Abstract

There are no solid arguments to sustain that digital currencies are the future of online payments or the disruptive technology that some of its former participants declared when used to face critiques. This paper aims to solve the cryptocurrency puzzle from a behavioral finance perspective by finding the parallelism between biases present in financial markets that could be applied to cryptomarkets. Moreover, it is suggested that cryptocurrencies’ prices are driven by herding, hence this study test herding behavior under asymmetric and symmetric conditions and the existence of different herding regimes by employing the Markov-Switching approach.

Introduction

The understanding of crashes in stock markets has been a difficult task both for economists and market analysts. Theoretical foundations in financial economics rely ultimately on the assumption of efficiency of markets. Nonetheless, several studies have found empirical evidence that contrariwise the cornerstone of efficient markets. The behavioral economics uncover systematic deviations from rationality exposed by investors, instead individuals are victim of their cognitive biases leading to the existence of financial market inefficiencies, fragility, and anomalies. Particularly, crypto-currency markets resemble in several fashion to the criticisms on financial markets exposed by behavioral finance advocates.

The digital economy have been increasing the exposure of state-of-art ideas, opportunities and changes in economics paradigms. By the same token, cryptocurrencies as well as Blockchain’s technology, and other potential applications are without a doubt a relevant concept that have emerged on the “new economy”. One could assure that most of the interest was fueled by Bitcoin, the first successful application of a peer to peer network. Responsiveness from the public has been driven in part for the extreme upswings in prices and volatility, which has been also present in some degree by other alternative coins such as Ethereum, Ripple, Tokens and Initial Coin Offering (ICO). As portrayed by Poyser (2017), it is difficult to align a future in which cryptocurrencies make a significant economic change under current extreme price movements exhibited without the existence of salient announcements.

Studies of behavioral finance seek to explain why investors in stock market settings act as they do. In this work, it is hypothesized that it is possible to explain cryptocurrencies market prices’ puzzle from a behavioral finance perspective in which investors’ cognitive biases play a major role to explain the volatility. In this context, this paper makes a literature revision on empirical and theoretical evidence in which investors’ actions have been proved are not aligned with a rational benchmark, that can also serve as a parallelism to the crypto-market problem (Akerlof and Yellen 1985; Conlisk 1996; Friedman and Rubinstein 1998; Kahneman and Riepe 1998; Simon 1982). Furthermore, this paper seeks as well to shed light on the price setting puzzle by attributing movements to investors herding behavior, that is, a collective decision-making process in which prices “as is” are the coordination mechanism to decision making. According to the literature, herding can trigger the formation of speculative bubbles, thus, the main objective of this chapter is to study cryptocurrency market under the hypothesis that crypto-investors have limited resources to process information and weak priors, as a consequence they rely on others sources to valuate cryptocurrencies.
The paper is structured as follows: first, I will contextualized the problem by comparing cryptocurrency market behavior with past speculative bubbles. Second, it is defined some of the most relevant theory on financial economics and the transition to behavioral economics to find the parallelism between crypto-markets and the evolution of the literature. Third, I will provide some of the most common biases evidenced in financial settings and their relation with our case. In the fourth and fifth sections it is explained the data and the methodology used for this work. Section six show the empirical results on herding behavior and concludes in section 7 the main outcomes.

From Tulips to Blockchain

Due to the incentive to generate profits from price differentials, speculation is ubiquitous to a market economy. Long time ago Fisher (1896) mentioned: “Every chance for gain is eagerly watched. An active and intelligent speculation is constantly going on, which, so far as it does not consist of fictitious and gambling transactions, performs a well-known and provident function for society.” Hence, a valid conjecture is that as long as market economy has been developing, speculation has been growing as a natural mechanism to those individuals who are willing to use strategical information to their own good.

However, certain conditions such as high degree of speculation by misvaluations or delinked relationships between risk and loss, are associated to market inefficiencies. There are several cases of price booms in financial and non-financial environments have occurred without any rational explanation, as a result, economic and financial jargon have created names like, “crashes”, “bubbles”, “financial crisis” or “tulip mania”. The latter name refers to the first documented “speculative bubble” when in the XVII century Tulips’ prices increased abruptly. Apparently, it is attributed a set of factors related to the economic growth. For instance, an rising in trade of goods inside Netherlands, increasing value in the national currency, a perception of facing the transition to a new economy, novel colonial possibilities, and an increasingly prosperous country, which led to create an atmosphere in which the now called “Tulip mania” (Mackay 1852; Sornette 2003).

