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The psychology of cryptocurrency prices☆

Arash Aloosh[a,*], Samuel Ouzan[b]

[a] Department of Finance, NEOMA Business School, 1 Rue du Maréchal Juin, 76130 Mont-Saint-Aignan, France
[b] Department of Finance, NEOMA Business School, 59 Rue Pierre Taittinger, 51100 Reims, France

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ABSTRACT

This letter analyzes the dynamic of cryptocurrency prices through the lens of behavioral economics. Cryptocurrency market participants seem to behave irrationally. We provide evidence of the presence of significant small price bias for the cryptocurrency market, consistent with the hypothesis that investors react to the news differently according to the price-level. We find that low-priced cryptocurrencies are much more volatile than their high-priced counterparts.

1. Introduction

Investors, regulators, and academics are all deeply concerned about the abnormal and excessive volatility of cryptocurrency (CC hereafter) returns. Furthermore, although some traditional financial market assumptions seem to hold for CCs, especially for Bitcoin, such as the basic risk-return tradeoff (Aalborg et al., 2018) or the unpredictability of returns (Thies and Molnár, 2018), contradictory evidence about whether CCs behave like traditional fiat currencies, commodities, stocks, bonds, or simply unrelated highly speculative assets, poses another great challenge for the development of this market.[1] Thus, this lack of consensus concerning their very function, coupled with the excessive volatility of CCs suggests that this market seems governed by investors' extreme sentiments rather than by rational judgments. The role of this study is therefore to assess this irrational environment by identifying the presence of behavioral biases in number-processing among CC investors. Specifically, we provide evidence for the dampening impact of the price level on the second moment of CC returns.

Concerns about whether CCs are part of a rationally well-functioning market are shared by several authors who have recently tested the efficient market hypothesis (EMH) of Bitcoin. Urquhart (2016), Kristoufek (2018), Jiang et al. (2018), and Lahmiri et al. (2018) provide evidence of inefficiency, while Nadarajah and Chu (2017) mitigate these results and point to a weak form of efficiency, where past returns and information have no predictive power on future returns. Bariviera (2017) and Vidal-Tomás and Ibañez (2018) find that efficiency improves over time while Tiwari et al. (2018), and Khuntia and Pattanayak (2018)

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* Corresponding author.
E-mail addresses: arash.aloosh@neoma-bs.fr (A. Aloosh), samuel.ouzan@neoma-bs.fr (S. Ouzan).

[1] Dyhrberg (2016) finds that Bitcoin shares many similarities with both gold and the American dollar. Whereas, Klein et al. (2018) show that Bitcoin does not have any similarities with gold, and Baur et al. (2018) provide evidence that Bitcoins are mainly used for speculative purposes and are uncorrelated with traditional assets. From a qualitative viewpoint, Yermack (2015) and Böhme et al. (2015) also question the true nature of CC and wonder whether Bitcoin could be assimilated to a real currency, given its low adoption rate.

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provide evidence for alternating periods of efficiency/inefficiency. More recently, Köchling et al. (2018) show that the introduction of futures on Bitcoin improves its price efficiency. As in the present study, Brauneis and Mestel (2018) depart from the analysis of Bitcoin only. They examine efficiency, through the random walk hypothesis for 73 CCs and find that Bitcoin is the most efficient CC and that liquidity is somehow positively related to efficiency. However, these authors raise a concern about the possibility of empirically testing for the EMH. We share their concern, particularly about what information can be relevant to price discovery, given the tremendous ambiguity and confusion that appear to dominate this market, for the reasons mentioned above. Rather than a direct, statistical test of efficiency, our approach, consisting of detecting irrational behavior among CC market participants, can be fairly considered as an ad hoc test for inefficiency.

