1120 | 0.2297 | 1.7667 | 37.1142 |
| skewness of | 48.4350 | 16.0559 | −2.4653 | 13.8643 |
| kurtosis of | 2628.1319 | 535.1127 | 56.3652 | 290.3837 |

**Table A.2**
This table presents descriptive statistics for the value-weighted market portfolio and bitcoin. All statistics are calculated for the entire sample period and individual years. All data was gathered from www.coinmarketcap.com.

| period | mean | min | q25 | median | q75 | max | sd | skewness | kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| **Value-weighted market** | | | | | | | | | |
| 2015–2019 | 0.0025 | −0.2367 | −0.0100 | 0.0032 | 0.0188 | 0.1761 | 0.0394 | −0.7658 | 5.1350 |
| 2015 | 0.0007 | −0.2133 | −0.0115 | 0.0014 | 0.0154 | 0.1602 | 0.0350 | −1.2736 | 8.5421 |
| 2016 | 0.0028 | −0.1586 | −0.0045 | 0.0023 | 0.0100 | 0.0993 | 0.0233 | −0.7291 | 10.5490 |
| 2017 | 0.0109 | −0.2367 | −0.0070 | 0.0131 | 0.0341 | 0.1761 | 0.0464 | −0.6388 | 3.7069 |
| 2018 | −0.0039 | −0.2367 | −0.0266 | 0.0000 | 0.0208 | 0.1319 | 0.0487 | −0.5911 | 1.9561 |
| 2019 | 0.0013 | −0.1090 | −0.0077 | 0.0014 | 0.0094 | 0.0868 | 0.0274 | −0.6773 | 4.6926 |
| **Bitcoin** | | | | | | | | | |
| 2015–2019 | 0.0016 | −0.2376 | −0.0110 | 0.0020 | 0.0167 | 0.2251 | 0.0390 | −0.4048 | 5.5990 |
| 2015 | 0.0008 | −0.2376 | −0.0114 | 0.0012 | 0.0170 | 0.1640 | 0.0368 | −1.3751 | 9.5156 |
| 2016 | 0.0022 | −0.1664 | −0.0054 | 0.0018 | 0.0097 | 0.1129 | 0.0252 | −0.6991 | 9.8472 |
| 2017 | 0.0074 | −0.2075 | −0.0139 | 0.0088 | 0.0322 | 0.2251 | 0.0493 | 0.0377 | 3.2069 |
| 2018 | −0.0036 | −0.1846 | −0.0240 | 0.0008 | 0.0158 | 0.1241 | 0.0429 | −0.4459 | 1.9798 |
| 2019 | 0.0007 | −0.0925 | −0.0060 | 0.0011 | 0.0080 | 0.0757 | 0.0230 | −0.4952 | 5.3858 |

**Table A.3**
This table presents regression results for cap-weighted CSAD (referenced to the market portfolio) in relation the market portfolio.

| | *Dependent variable:* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| const. | 0.021*** | 0.022*** | 0.021*** |
| | $p = 0.000$ | $p = 0.000$ | $p = 0.000$ |
| $R_{m,t}$ | | 0.083*** | |
| | | $p = 0.000$ | |
| $\|R_{m,t}\|$ | 0.405*** | 0.360*** | |
| | $p = 0.000$ | $p = 0.000$ | |
| $R^2_{m,t}$ | − 1. 590*** | − 1. 165** | |
| | $p = 0.001$ | $p = 0.018$ | |
| $D \cdot R_{m,t}$ | | | − 0. 227*** |
| | | | $p = 0.00005$ |
| $(1 - D)\cdot R_{m,t}$ | | | 0.521*** |
| | | | $p = 0.000$ |
| $D\cdot R^2_{m,t}$ | | | −0.578 |
| | | | $p = 0.298$ |
| $(1 - D)\cdot R^2_{m,t}$ | | | − 2. 131*** |
| | | | $p = 0.00005$ |
| $R^2$ | 0.18 | 0.22 | 0.22 |

*Note:* *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

**Table A.4**
This table presents regression results for cap-weighted CSAD (referenced to bitcoin) in relation to the market portfolio.

| | *Dependent variable:* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| const. | 0.025*** | 0.025*** | 0.025*** |
| | $p = 0.000$ | $p = 0.000$ | $p = 0.000$ |
| $R_{m,t}$ | | 0.062*** | |
| | | $p = 0.003$ | |
| $\|R_{m,t}\|$ | 0.624*** | 0.590*** | |
| | $p = 0.000$ | $p = 0.000$ | |
| $R^2_{m,t}$ | − 2. 238*** | − 1. 920*** | |
| | $p = 0.0001$ | $p = 0.002$ | |
| $D \cdot R_{m,t}$ | | | − 0. 549*** |
| | | | $p = 0.000$ |
| $(1 - D) \cdot R_{m,t}$ | | | 0.619*** |
| | | | $p = 0.000$ |
| $D \cdot R^2_{m,t}$ | | | − 2. 160*** |
| | | | $p = 0.002$ |
| $(1 - D) \cdot R^2_{m,t}$ | | | − 1. 527* |
| | | | $p = 0.094$ |
| $R^2$ | 0.21 | 0.22 | 0.22 |

*Note:* *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

**Table A.5**
This table presents the variance of the state-space equation of model (7), and its 95% and 99% confidence intervals. We present the results for betas estimated from the value-weighted market ($x = m$) and from bitcoin ($x = bc$). Additionally, to highlight the importance of using a value-weighted standard deviation ($Std_w$) we also present results for an equally weighted standard deviation ($Std$).

| | $ln(Std(\beta_{m,t}))$ | $ln(Std_w(\beta_{m,\ t}))$ | $ln(Std(\beta_{bc,t}))$ | $ln(Std_w(\beta_{bc,\ t}))$ |
|---|---|---|---|---|
| $\sigma^2_{\eta,x}$ | 0.1923 | 0.1599 | 0.3436 | 0.3047 |
| lower 95% | 0.1335 | 0.1228 | 0.2007 | 0.1581 |
| upper 95% | 0.2355 | 0.2865 | 0.5764 | 0.6093 |
| lower 99% | 0.1100 | 0.1018 | 0.1829 | 0.1278 |
| upper 99% | 0.2407 | 0.3145 | 0.5919 | 0.6093 |

## Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2019.06.012.

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