According to Mackay (1852), tulips’ bulbs were initially imported at retail from Turkey in the middles of the sixteenth century. During the first stages of the market build-up, bulbs sales barely covered production costs (Sornette 2003), albeit, by the end of 1500s professional cultivators and wealthy marketers started to offer exotic varieties of bulbs which rapidly gather the attention of rich people willing to pay the extraordinarily high amount of money for the bulbs. Sooner, tulips became a symbol of wealth and as the rumors dispersed in the society, other groups such as middle-class people realize of the possibility to easily obtain profits from buying low and selling high in the market. As Sornette (2003) mentions the now named “tulip mania” was perceived as a “sure thing”, suddenly, an atmosphere of euphoria where any hesitation was dismissed, a complete confidence on the rumors of even higher prices led people to sell houses, properties in order to invest in this activity. Prices of rare tulip bulbs escalated at a point where there was no rational concordance with the price of other goods and services (Sornette 2003). The process of continuous increases in prices attracted speculators who started to play with the information in order to generate market fluctuations with the objective generate profits from arbitrage activities. Interestingly, “many individuals grew suddenly rich. A golden bait hung temptingly out before the people, and, one after the other, they rushed to the tulip marts, like flies around a honey-pot” (Mackay 1852). As Sornette (2003) mentioned, “the conditions now generally associated with the first period of a boom were all present: an increasing currency, a new economy with novel colonial possibilities, and an increasingly prosperous country together had created the optimistic atmosphere in which booms are said to grow”. Nonetheless, the “unexpectedly predictable” occurred, in February 1637 prices collapsed at a 10% of the peak values shown months before, and never rose again. The tulip mania has been since that time portrayed as the characterization of irrationality in markets.

Even though the tulip-mania was one of the former cases in which markets deviates greatly from expected, it has not been as striking and extended as financial crashes. This is exemplified by the major historical stock market crash occurred in October of 1929 known as “Great Crash” that also set the precedent for the Great Depression. Other examples are the “Black Monday” denoting stock market boom ensued on October 19, 1987, or the “Dot-com” bubble occurred in the period 1997-2001. As Garber (1990) portrayed, these events have “emerged from specific speculative episodes have been sufficiently frequent and important that they
underpin a strong current belief among economists that key capital markets sometimes generate irrational and inefficient pricing and allocational outcomes”. Given that the scope and impact such market collapses is significant, they remain at the central debate between financial economics theorists, who try to explain the reason to such exceptional deviations from the “fundamental values” and those who believe in markets driven by psychological factors.

Historically, several products or services that ended in a crash were in the beginning exposed as “disruptive”, “new”, “innovative” and so on. Cryptocurrencies have not been different, in Poyser (2017) I have briefly described how people describe them as the precursor of the new form of performing empowered by the people. Certainly, news media have been playing a relevant role into forming expectations and increasing the hype, by broadcasting insiders and speculators’ ideas about new projects, technological implementations, security advances and future applications.

Nonetheless, there is a lot of noise that oftenly displace the discussion from tangible projects based on Blockchain to an investment schema. To some extent it is expected such outcome taken in count that Blockchain is difficult to understand even for information technology enthusiasts. As expressed before, any disclosure evoking a new economy will always be an allure for people ready to obtain profits, notably in cryptocurrency markets it is accompanied by a perception of foolproof investment, a sense of low probability of losing money. As expected, extreme events such as 2013 price boom not only led the genesis of mass hysteria, it also incentivated speculators to play with the information. For instance, by the end of 2017 Bitcoin’s price had a run up that caught public attention, increasing the consensus among economists that it is hard to conciliate high volatility with a the store of value function that any currency should exhibit (Also discussed in (Poyser 2017)). In a nutshell, price increases attract large groups of investors, who believe that they can “jump into bandwagon” in order to generate profits easily, even without figuring out how cryptocurrencies really works and their potential, though aware that the opportunity cost of missing out is relative high. Such enthusiasm has been promoted by news media, thus, price bid ups, create further price rises, that is, a self-fulfilling prophecy. Under this situation, it is expected that cryptocurrencies exhibit characteristics of a speculative bubble as many others have mentioned, however, it is almost impossible to predict when it is going to occur.

Theory

An intent to find the parallelism of rationality

It is been said that theory on financial economics formally started in the 1900 with Bachelier (1900) who was interested in the application of random motion to explain the movements of prices of a popular investment tool named perpetuity bond (Read 2012). In order to explain this price dynamics he implemented the random walk, that is, a path created by the succession of random uncorrelated steps in which each move is buffeted by a given equal probability. The first insight present in Bachelier (1900) in that on average the prices movements will tend to be on the average given on an equal probability of going “up” or “down”, therefore the trajectories are neutralized or canceled. Additionally, the level in which prices fluctuate is named “fundamental value”, and any deviation or fluctuation created by the forces of the market (active participation from multiple investors) around this value is governed by the so-called Gaussian distribution. Hence, any possibility of predicting future values is impossible and therefore there is no deterministic chance to arbitrage even for professionals or new investors. This is possible due to the constant feedback dynamics products of the constant participation, that is, any strategic information in hands of an investor is quickly recognized and eliminated others in the market who analyze prices.