The psychology of stock price levels has recently been revealed through skewness as well as analysts' recommendations channels. Birru and Wang (2016) find evidence that investors systematically overestimate the skewness of low-priced stocks.[2] They called this phenomenon the nominal price illusion. More recently, Roger et al. (2018) introduce small price bias and show that financial analysts amplify their forecasts for small prices. These number-processing biases doubtless originate in Weber's famous law, which states that a person's subjective price scale seems to follow a logarithmic scale (Nieder, 2005). Because of the seemingly irrational environment of the CC market, we expect these biases to be even more pronounced in this market. To test the small price bias, we conduct a digression and assume that if analysts issue more optimistic (pessimistic) forecasts for small price stocks than for large price stocks when they are optimistic (pessimistic) (Roger et al., 2018), investors' expectations of CC prices should follow a similar pattern. Therefore, CC price volatility should be higher for low prices than high prices, ceteris paribus. We are not aware of any previous work that sheds light on aspects of the irrational environment that might surround the CC price formation process. Beyond the contribution to the ongoing debate on CC market efficiency, we think it is particularly important to fill this gap because it should alert regulators as well as CC investors on the fragility of this market. While the price-level does not provide, a priori, relevant information, it appears to be closely linked to the dynamic of CC prices.

2. Data

Coinmetrics.io provides data on price, volume, and market cap. our results are based on a sample period from December 27th, 2013 to May 3rd, 2018.[3] Table 1 reports the initial sample of 63 tokens referring to the most traded CCs with the highest market caps. The CCs data series start at different dates. We report the starting date of each series in Table 1. We exclude cennz, ctxc, loom, poly, srn, and zil from our sample, due to their relatively short data series. Our final sample includes 57 tokens.

We estimate past volatility and skewness by estimating sample volatility and skewness of daily returns using past 28-day rolling samples. We estimate past returns $R_{t\text{-}28,\ t\text{-}1}$ and $R_{t\text{-}84,\ t\text{-}29}$ using log returns from day t-28 to t-1, and from day t-84 to t-29, respectively. Contrary to Birru and Wang (2016) who construct lead skewness using daily data over next year (12 months), we construct lead skewness and lead volatility using daily data over 1-month (and 3 months for a robustness check) due to our short sample period. Price, volume, and market cap are given in US dollars. Volume is the cumulative daily volume of past 28 days and we divide both volume and market cap by price to compute volume and market cap in the denominated coins.

We first test the relation between price, volatility, and skewness in the pooled cross-section. Table 2 reports descriptive statistics of CCs sorted into price deciles at the last day of each month. Our sample exhibits a huge spread of prices. The average US dollar price of the lowest CC decile is less than 0.001, while that of the highest decile is 1220.746.[4]

Both past volatility and past skewness decrease from the lowest decile to the highest decile. The lowest decile is about two times more volatile than the highest decile, with monthly volatility of 0.111 and 0.061, respectively. Similarly, the lowest decile is about two times more positively skewed than the highest decile, with monthly skewness of 0.723 and 0.334, respectively. This is consistent with the earlier findings of a negative relation between price-level and stock return skewness reported by Birru and Wang (2016), and of a negative relation between price-level and stock return volatility reported by Brandt et al. (2010). However, CCs are much more widespread in price, volatile and skewed, which provides us with stronger relations (to test) than stocks do. In addition, CCs' past trends in skewness and lead skewness are in the same direction, while stocks exhibit opposite directions as reported in Birru and Wang (2016).

In addition, low-priced CCs have much less volume, much less market cap, and lower past monthly and quarterly return.[5] Interestingly, low-priced CCs have higher numbers of coins, and as a result, their coins are more traded (despite their lower trading volume in US dollars). These novel and interesting descriptive statistics of CCs are arguably informative for CC issuers, investors, and researchers.

3. Empirical findings

We now present striking evidences using monthly Fama and MacBeth (1973) regressions to analyze the cross-sectional relation

[2] The authors clearly isolate the effect of nominal price from valuation, while a positive relation has been reported between skewness and valuation in the cross-section (see, e.g., Conrad, Dittmar,and Ghysels (2013))

[3] Our initial sample period is May 1st, 2013 to July 8th, 2018. However, the volume data series are available from December 27th, 2013. We also drop observations in the last 84 days, when the lead 84-day volatility and skewness cannot be calculated completely.

[4] Most observations in the highest decile are Bitcoin prices.

[5] The low-priced CCs have higher past daily returns. Thus, the differences in return between low- and high-priced CCs depend on the horizon.

