Prohibiting the sale to retail clients of investment products that reference cryptoassets

Technical Annex

October 2020

Introduction

1. This annex provides a description of the supporting data and analysis for Consultation Paper (CP) 19/22 and Policy Statement (PS) 20/10. Including our analysis of:
    - cryptoasset valuation models
    - correlation between cryptoasset prices and Google trends data
    - price dislocation across exchanges
    - time period used to assess client outcomes

Datasets we used in our analysis

2. We have used a wide range of data including:
    - public cryptoasset price data
    - public cryptoasset exchange pricing data
    - Google Trends data
    - aggregated client data from firms selling crypto-derivatives and ETNs
    - anonymised trading data from firms selling crypto ETNs

Valuation models

3. In the PS, we said that we analysed and considered the alternative valuation models provided by respondents to the consultation. These valuation models support our conclusion that cryptoassets cannot be reliably valued as they provided a wide range of valuation predictions from US$0 to US$800,000 for the same [single "coin"].

4. These models use a variety of techniques and factors to value cryptoassets, including different subjective inputs, suggesting there are no clear indicators to predict the price of cryptoassets reliably over different time frames. This includes different metrics, fundamentals and models that analysts use to attempt to value cryptoassets.

5. The valuation models that were put forward by respondents which we analysed are as follows:

    - **Metcalfe's Law as a model for Bitcoin's value** - Bitcoin's price is modelled as a network, to explain the long-term value of bitcoin. The authors accept that short term price movements can be driven by multiple factors such as the size of the network and the number of users.

    - **Valuing Bitcoin based on hedging political and economic risks** - Respondents used press reports and market studies to demonstrate that cryptoassets are a store of value, have characteristics similar to cash, and perform well in times of political uncertainty (eg Brexit and the Greek debt crisis). This behaviour can also lead to localised premiums in cryptoasset prices (eg Venezuelan inflationary crisis, Turkey and Argentina).

    - **Scarcity and stock-to-flow** - A respondent argue that bitcoin has value as the future supply of Bitcoin and total number of Bitcoin is limited. Stock flow analysis uses the scarcity of cryptoassets to estimates a price of bitcoin based on the total supply in circulation and any future increases in the amount of bitcoin.

- **Size of the Bitcoin network, and the yield spread on BBB rated bonds** - An analyst created a model looking at the Bitcoin network and a negative correlation to the yield spread on BBB-rated bonds.

- **Black-Scholes option theory** - Equates the purchase of a utility token as buying a European-style call option, taking into account adoption of the token and real economic utility.

- **Valuing Bitcoin as a store of value** - Assumes cryptoassets can be valued by the probability of a token 'winning the race' to become the accepted digital store of value.

6. These valuation models result in the following predicted prices:

Table 1: Predicted prices of 1 Bitcoin according to cryptoasset valuation models

Model	Price
Elliott wave theory[1]	US$13,971
Cost of production[2]	US$5,000
Equation of exchange[3]	US$45,000
Linear replacement[4]	US$4,400
Black-Scholes[5]	US$0 - US$undefined
Mixed[6]	US$25,000
Stock-to-flow[7]	US$55,000
Store of value[8]	US$0 - US$800,000
Size of network[9]	US$6,000

Correlation between different cryptoassets

As outlined in in PS20/10, we analysed data from the 5 exchanges listed below (see Price Dislocations Across Exchanges) over a longer period of time (January 2016 to December 2019). We analysed the top 5 cryptoassets by market capitalisation (ethereum, XRP, bitcoin cash, bitcoin SV, and litecoin). We think that assessing cryptoasset price correlation against bitcoin is appropriate because bitcoin (excluding tether which is pegged to the dollar) is the largest cryptoasset by trading volume and the largest by market capitalisation.

7. Cryptoassets are differentiated by their underlying technology, yet compete in the same market. With this we would expect to see a greater level of variation

[1] https://www.scribd.com/document/421604963/Goldman-Sachs-slide-deck

[2] https://www.bloomberg.com/news/articles/2019-05-20/jpmorgan-says-bitcoin-s-jump-mirrors-2017-s-boom-bust-pattern

[3] https://vitalik.ca/general/2017/10/17/moe.html

[4] https://www.dropbox.com/s/5brcacxmecnp7e3/GABI%20Newsletter%202015_12.pdf?dl=0

[5] https://medium.com/blockchain-advisory-group/an-efficient-markets-valuation-framework-for-cryptoassets-using-black-scholes-option-theory-a6a8a480e18a

[6] https://medium.com/@alabs.ken/a-macro-mathematical-model-for-the-observed-value-ofdigital-blockchain-networks-23cc8e0dc7ea

[7] https://medium.com/@100trillionUSD/modeling-bitcoins-value-with-scarcity-91fa0fc03e25

[8] https://s3.eu-west-2.amazonaws.com/johnpfeffer/An+Investor's+Take+on+Cryptoassets+v6.pdf

[9] https://www.businessinsider.com/credit-suisse-bitcoins-fair-value-is-almost-half-current-price-2018-1?r=US&IR=T

between asset prices relative to demand based on how widely they are used and/ or their prospects for future usage.