Fama (1965) describes accurately what an efficient market means by saying: “An efficient market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time, the actual price of a security will be a good estimate of its intrinsic value”

1Fama (1965)
Several conclusions stems from the statements exposed above, fist, financial prices embed inside the sum of all information provided publicly over time, hence assets price are always correct, and any deviation in which “price may appear to be too high or too low at times, but, according to the efficient markets theory, this appearance must be an illusion.” Shiller (2015). Second, it is not possible to forecast any additional price change, therefore, one could not systematically bear the market (Read 2012). I have described the origin and some of the cornerstone characteristics of the EMH which had been intensively improved by other significant contribution of Eugene Fama, Stephen Ross, Robert Merton, Myron Scholes, William Sharpe, among other whom works set the basis to the contemporaneous modern finance theory. Another implication (probably simplification as well) is that any asset has a fundamental and speculative components. According to the EMH the latter follow a known probabilistic distribution, and constantly fluctuates around the fundamental. Nonetheless, this argument has the most controversial given that hardly explain extreme volatility events such as speculative bubbles and market crashes.

Speculation has been a concern that takes back upon the times of John Maynard Keynes who proposed a tax on financial transactions that were excessively speculative. With the purpose of limits the markets to legitimated investors and thus mitigate the impact on the economy in case a potential burst (Keynes 1936; Read 2012). Speculative bubbles have been increasing in attention since modern finance cannot explain how events such as crashes in Black Monday, Dot-Com and the financial crisis in 2008. On this position, Robert Shiller has assuring that financial market are driven exclusively by behavioral issues among the participants (speculative component outbound the fundamental effect).

In this study it has been asked if cryptocurrencies can be analyzed from the efficient markets markup. A first step is to dispel and characterize commonalities across the different cryptocurrency, that is, asking if any given cryptocurrency met all the three functions of money. It is likely several of them meet the unit of account and medium of exchange functions, nonetheless it is hard to conciliate the store of value function given that all of them exhibit great volatility. The second step is to question if any given CC has a fundamental value. Devotes might considered Blockchain as itself has a value, but how can it objectively measured? And if it has fundamental value, why are they so volatile without any reasonable explanation? For many people CC are investments, independently if they classified as token, ICO, currency... In absence of fundamental or intrinsic value the speculative component drive prices. In the next section, I will provide the characteristics that Bitcoin market has and how they comply with the exuberance irrationally promulgated by Shiller.

Beliefs formation and biases present in cryptocurrencies markets

During the Committee on Banking and Financial services in 1998, Alan Greenspan exposed his views regarding the conjuncture of financial markets. He mentioned that human behavior is the main factor that drives markets, and in spite of corrections there is a constant evolution that makes behavioral issues pervasively which yields with violent and unexpected results. Even though this is anecdotic, it has a great coming from someone who served as Chairman of the Federal Reserve of the United States for almost 30 years. As it had been discussed before, the EMH had been the central ideological domain of study among the classical financial theorists and empiricists until the late seventies, however, in this case, it has several drawbacks to explain large deviations in prices such as cryptocurrency phenomena.

A basic tenet of classical economic theory is that investment decisions reflect agents’ rationally expectations, that is, decisions are made using all available information in an efficient manner. A contrasting view is that investment is also driven by herd behavior, which weakens the link between information and market outcomes (Scharfstein and Stein 1990). In one sense, the EMH was so successful because it seemed to dispel the previously dominant notion of an irrational market driven by herds2. The perceptions of Mackay (1852) and Kindleberger, Aliber, and Wiley (2005) were that there was convincing evidence of “bubbles” of mass errors caused by the fickle nature of herds (Devenow and Welch 1996).

Therefore, what it has been happening with cryptocurrencies is closely related to the criticisms on the

2Keynes (1936) famous adage was that the stock market was mostly a beauty contest in which judges picked who they thought other judges would pick, rather than who they considered to be most beautiful
rationality of investors. Behavioral finance tries to unveil market outcomes under the existence of a large group of irrational investors by studying real-world investors’ beliefs and valuations. However, the inclusion of psychological domain into economics goes beyond finance field and certainly did not started with Shiller on the financial setting” [For a broader discussion on economy theory foundations see Dittmar (2011), the concept of bounded rationality models from Kindleberger, Aliber, and Wiley (2005). During the rest of this section, I will provide an overview of rational agent criticisms on a broader economics perspective, while the behavioral strictly bounded arguments are described in a further section.

Since cryptocurrencies advising is mostly available online, naturally, new investors be dependent on information on fairly diversified sources, that is, individuals interested in cryptocurrencies usually form beliefs and decisions based on two main sources: news and social media. Nowadays, many trends start in specific forums, in these spaces users share impressions about last news and recent issues like unexpected upswings or downswings in cryptocurrencies price or innovations in Blockchain platform. That is case of Reddit, a social news aggregation website in which people discuss a wide range of topics, particularly the community of Cryptocurrencies is the biggest one among the internet, with more than 600.000 subscribers. There are a wide variety of users, ranging from experienced to “newbies”, as a result, opinion formation on this community of heterogeneously informed market participants with different incentives has an impact of how investor process information and take decisions such as following advice to buy and sell, investment in new altercoin and “wise” price pattern recognition. Another type of feedback formation occurs in specialized websites that impulse new users to follow “experienced”, “professional” and “successful” investors, thus, disregarding private information, and following others’ actions is precisely a clear contradiction with the EMH that states randomization irrational investors’ decisions.