Table 1
Initial sample with starting dates.

Name	Start date	Name	Start date	Name	Start date	Name	Start date	Name	Start date
btc	5/1/2013	dcr	2/13/2016	pay	6/30/2017	ven	8/25/2017	powr	11/4/2017
ltc	5/1/2013	pivx	2/16/2016	snt	7/1/2017	nas	8/26/2017	btg	11/16/2017
xrp	8/7/2013	lsk	4/9/2016	eos	7/4/2017	wtc	8/30/2017	qash	11/24/2017
doge	12/18/2013	etc	7/27/2016	gas	7/9/2017	lrc	9/2/2017	drgn	12/6/2017
vtc	1/23/2014	neo	9/12/2016	mtl	7/12/2017	trx	9/16/2017	elf	12/24/2017
dgb	2/9/2014	icn	10/3/2016	ppt	7/14/2017	knc	9/27/2017	srn	12/31/2017
dash	2/17/2014	zec	11/1/2016	omg	7/17/2017	salt	10/2/2017	zil	1/28/2018
xmr	5/24/2014	gno	5/4/2017	cvc	7/20/2017	ada	10/4/2017	poly	2/5/2018
xlm	8/8/2014	ant	5/21/2017	ethos	7/21/2017	rhoc	10/9/2017	cennz	3/16/2018
xvg	10/28/2014	ae	6/4/2017	bnb	7/28/2017	eng	10/16/2017	loom	3/17/2018
xem	4/4/2015	bat	6/4/2017	bch	8/3/2017	aion	10/21/2017	ctxc	4/19/2018
eth	8/10/2015	veri	6/11/2017	btm	8/11/2017	kcs	10/27/2017		
rep	10/30/2015	fun	6/30/2017	zrx	8/19/2017	icx	10/30/2017		

This table reports the starting dates of the initial sample of CCs. In our final sample of 57 CCs, cennz, ctxc, loom, poly, srn, and zil are excluded due to their short data series. The sample period ends on July 8th, 2018 for every CC except for eos, which ends on June 2nd, 2018.

Table 2
Descriptive statistics by price deciles.

	Price deciles Lo	2	3	4	5	6	7	8	9	Hi
Price ($)	0.000	0.003	0.036	0.252	0.807	1.962	4.076	11.131	69.272	1220.746
Past volatility	0.111	0.079	0.110	0.103	0.106	0.100	0.086	0.091	0.095	0.061
Past skewness	0.723	0.753	0.798	0.522	0.699	0.635	0.587	0.668	0.684	0.334
$R_{t\text{-}28,t\text{-}1}$	0.024	0.118	0.135	0.067	0.070	0.131	0.200	0.220	0.121	0.099
$R_{t\text{-}84,t\text{-}29}$	0.048	0.151	0.219	0.186	0.179	0.262	0.246	0.437	0.322	0.257
Volume (M$)	0	4	69	65	89	137	25	95	246	1760
Volume (M coins)	912	1440	1420	287	118	64	6	9	7	1
Market cap (M$)	7	85	390	1190	1930	928	307	781	1610	23,500
Coins (M)	36,500	26,300	13,000	5030	2550	450	72	75	33	22
Volatility	0.114	0.087	0.131	0.102	0.109	0.092	0.078	0.081	0.088	0.057
Skewness	0.784	0.900	0.646	0.715	0.753	0.570	0.515	0.602	0.658	0.236
Sharpe ratio	0.2	1.5	1.2	0.7	0.7	1.3	2.3	2.4	1.3	1.6
# observations	107	103	105	99	98	98	106	108	107	106

This table reports the mean of the main variables of CCs, sorted by price at the last day of each month. We include 57 CCs with the highest market cap reported by Coinmetrics.io. We estimated past volatility and past skewness using sample volatility and skewness over the past month (28-day) of daily returns. $R_{t\text{-}28,\,t\text{-}1}$ is log return from day t-28 to day t-1. $R_{t\text{-}84,\,t\text{-}29}$ is log return from day t-84 to day t-29. Volume is the cumulative daily volume over past month (28-day) in US dollars. We calculated volume (coins) as the US dollar volume divided by the US dollar price of the coin. Coins is the number of issued coins, calculated as the US dollar market cap divided by the US dollar price of the coin. We calculated (lead) sample volatility and skewness using daily data from day $t + 1$ to $t + 28$. The sample period is from December 27th, 2013 to May 3rd, 2018.