Methodology

8. We calculate the correlation between cryptoassets and how these have changed over time.

9. The Pearson correlation coefficient, r, can take a range of values from +1 to -1. A value of 0 indicates that there is no linear association between the two variables. A value greater than 0 indicates a positive association; that is, as the value of one variable increases, so does the value of the other variable. A value less than 0 indicates a negative association; that is, as the value of one variable increases, the value of the other variable decreases.

$$r = \frac{COV(X,Y)}{\sigma_X \sigma_Y}$$

Where X and Y = price of cryptoassets
COV = covariance and;
σ = standard deviation

10. For the purposes of the analysis below, a correlation of greater than 0.7 will be classified as a 'large correlation' (see Table 1).

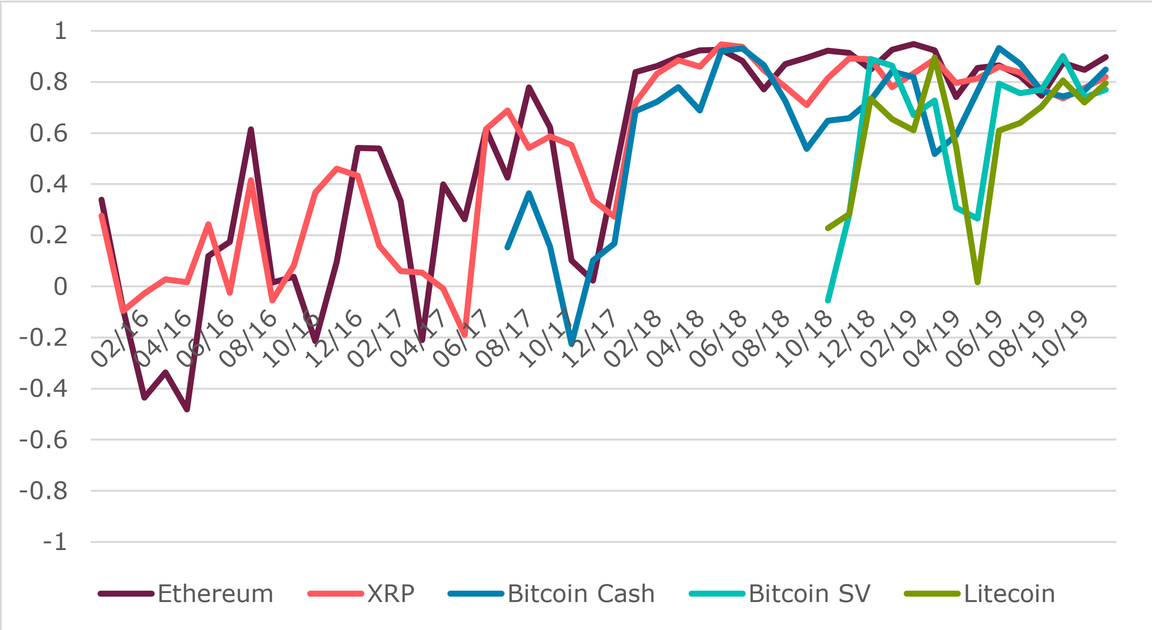
Table 2: Strength of association in a Pearson's R

	Coefficient, r	
Strength of Association	Positive	Negative
Small	0.0 to 0.3	-0.0 to -0.3
Medium	0.4 to 0.7	-0.4 to -0.7
Large	0.7 to 1.0	-0.7 to -1.0

11. From the analysis (chart 1), we have found that the average 30-day correlation in daily price movements of these cryptoassets:

- Is increasing over time
- At times, the correlation is close to 1
- There are limited periods of time where correlation is close to 0 or negative.

Chart 1: The correlation of cryptoassets bitcoin[10]



Google Trends data

12. In PS20/10, we said that, in relation to our use of Google trends data, we think it is reasonable to conclude that:

- Google trends data are an appropriate proxy for retail investors' interest in bitcoin
- Retail investor interest (evidenced by Google searches for Bitcoin) were correlated to the increasing price of bitcoin
- During November and December 2017, a feedback loop appears to have emerged, temporarily creating exponential growth in the value of cryptoassets. This loop appears to have been purely speculative (an 'investment mania' as the Financial Times called it), where price increases and reports of gains encouraged more retail participation.