Expectations formation on other’s investor’s opinions has been widely studied for years, for instance Keynes (1936) wrote a clever metaphor to describe the heuristics’ individuals performed to invest in stock markets and newspapers competition for the most beautiful women among many options during the thirties:

“...so that each competitor has to pick, not those faces which he himself finds prettiest, but those which he thinks likeliest to catch the fancy of the other competitors, all of whom are looking at the problem from the same point of view. It is not a case of choosing those which, to the best of one’s judgment, are really the prettiest, nor even those which average opinion genuinely thinks the prettiest. We have reached the third degree where we devote our intelligence to anticipating what average opinion expects the average opinion to be. And there are some, I believe, who practice the fourth, fifth and higher degrees.”

The scenario described by Keynes seemly relates to cryptocurrencies market, both on price determination and which of them to choose invest. Discerning compliance’s degree at which group of users operates and is a challenging task since experienced users can take advantage of curious and ignorant ones in diverse settings, an aspect that I will consider further. Another concept attributed to Keynes is “animal spirits” which originally described business calculation, which he considered the role of confidence, uncertainty and framing on investment heuristics is inexorable due to our human nature, more precisely of “...a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities.” (Kahneman and Riepe 1998; Stracca 2004; Thaler 1986). Nowadays we count on more assertive evidence on Keynes’ anecdotal arguments thanks to empirical and experimental evidence (Kahneman and Riepe 1998). Until now, I have described some of the belief formations on feedback, which has been widely studied behavioral finance literature, thus, it seems that this field is a good fit to describe Bitcoin market since efficiency is hardly possible for the existence of many contradictions with the statements of the Efficient Market Hypothesis.

Returning to the descriptive approach (also called positive), it is relevant to describe common biases in judgments and decision-making, also identified as cognitive illusions that people usually reflect Kahneman and Riepe (1998). It is also related to the bounded rationality concept attributed to Simon (1982), he was concerned with the human decision making “shortcuts” that could lead to suboptimal outcomes. Naturally, there is a vast set of systematic behavioral biases that characterize individuals in financial-like markets such as Bitcoin, however, they emerge from a setting in which heuristics are altered by market participants and diverse information signals and noise. Moreover, it is been proved that in asset markets the existence of irrational investors generates deviations from fundamentals, hence, under the special case with Bitcoin the
absence of a parameter of value creates a different puzzle. **This has to be mentioned, but do not waste**

At this point, it is relevant to classify the different cognitive biases found in the literature on which people are affected. Hence, I will seek to create a properly standardized aggregation based on literature reviews studies on behavioral finance from (Kahneman and Riepe 1998; Kumar and Goyal 2015; Shiller 1999; Stracca 2004; Subrahmanyam 2008).

A crucial starting point in decision-making framework is to distinguish between beliefs and preferences. Beliefs are salient in expectation formation, and usually, people develop non-optimal judgments in what to believe due to a set of experimentally proved systematic errors called biases Kahneman and Riepe (1998). My own view is that people involved in cryptocurrencies market presumably suffer from several of the same judgment biases that have been documented in financial markets settings, which can even get intensified by crypto-market idiosyncratic uncertainty and complexity.

**Overconfidence and optimism**

Among the biases, people display in financial market exist the exacerbated trust on our own ability, knowledge, and skills are entitled as overconfidence which is intrinsically related with optimism. Moreover, this self-reliance on personal judgments entails concepts such as miscalibration, over-precision, and optimism, which are at the same time associated with an overreaction to random events (Barber and Odean 2013; Barberis and Thaler 2002; Kahneman and Riepe 1998). A classic illustration of overconfidence bias is the better than the average beliefs, which is the perception of a more than proportional of a group’s composition that they perform better than the mean for the same group for certain activities. For instance, Svenson (1981) found 90% of Swedish car drivers considered themselves better than the average. Another example the seemingly narrow uncertainty in judgments, in other words, people assign significantly less weight on chances of surprises than they really occur. The typical example is when people were asked to evaluate 1 and 99 percentiles of an index such as exchange rates or inflation a year from the reference point, the resulting 98% percent confidence interval capture far less the expected value in comparison with true ones Alpert and Raiffa (1982). Hence, it has been proved that there are too many out of range certainty, in fact, the surprise rate is about 20% where the accurate calibration would yield 2% Kahneman and Riepe (1998). Also, Barber and Odean (2001) found on the premise that men are more prone to overconfidence than women, that the former gender trade more and display lower return than women. Other great contributions can be found in Daniel, Hirshleifer, and Subrahmanyam (1998) and Daniel and Hirshleifer (2015), which also stated how unlikely is the purely rational model to explain variability in stock prices due to systematic departures from rational behavior.