between volatility, skewness and price, while controlling for market cap, volume, past skewness and past volatility.[6] Table 3 reports the results. We regress volatility and skewness on the log price at the last day of each month. To control for size and volume, we use log market cap and log daily traded coins. We separately examine lead volatility and lead skewness, and present both univariate (without control) and multivariate analyses for each of them.

The coefficient of the log price is negative and statistically significant in univariate models for both volatility and skewness. This is consistent with a negative relation between price and both volatility and skewness, as documented in Table 2. A 100% increase in price is associated with a 2.639 (0.693×4.19) decrease in lead volatility, and a 2.1829 (0.693×3.150) decrease in lead skewness. As the dispersion of skewness is similar to that of volatility in Table 2, it seems that the price level is economically more important for CC volatility than for skewness. After controlling for past skewness, past volatility, size, and volume, a very strong and highly significant negative relation remains between price level and volatility.[7] In fact, a 100% increase in price is associated with a 2.2051 (0.693×4.179) decrease in lead volatility. However, the coefficient for log price in the regression on lead skewness becomes positive and statistically insignificant in the presence of control variables. In addition, CCs with lower market cap, past volatility, volume (traded coins), and past skewness are much more volatile.

While our analysis unambiguously provides evidence of the presence of a strong small price bias among CC investors, it is

[6] Obviously, our control variables do not include any firm-specific characteristics (like book-to-market, cash flows, leverage, etc.) usually used as control variables for stocks in the literature.

[7] The negative relation between lead volatility and log price remains statistically significant, with and without control variables, when we use the past and lead volatility measures using the 3-month horizon.

Table 3
The relationships between nominal price and volatility: Fama–MacBeth regressions.

Variable	Volatility		Skewness	
Log price	−4.190***	−3.182***	−3.150***	0.081
	(−3.81)	(−5.07)	(−5.28)	(0.08)
Past volatility		−0.077**		0.052**
		(−2.06)		(2.13)
Past skewness		−0.544		0.306
		(−0.90)		(0.81)
Log market cap		−3.040***		−0.018
		(−4.73)		(−0.02)
Log volume (Coin)		−2.377***		0.959
		(−3.55)		(0.96)
Constant	0.101***	0.143***	0.480***	0.525***
	(9.98)	(5.84)	(7.39)	(7.39)
Adj. R^2	0.356	0.498	0.121	0.405
# Obs.	53	53	53	53

This table reports the relation between nominal price, volatility and skewness, using Fama-MacBeth regressions, as follows: $Y_{i,t} = \alpha + \beta\ Log(Price_{i,t-1}) + X_{i,t-1} + \varepsilon_{i,t}$
This cross-sectional regression is run monthly at the last day of the month. Y is either lead sample volatility or skewness, calculated using daily data from day $t + 1$ to $t + 28$. We calculated past sample volatility and past sample skewness using past one-month (28 days) daily returns. We calculated volume (coins) as the US dollar volume divided by the US dollar price of the coin. We include 57 CCs with the highest market cap reported by Coinmetrics.io. The sample period is from December 27th, 2013 to May 3rd, 2018. We report t-statistics in parentheses. $*$, $**$, and $***$ denote significance at the 10%, 5%, and 1% levels, respectively. Reported adj. R^2 is the average adjusted R^2 across all the months.

important to mention that testing the nominal price illusion using ex-post measure of skewness (lead skewness), requires the strong assumption that the ex-post measure of skewness is the unbiased skewness expectation of investors (Zhang, 2013). Using option data,[8] the result of Birru and Wang (2016) suggests that investors fail to realize that the univariate relation between price and physical skewness is driven by other factors, expecting therefore from low-priced stocks important upside potential. Although it appears that the univariate relation between skewness and price level is stronger for the CC market than for the stock market, option data is unfortunately not available for the CC market to test further this hypothesis.

