**Literature review**

*Cryptocurrency literature is growing at a fast pace, especially after the rise of interest in the market and its prices, in December 2017. As a relatively new field, it oﬀers an opportunity to researchers to implement new and old methodologies, in order to unveil new properties and characteristics of the market.*

***A first branch of the literature aims to classify cryptocurrency as an asset class.***

Frisby D. (2014) states that Bitcoin owns money’s characteristics, and it performs even better: its limited supply and creation process, make Bitcoin a valid store of value, while other intrinsic characteristic, such as durability, divisibility, portability, liquidity and low transaction costs make its circulation simple, fast and cheap. Another view is given by Dyhrberg A. (2015) that recognizes the store of value and medium of exchange properties of Bitcoin and defines it as a **hybrid** between currency and commodity. *These results come out from a detailed analysis of Bitcoin, gold and dollar based on asset properties, GARCH model and reaction to news*. More recent literature by Demir E. et al. (2018) examines the relation between Bitcoin and economic uncertainty, concluding that Bitcoin has the properties of a hedge against uncertainty. In the same year Corbet et al. (2018) in a systematic research review, evidence the uncertainty to classify cryptocurrencies as commodity, medium of exchange or speculative investment and points out the trilemma that cryptocurrency needs to overcome in order to keep its space in the market: Potential for inherent bubbles, Cybercriminality and Regulatory alignment.

**While the debate on the cryptocurrency classification is still open, the assessment of efficiency sees more homogeneous results.**

Urquhart A.(2016) published the most cited article in the field, that discovers the increasing efficiency of Bitcoin from 2010 to 2016 by analysing autocorrelation (*Ljung and Box (1978)),* independency of returns (Wald and *Wolfowitz (1940) and Bartels (1982)),* long memory in prices (*Hurst (1951))* and others.   
His studies have been followed up by Nadarajah S. and Chu J. (2016) and Barivera A. (2017) . The firsts, reject inefficiency since the year 2011 by applying an odd power transformation of returns, while the latter confirms the increasing efficiency of the market in terms of returns and points out the persistent volatility behaviour during the 2010- 2017 period.   
Caporale G., Gil-Alana L and Plastun A. (2018) examines persistence with two different long-memory methods, finding a positive correlation between past and future values. This market inefficiency can be used to generate abnormal profits with trend following strategies.  
A different method has been used by Khuntia S. and Pattanayak J. (2018) by applying tests with a rolling window approach that produces results that deviate both from the efficiency and inefficiency theories. “Existence of behavioural bias and creation of events can change efficiency overtime”. This implies that arbitrageurs can earn abnormal returns, but not always. In the same year, Brauneis A. and Mestel R (2018) studied the efficiency of several cryptocurrencies and observes that as liquidity increases, a cryptocurrency become less predictable/inefficient.

**One of the widest branch of literature in the cryptocurrency space studies the price behaviour and its evolutions.**

Bouoiyour J. et al. (2016) disentangle Bitcoin price dataset into several models, finding that even if Bitcoin is labelled as purely speculative asset, its price it’s driven by long term fundamentals.   
Part of these fundamentals are identified by Van Vliet B. (2018): he created a model based on Metcalfe’s Law that explains Bitcoin price as a function of the number of Bitcoin mined and its diffusion between the users.  
This uncertainty upon fundamentals, could lead to high volatility, high risk and bubbles. At this scope Gkillas K. and Katsiampa P. (2018) examines the tail behaviour of the return of 5 major cryptocurrencies, discovering higher values of risk with respect to other currencies and that this risk is not diversifiable investing solely in cryptocurrencies. Also Fry J. (2018) develops a bubble model that combines heavy-tails with measures of risk/return that sees the possibility of a complete collapse in absence of central regulation.  
Co-movements in the cryptocurrency market are a common behavior: Bouri E., Shahzad J. and Roubaud D. (2018) analyse whether explosivity in one cryptocurrency causes explosivity in other cryptocurrencies. The results show a multidirectional co-explosivity structure, that could be leaded also by smaller currencies. On the same topic, Ji Q. et al. (2018) shows that Bitcoin and Litecoin share the dominant role in transmitting return and volatility spillovers, while Ethereum seem to be a spillover receiver. *Asymmetries in negative-return spillovers have a more substantial magnitude than in positive-return spillovers, implying that negative returns are not decreased by positive return spillovers.*  
The effectiveness of technical trading strategies on Bitcoin, such as moving averages and break outs, is studied by Corbet S. et al. (2019), finding significant support for the moving average strategies.  
Predictability based on tweets is analyzed by Shen D., Urquhart A. and Wang P. (2019). They show evidence that the number of tweets are drivers of tomorrow’s Bitcoin realized volatility and volume (supported by Granger causality tests), but not returns.  
What is instead the role of exchanges in the price behavior? Giudici P. and Pagnottoni P. (2019) answer the question by studying Bitcoin’s price discovery using high frequency data. Results confirm previous literature such as Brandvold et al. (2015): high volume markets (Bitstamp, Gemini) drive price and spillovers. *The exchanger role, however, is provisory, because exchanges, dramatically evolve over time.*