**Information and social wisdom**

Confrontation of different ideas has been playing a essential role in the development of the society. The invention of the printing press is one of the most significant, if not the most dramatic event that yields to the conception of information as a near public good. There is evidence that the decline in the cost of dissemination of knowledge and ideas due to press accounted for 18 and 68 percent of European city growth between 1500 and 1600 Dittmar (2011). Nowadays, in the digital economy, information is no longer a scarce commodity, in fact, the opposite is exposed, there is an overload of data that demands the creation of mechanisms to discern which is relevant and which is not. On this matter, H. Simon accurately described the situation by saying “wealth of information creates a poverty of attention” **Improve attention** see Barber Odean 13. Furthermore, as humans, we have limited computation capabilities and increasing number of constrains to develop a single activity, hence, the formation of “rules of thumb” usually takes place instead of coherent reasoning according to what each state demands. According to Barber and Odean (2013), the extension to financial markets stems to the limited devotion to investing in two main fashions: delayed reaction to salient information and overstated attention to stale information that can lead to overreaction. As a result, an active agent in crypto marketplace may face uncertainty and not be able to assess probabilities of events, accuracy, well-timed choices, the degree of utility, and quality from some sort of heterogeneous

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3 More examples in chasing action
information extracted from sources such as social media, newspaper, forums, and so on. Social judgment is intrinsic to cryptocurrency market since the valuation of any currency is contingent to the extension of the group that founds it valuable. As with Bitcoin, most of the information technologies exhibit network effects or network externalities which is also particularly strong in communication platforms. Under these scenarios, the strategy is to achieve the interest of a critical mass of users/investors that yield a higher market capitalization. Those early adopters (“Whales” in cryptocurrencies’ slang) can be positioned and exert market power by manipulating prices and making profits, this practice normally described as “Pump and Dump”. The objective of boosting prices has a mechanism the exposition of exaggerated announcement about the future of Bitcoin, for instance, presumed cryptocurrency’s experts declare higher prices predictions (anchoring prospects), narrative stories of success, or Blockchain’s innovative applications in social media, news, and forums. Once people receive this information, they have to discern if it is accurate, but prices often react faster, then, it is strategically rational to follow not only what others do, also movements of prices. The practice of imitating behavior has been studied in extension in financial and non-financial markets settings, it has been named as positive feedback, informational cascades or herding, with some commonalities and differences which I will try to expose in the section about crypto-markets speculation.

The role of news, social media and discussion forums

The invention of newspapers permitted a rapid spreading of salient and not relevant information. Moreover, it also provides as a ploy for the transmission of hypes with the purpose of capturing reader’s attention towards different issues, being markets one of many of them.

One important aspect of cryptocurrencies is the fact that prices only rely purely on market participants’ expectations on the future. Hence, heuristics regarding which cryptocurrency to trust and second which trade strategy to follow given the information available. Regarding this point, Figure 1 demonstrates the relevance of people interest and the correlation with Bitcoin price. Bitcoin is an example of the limitations of the efficient market hypothesis.

“A mania involves increases in the prices of real estate or stocks or a currency or a commodity in the present and near-future that are not consistent with the prices of the same real estate or stocks in the distant future” (Kindleberger, Aliber, and Wiley 2005).

Reflecting a growing recognition of the role of fads and endogenous market fluctuations, much research has focused in recent years on why large deviations of market values from fundamentals occur in the first place and how “false” information or fads can be disseminated in the market. Studying herd behavior has been the object of considerable effort in recent years for its possible role in amplifying fads and lead market prices astray from fundamentals.

I suggest that these patterns can be explained by the difficulty of evaluating a large number of securities available for investors to buy, by investors’ tendency to let their attention be directed by outside sources such as the financial media, by the disposition effect, and by investors’ reluctance to sell short (Barber and Odean 2001).

Positive feedback, Herding, and Informational Cascades

None of the theory on behavioral or “orthodox” finance has considered the scenario in which there is no reference to be attached for. In my view, there are three levels of convictions regarding positions about markets. The first is associated with the rational expectations assumption that conveys investors react coherently to announcements that affect fundamentals. The second degree stems from the debatable conjecture that prices movements are truly ruled by fundamentals, in which Shiller (2015) has been severely criticized by showing evidence of an excess of volatility[Reference to excess of volatility]. Finally, we reach a third-degree exceptionally exposed by cryptocurrencies markets, in which by construction there is no fundamental value,

4Check Shapiro & Varian’s book
5for a survey, Devenow and Welch (1996) and Bikhchandani and Sharma (2000)
then prices will be determined in large extension by fuzzy valuation. Noting the crypto-markets nature, and the compelling evidence regarding human behavior systematic biases exposed in financial-like markets which represent the most evidence supported economic theory, there is a final question to solve: in the absence of reference points to prices, how do individuals take decisions in crypto-markets? In a broad context, comparing the information or digital economy to the industrial, Shapiro and Varian (1999) stated that old economy differentiates from the new in the substitution of economies of scale by the economics of networks. That is, in a technological world, one finds utility as far other people’s preferences are aligned. For instance, a messaging app has as the main purpose of communicating with a counterpart that can be a group or individual. Nevertheless, if those whom I want to communicate with does not find the same platform valuable, makes it worthless for me too. According to the same authors, in the beginning, it is essential to reach a certain amount of users or critical mass, and the mechanism to increment the number is driven by a positive feedback behavior.