CC investors' behavior appear nonetheless to be biased and largely driven by price level and its impacts on their beliefs. As a robustness test, we investigate the correlations among low-priced and high-priced CCs. Table 4 reports the average, minimum, and maximum correlations among low-priced CCs including doge, dgb, fun, snt, xvg, and zil and those among high-priced CCs including btc, bch, btg, gno, veri, and zec.[9] Under rational decision making, since low-priced CCs are more volatile, we would expect they exhibit higher idiosyncratic volatility, and consequently, not higher correlations among them, than their high-priced counterparts. Moreover, the presence of a common risk factor for CCs can hardly be rationalized given the near zero correlation reported between CCs and traditional financial assets (Elendner et al., 2018; Baur et al., 2018). Surprisingly, the correlation level among both high and low-priced CCs is high, and in particular, we observe higher correlations among low-priced CCs.[10] This is consistent with the hypothesis that CC market participants tend to exhibit small price bias, reacting to the news differently according the price-level, ceteris paribus.

Finally, the low-priced CCs are more volatile but have lower past monthly returns, while high-priced CCs are less volatile and have higher past monthly returns, suggesting that investing in low-priced CCs rather than in high-priced CCs appears suboptimal. Asset allocations in high-priced CCs (like Bitcoin) provide indeed better monthly Sharpe ratio than those in low-priced CCs.[11] These findings seem important to CC issuers and investors and certainly provide motivation for further studies.[12]

4. Conclusion

We provide evidence that CC price levels are linked to their volatility substantially. Our results are consistent with the evidence that investors exhibit small price bias. This impact appears to be much more pronounced in CC market than in stock market. We also document a very high correlation among low-priced and high-priced CCs, with a higher correlation among low-priced CCs. To our

[8] Conrad et al. (2013) provide evidence that the risk-neutral skewness measure constructed from option data is a market-based forward-looking prediction.

[9] To pick the highest and lowest priced CCs, we double sort CCs to their max and min (min and max) pooled price ranks and we select the six highest (lowest) priced CCs.

[10] Our results on correlations still hold when zil is excluded from the sample, to allow for a longer time horizon.

[11] As can be seen in Table 2, asset allocations in high-priced and low-priced CCs provide an average Sharpe ratio of 1.6 and 0.2, respectively.

[12] The evidence documented by Elendner et al. (2018) that the correlation among CCs arises principally during downward price movements rather than during upward price movements may provide some supportive grounds that low priced CCs exhibit greater downside risk than high-priced CCs. Investigating further the irrational behavior of CC participants on asset allocation is however beyond the scope of this letter.

Table 4
The correlations among low- versus high-priced cryptocurrencies.

	Correlations low-priced	High-priced
Average	0.635	0.566
Max	0.767	0.738
Min	0.524	0.334

This table reports correlations of low-priced versus high-priced CCs, using daily returns in the common sample. The low-priced CCs includes doge, dgb, fun, snt, xvg, and zil and the high-priced CCs includes btc, bch, btg, gno, veri, and zec. The common sample period is limited to the availability of zil prices from January 28th, 2018 to July 8th 2018.

knowledge, it is unique to CC market and has not been tested yet for the stock market, which would represent an interesting extension to the present study. The correlations' features, coupled with the amplified relation between log price and volatility compared to stocks, hint strongly about the irrational behaviors of CC market participants.

Our results also contribute to the literature on CC market efficiency. Since it is quite unclear what information is relevant for CC price discovery (Brauneis and Mestel, 2018), the seemingly strong presence of small price bias among CC market participants, even after controlling for past volatility and skewness, size and volume, may provide even more robust evidence of inefficiency than statistical or information-based tests.

When controlling for past skewness, past volatility, size and volume, relatively low price-levels do not indicate more future upside potential. To explore further the relation between investors' perception of the upside potential (skewness expectation) of CCs, and their current price-level, we need CC options data, which currently do not exist. Nevertheless, the puzzling relation between the number of circulated coins, price, volume, volatility, and skewness reported in this letter is informative for CC issuers and investors, and hopefully foster even more interest for further research on the seemingly unique properties of this market.

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