**Another nieche of literature is focused on the investibility and liquidity of cryptocurrencies.**

Loi H. (2017) notices that Bitfinex provides the highest liquidity on spot Bitcoin trading in 2015. Comparing the liquidity of Bitcoin and stocks, the results indicate that stock of any size are more liquid than Bitcoin in 2014/2015

Liquidity and volume analysis let Dyhrberg A., Foley S. and Svec J. (2018) find that the highest trading activity, highest volatility and lowest spreads coincide with US trading hours, suggesting the prevalence of non-algorithmic, retail investors. A further analysis recognize that the spreads are lower than the one on major equity exchanges, implying high investibility, and that volume of trades is positively correlated with volatility, while negatively correlated with spreads

Furthermore, Wei W. (2018) analyses 456 cryptocurrencies and shows that predictability and liquidity are inversely correlated, with the low liquidity coins to have a higher chance of return autocorrelation and higher volatility. The illiquidity premium analysis come from Begusic S. and Kostanjcar Z. (2019): they find a statistical significance for momentum effect (this supports the theories of investors herding in the market) but does not find any significance for illiquidity premium.

**Another phenomenon that is studied in the literature is the connectedness between cryptocurrencies and other asset classes.**

Baumöhl E. (2018) demonstrate various types of connectedness between forex and cryptocurrencies, but also inter-group co-movements for cryptocurrencies, especially in the extreme quantiles. This implies diversification benefit both intra and inter classes.  
Symitsi E. and Chalvatzis K (2018) analyze Bitcoin with energy and tech companies. There is significant return spillovers from energy/tech to Bitcoin. Short-run Volatility spills over from tech companies to Bitcoin, while Bitcoin has long-run volatility effects on them. As the paper shows low correlation between Bitcoin and stocks, this implies diversification benefits.  
Support of these theories comes from Liu J. and Serletis A. (2019) that show interdependence within the cryptocurrency market. They also find that the linkage with other markets is stronger in the countries where cryptocurrencies are more accepted and used.  
A result out of the chore comes from Corbet S. et al. (2018), who evidence the relative isolation of cryptocurrencies with respect to other economic or financial assets.  
Yi S., Xu Z and Wang G.(2018) focus instead on the fact that volatility spillovers between cryptocurrencies is not necessary linked to capitalization and identify a strong tendency of herding between investors, especially when uncertainty is high.

**A last branche of literature, the most relevant for our topic, analyse properties of the future market.**

Corbet S. et al. (2018) shows that volatility increased around the announcement of futures creation and that price discovery is coming from the spot market rather than CBOE/CME, assessing that futures market traders are uninformed noise traders.

More recent literature contradicts this result, starting from Akyildirim E et al. (2019): information flows and price discovery are transmitted from future (CBOE/CME) to spot, due to the influx of institutions. This increases the maturity of the market. In this paper BitMEX and Binance futures are not considered, even if they have the highest future volume.

Alexander C. (2019) includes them and points out that relative bid-ask spreads, relative trading volume and inter-exchange spreads are determinants for price discovery, where BitMEX is leading (2019). BitMEX has also positive net spillover to other exchangers, is informationally more eﬃcient, and its products can hedge up to 99.39% of the spot price volatility risk.

Same results are valid for Ether: Alexander C. et al. (2020) analyze the microstructure of ether trading on derivative (BitMEX) and spot (Bitstamp, Coinbase, Kraken) finding that the derivative plays a dominant price discovery role, being a spillover for the spot price. Moreover, since the BitMEX swap was introduced, the spot volume increased and volatility decreased: signs of increased institutional arbitrageurs. (**Price discovery and microstructure… GOOD DATA CHAPTER**!)

The topic of funding rate is still not well explored. The only result comes from Nimmagadda S. and Sasanka A. (2019). They find that Granger Causality between funding rate and price exists in both directions, and present a model for predicting funding rates: due to the causality this allows to trend prediction in the Bitcoin derivative market.

**Conclusion of literature review**

The fact that there are many contradictory results in the cryptocurrency literature show how fast the market is changing: inefficiencies are shrinking, new financial products are released every month making the entry barriers smaller and smaller.

**Where this paper stands**

This paper aims to extend the current literature on cryptocurrencies by analyzing in depth the funding rate properties at BitMEX and Binance, exploring eventual inefficiencies and a concrete way on how to exploit them.

**Not on crypto**

Cont R., Stoilkov S. and Kukanov A. (2010) show relation between high-frequency price changes, and OFI (market, limit and cancel orders). Prices react to changes in the supply and demand at the best quotes, with an inversely proportional magnitude with respect of the depth of the market.