It seems coherent to hypothesize that one detonating factor that has converted Bitcoin into the main cryptocurrency independently for the fact that it is the first successful cryptocurrency implementation, is a combination of positive feedback mechanism and self-fulfilling prophecy. The sociologist Merton (1948) defined a self-fulfilling prophecy as: “... a situation, evoking a new behavior which makes the originally false conception come true.”, translating this situation to our case, it can be interpreted as those initial opinions which featured digital currencies, particularly Bitcoin as a milestone of a new era, even though few people then (probably now too) understand it. Indeed, little of the main foresight have been fully realized, but reality seems blurry enough to keep the fad going on. Merton adds: “For the prophet will cite actual course of events as proof that he was right from the very beginning.” This is potentially related to market value foresight exposed in social media and forums that declared exaggerated markups such as 10.000 or 20.000 dollars per BTC that eventually came true.

Anybody has been in a situation where our thoughts and actions are seemingly aligned with what others do. Typical transmission mechanisms are expressed as word-of-mouth communication, news and social media exposition, in-place observation, or second degree manifestations such as market prices (see Grossman and Stiglitz 1976). One important feature herding or behavioral convergence is that it entails a coordination mechanism, it can be a social learning heuristic by observing other decision-makers or coordination based on some signal such as price movements Devenow and Welch (1996). Moreover, the among the range of situations where it has been reviewed we mentioned investor trading, managerial investment, financing choices, analyst
Several attempts have been made to describe crowd behavior in investing settings, particularly, a seminal article from De Long et al. (1990) reintroduced the “noise” concept formerly attributed to Black (1986) who defined it as the “opposite of information”. According to De Long et al. (1990) perspective, noise trader represents the irrational alter ego of the sophisticated investors, an investor who misperceive expected returns and generate beliefs and heuristics to buy and sell following a simple feedback rule to form insights about market dynamics (Lux 1995). Among the results exposed by De Long et al. (1990) I highlight that under the assumption of unpredictability in opinions and beliefs bared by noise traders, they can earn higher returns than sophisticated investors even though they distort prices, generating anomalies such as an excess of volatility and mean reversion. Evidently, those are strong outcomes, coming from a branch of economics solidly emphasize in the idea that markets are rational. **Maybe overreaction is a good addition here** (Fama 1965). From the behavioral economics perspective, the literature on crowd behavior is called herding. It is defined a decision-making approach characterized by mimicking actions of others, concretely, Kumar and Goyal (2015) defines it as a “situation wherein rational people start behaving irrationally by imitating the judgments of others while making decisions.”, it is also defined as any behavior similarity/dissimilarity conveyed by the interaction of individuals Hirshleifer and Hong Teoh (2003). According to Graham (1999) the herding literature can be organized into four distinct categories: informational cascades, reputational herding, investigative herding and empirical herding, conversely. An informational cascade is described as a process that stems when someone (optimally) choose to ignore her private information and instead jump to the bandwagon by mimicking the actions of individuals who acted previously (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992; Graham 1999). In Bayesian reasoning context, it is the process of updating posterior by gradually shrinking prior’s weight as new and supposedly strong information is presented in a sequential manner. Or in other words, cascades assumes that private signal (prior) likelihood ratios are unbounded. As a result, it is likely that individuals in further chain of events will also fall into mimicking due to the overwhelming nature of the mass beliefs, providing no useful information for latter observers-actioners.

Among the most related and relevant theoretical contributions we have Banerjee (1992) who found that decision rules chosen by optimizing individuals will be characterized by herd behavior. Bikhchandani, Hirshleifer, and Welch (1992) provided proofs that informational cascades could explain conformity, fads, fashions, booms and crashes. Along the same lines with informational cascades, Scharfstein and Stein (1990) stated that in individual investment environments (and reputational herding), managers usually disregard private information by adopting a follow-the-crowd strategy which is an inefficient behavior from market perspective, albeit, this situation is rational from their individual standpoint. Similarly, Welch (1992) results show in IPO settings where shares are sold sequentially, latter investors based their buying decisions on previous actions, and by extension forming cascades. Among the causes of herding we can mention limits of attention exposed before can also increase the probability of herding or cascade due to the difficulty to accurately process information Hirshleifer and Hong Teoh (2003). It is import to highlight that ‘rational herding (maximizing the individual market participant’s utility) could involve the creation of negative externalities (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992).