13. We did not conduct any further analysis of Google data since CP19/22. But, given feedback, we are disclosing the data and methodology we used to conduct the analysis in CP19/22.

14. As stated in CP19/22, we conducted 'noise analysis' using the search trends of bitcoin and ethereum as a proxy for retail consumers' interest in cryptoassets. This showed a strong correlation between the price of cryptoassets and the number of Google searches for these cryptoassets.

15. In our recently published consumer research, when asked why they bought cryptocurrencies, 47% of consumers said they bought cryptocurrencies 'as a gamble that could make or lose money' compared with 31% in the 2019 consumer research (noting this year's survey was online whilst last year's was face to face) as one of the main reasons. 15% stated that they were 'expecting to make money quickly'.

[10] The data for some cryptoassets is incomplete as they were created during the observation period.

16. **Data** – This analysis was based on publicly available data that can be found at trends.google.com.

17. **Methodology** – We used Pearson's R to assess the correlation between google trend data and the price of bitcoin.

18. Based on this analysis, we found that:

    - We have looked at the correlation coefficient between cryptoasset prices and Google searches over a rolling 60-day period, this shows an average correlation coefficient over 0.5 between June 2015 and December 2018.

Price dislocation across exchanges

19. To inform PS20/10, we conducted further analysis of other exchanges to assess whether there was significant price dislocation across exchanges. Our additional analysis considered the following in order to be reasonably representative of the market for cryptoassets:

    - Exchanges that reflected actual trading volumes
    - A longer time frame over which we analysed dislocation of prices
    - A different, and we think more reliable source of the data

20. **Exchanges** - We examined the spreads across 5 exchanges (Binance, Bitfinex, Kraken, Bitstamp, Coinbase). We chose these exchanges as they are all verified by the Blockchain Transparency Institute (BTI) which tests the accuracy of data collected from exchanges and monitors instances of wash-trading.

21. **Time period** – We extended the date range from the 14 day-period in our original analysis, to a longer three-year horizon, covering January 2016 to December 2019.

22. **Source of the data** – These data were taken from https://www.cryptodatadownload.com/, which sources its data from publicly available exchange application programming interfaces (APIs). These data were extensively cleaned for outliers and stale prices before we analysed them.

23. To calculate the spread across exchanges we calculate the difference between the maximum prices between the exchange with the highest maximum price and the exchange with the lowest maximum price.

$$Spread = Max\ Price_{Max} - Max\ Price_{Min}$$

24. There are other ways to calculate this range and carry out this analysis. In response to this we also considered other ranges such as highest and lowest minimum prices and found similar results.

25. The results of this analysis show that there have been periods of high differences in maximum prices across these exchanges (chart 2 and table 2). This is more prominent around December 2017 to January 2018 and December 2018. Table 2 shows the highest spreads across the selected exchanges and the dates that these occurred.

Chart 2: Spreads across exchanges (January 2016 – December 2019)

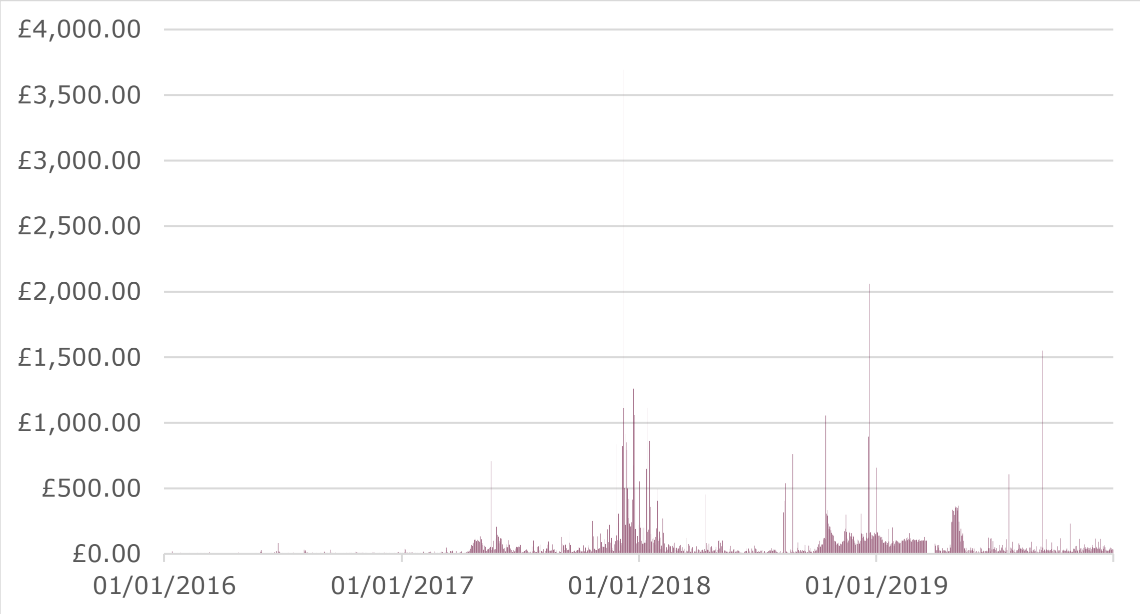


Table 2: Highest spreads across exchanges January 2016 – December 2019)