On the empirical side we found Welch (2000) found that analysts herd in their stock recommendations from data about buy and sell, exposing significant positive correlation between adjacent analysts. Additionally, Welch showed that analyst’s elections are correlated with the prevailing forecast and asymmetry towards a tendency to herd under the existence of optimism or positive news, concluding that this situation can create fragility and further crashes. Those results are aligned with a famous phrase in Keynes (1936) which says: “*Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally*.” Stracca (2004) explains that several factors may reinforce a tendency to herding, including reputation in a principal-agent context if the performance of the portfolio manager (the agent) is costly to monitor, and the fact that compensation is often computed comparing with other investors performance, pushing risk-averse traders to conform to the “average” assessment of the market.[Cambiar esta redacción]. After describing some

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6Some other authors include payoff externalities (network externalities) models that show that the payoffs to an agent adopting an action increases in the number of other agents adopting the same action Devenow and Welch (1996). However, they have little relation with this study, further literature can be viewed in Hirshleifer and Hong Teoh (2003)
of the evidence, we can draw understandings about Bitcoin price formation, given cryptocurrency markets idiosyncrasy formation of pure beliefs and fuzzy expectations. Particularly, herding in crypto-markets could stem through price coordination mechanism that is it can be (errors are implicit) the most efficient social learning model. This is described by empirical herding category, which has been studying investors’ behavior when they do a momentum-following or positive feedback investment that is, taking decision based on price patterns Sornette (2003).

Strategies and price bubbles

The last two chapters were focused on describing common biases and heuristics to Bitcoin investors respectively. We have determined that individuals in crypto-markets have several incentives to chase the action, and base their decisions through prices as coordination mechanism due to the lack of salient information or fundamental news. This scenario seemsly relates to the Internet Bubble (also known as dot-com, or Y2K) when companies like Amazon, Ebay, and Yahoo! emerged. It was characterized by an over-expectation of future profits, as a product of recent rises prices for internet related firms, investor were eager to invest in companies that were associated with e-commerce, fiber optics, servers, chips, software, improved hardware, telecommunications or any prefix that could sound as part of the “new economy” Kindleberger, Aliber, and Wiley (2005). The bubble was characterized by a rapid increasing NASDAQ Composite index, coming from 1300 in 1996 to 5400 only three years later[ It is relevant to highlight that during December 1996 Alan Greenspan (chairman of the Federal Reserve Board) coined the famous concept of “Irrational Exuberance” to illustrate the effect of psychology in stock markets.]. According to Ofek and Richardson (2001) rational explanations had little power to explain what happened, since internet stock prices were significantly deviated from their underlying fundamentals and volatility of prices were out/bounded expressing over-optimistic sentiment, lack of caution, and the panic of “not being part” among the investors. Particularly, on the last element, cryptocurrency slang has a special acronym to express this behavior, it is known as #FOMO or “Fear of Missing Out”, that is, the anxiety of not get into the market when an unexpected event unchain a rapid valorization of a certain digital coin. Another example about investors' irrationality was Black Monday, the crash that took place in October 29 of 1987, on this matter Shiller (1987) expressed that nothing seemed to be different during those days among the investors whom he surveyed besides a perception that the market was overpriced, he also emphasized in the existence of large price movements without any news breaks, which is not consistent with the EMH which had been criticized for other authors Add more references (De Bondt and Thaler 1985). Shiller insisted in stating that crashes seems to be determined endogenously by investors, either by reaction to others’ actions or manifestations expressed in prices (from here devised the concept of positive feedback trading). Moreover, some investors conveyed they rely on “gut feeling” as their forecasting method (in contraposition to fundamental or technical analysis). One of the main aspects to consider in such scenarios is the impact of speculative price movements, particularly Kindleberger, Aliber, and Wiley (2005) stated that:

“The insiders destabilize by driving the price up and up and then sell at or near the top to the outsiders. The losses of the outsiders necessarily are equal to the gains of the insiders. [...] But the professional insiders initially destabilize by exaggerating the upswings and the downswings; these insiders follow the mantra that the ‘trend is my friend.’ At one stage, these investors were known as ‘tape watchers;’ more recently they have been called ‘momentum investors.’ The outsider amateurs who buy high and sell low are the victims of euphoria that affects them late in the day. After they lose, they go back to their normal occupations to save for another splurge five or ten years in the future.”

On one side there are those who think markets are rational and efficient, are explaining deviations as an exceptional movement from fundamental value. The other side is composed by those who believe psychological behavior as the main driver. The way investor believes they act as they are more intelligent as the average investor in the market, hence having a big chance to take out the money safe and the sound is described by Read (2012) who mentioned:

“Since the crash is not a certain deterministic outcome of the bubble, it remains rational for investors to

Footnote 7: Consistent with the argument that noisy participants can affect markets in a non-transitory fashion.
remain in the market provided they are compensated by a higher rate of growth of the bubble for taking the risk of a crash, because there is a finite probability of ‘landing smoothly’, that is, of attaining the end of the bubble without crash.”

In this work, we hypothesize that when prices in cryptocurrency goes up or down can be attributed in great to herding or positive feedback reaction to past price changes. The parallelism to the insiders can be attributed to the whales in crypto-markets seemly behave as insiders or private informed investors which as Kindleberger, Aliber, and Wiley (2005) states, manipulate price’s movements as to destabilize the market by artificially creating exaggerated successive upswings and prices decrease to make the less informed to buy high and sell low, making them only victims of the euphoria (Shiller 1999; Shiller 2015; Shleifer 2004).