Date	Spread	Date	Spread
07/12/2017	£3,692.65	**17/01/2018**	£861.89
21/12/2018	£2,060.02	**12/12/2017**	£849.99
13/09/2019	£1,550.25	**26/11/2017**	£836.80
23/12/2017	£1,262.00	**06/12/2017**	£822.40
13/01/2018	£1,115.70	**13/12/2017**	£792.97
08/12/2017	£1,111.03	**25/08/2018**	£760.00
24/12/2017	£1,059.27	**18/05/2017**	£707.20
15/10/2018	£1,055.52	**22/12/2017**	£674.66
10/12/2017	£915.00	**01/01/2019**	£658.83
20/12/2018	£893.87	**12/01/2018**	£648.79

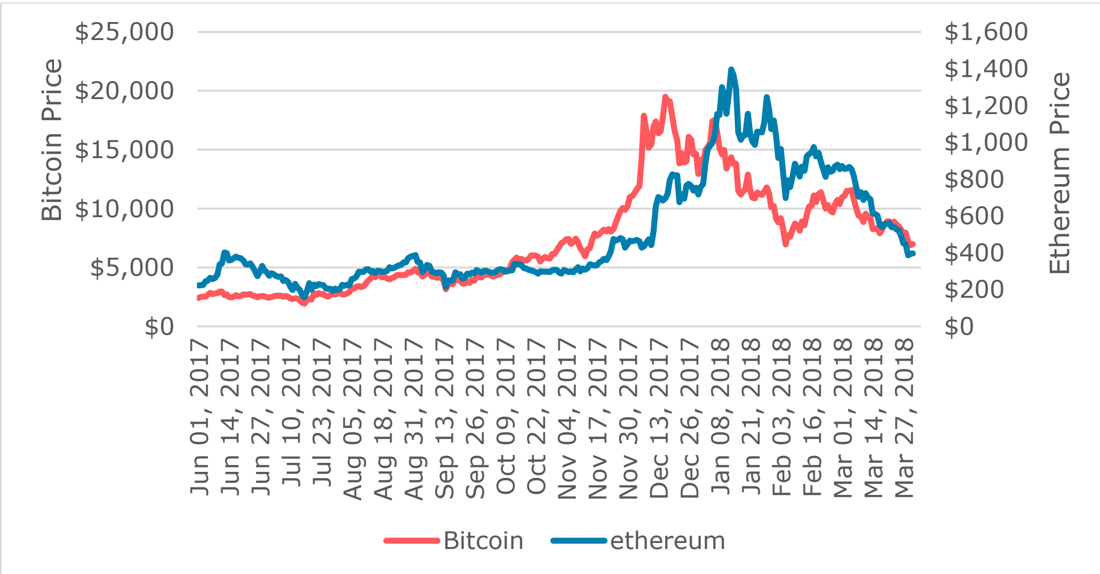
Time period used to assess client outcomes

26. In PS20/10, we have analysed client outcomes from trading ETNs using client data from 1 April 2018 to 31 December 2019. The price of bitcoin during this period can be seen in chart 3. We chose this period because it avoids the period of extreme increases and decreases in the price of cryptoassets (Chart 4).

Chart 3: Bitcoin prices between 1 April 2018 and 31 December 2019

27. In choosing to avoid extreme price changes, we avoid periods from June 2017 to 31 December 2017 and the period January to March 2018**.** In these periods, we see large increases and decreases in the price of cryptoassets which distorts client outcomes.

Chart 4: Price of bitcoin and ethereum between June 2017 and March 2018



28. To avoid the bubble and the large price increases associated with this, we started the analysis in April 2018, this also avoids the reduction in the price of bitcoin from US$14,112 on 1 January 2018 to US$6,973 on 31 March 2018. We also avoid the fall in the price of Ethereum from highs of US$1,146.00 on 9 January 2018 to US$396.46 on 31 March.

29. As extreme price increases distort client outcomes it is reasonable to exclude extreme price decreases in our analysis of ETNs when calculating client outcomes and expected benefits. For this reason, we start our analysis in April 2018.