Data

According to the site coinmarketcap.com up to April 2018 there were 1564 different cryptocurrencies available in the market, nonetheless, in this study dampens the sample to the first 100 leading ones which in aggregated terms account for nearly 96% of total cryptocurrency’s (CC) market capitalization. Getting information about all cryptocurrencies prices, market capitalization and descriptions is not a completely easy task. The easy way would be to buy information on specialized websites that sell datasets, however, I have decided to scrape the website www.coinmarketcap.com using the rvest (Wickham 2016) package for R software. The original data includes open, close, highest and lowest prices, besides its current market capitalization given a day for each CC. Since crypto-markets are relative new, it is easy to deduce that non all 100 original presented CC have the same starting dates, particularly, the two with more observations (1801) are Bitcoin and Litecoin which extends from April 29, 2013 and ends as all the rest in April 3, 2018.

Measuring herding intensity by analyzing prices demands to work with returns, thus I determined the daily return of each cryptocurrency arithmetic as follows:

\[ R_{c,t} = \frac{P_{c,t} - P_{c,t-1}}{P_{c,t-1}} \]  

Where denote the closing price of c on day , and is the closing price of cryptocurrency on day. Table 1 reports some descriptive statistics of returns for the first 50 cryptocurrencies. One of the most iconic features of cryptocurrencies is the existence of large deviations from the mean, this volatility is illustrated by the existence of long tail distribution for most of the sample CC this study considered. For instance, taking in count the subsample seen in table 1, the “grand” average return is 1.3%, while the average median is -0.1%, as a result is not surprise to find a third moment average of 3.7.

Apart from considering herding at the top 100 CC, it is also proposed to study herding through two different portfolios ranked according to a couple of criteria’s: the 10 oldest and 10 biggest in terms of market capitalization.
Table 1: Summary statistics of returns for the top 50 cryptocurrencies

| Cryptocurrency     | Obs. | Mean  | S.D.  | Min   | Q25  | Median | Q75  | Max   | Skewness | Kurtosis | Jarque Bera |
|--------------------|------|-------|-------|-------|------|--------|------|-------|----------|----------|-------------|
| 0x                 | 230  | 0.010 | 0.112 | -0.290| -0.054| -0.006 | -0.054| 0.632 | 1.328    | 7.9      | 296.0       |
| Aeternity          | 306  | 0.017 | 0.168 | -0.701| -0.056| 0.007  | -0.056| 0.875 | 0.751    | 9.6      | 577.7       |
| Aion               | 167  | 0.023 | 0.186 | -0.610| -0.067| -0.002 | -0.067| 1.046 | 1.739    | 11.0     | 529.3       |
| Ardor              | 551  | 0.008 | 0.099 | -0.408| -0.049| 0.002  | -0.049| 0.666 | 0.989    | 8.4      | 752.3       |
| Augur              | 789  | 0.009 | 0.105 | -0.532| -0.040| 0.000  | -0.040| 1.014 | 2.261    | 23.1     | 14006.4     |
| Binance Coin       | 252  | 0.028 | 0.142 | -0.335| -0.047| 0.006  | -0.047| 0.964 | 2.008    | 12.2     | 1062.6      |
| Bitcoin            | 1801 | 0.003 | 0.045 | -0.234| -0.012| 0.002  | -0.012| 0.430 | 0.512    | 12.9     | 7465.8      |
| Bitcoin Cash       | 254  | 0.009 | 0.119 | -0.360| -0.051| -0.008 | -0.051| 0.540 | 1.396    | 7.8      | 322.5       |
| Bitcoin Diamond    | 130  | 0.010 | 0.356 | -0.692| -0.109| -0.014 | -0.109| 3.215 | 5.917    | 52.4     | 13992.4     |
| Bitcoin Gold       | 162  | -0.001| 0.166 | -0.714| -0.070| -0.013 | -0.070| 1.002 | 1.874    | 15.5     | 1151.3      |
| BitShares          | 1352 | 0.005 | 0.086 | -0.324| -0.035| -0.003 | -0.035| 0.682 | 2.063    | 14.7     | 8693.1      |
| Bytecoin           | 1386 | 0.010 | 0.159 | -0.467| -0.053| 0.000  | -0.053| 3.942 | 12.114   | 277.1    | 4373159.0   |
| Bytom              | 238  | 0.014 | 0.131 | -0.428| -0.050| -0.004 | -0.050| 0.825 | 1.757    | 11.8     | 889.8       |
| Cardano            | 184  | 0.021 | 0.169 | -0.251| -0.063| -0.002 | -0.063| 1.367 | 4.186    | 29.3     | 5822.8      |
| Dash               | 1509 | 0.009 | 0.107 | -0.374| -0.028| -0.002 | -0.028| 2.563 | 10.377   | 225.1    | 3129151.5   |
| Decred             | 783  | 0.009 | 0.096 | -0.290| -0.044| -0.001 | -0.044| 0.555 | 1.614    | 8.3      | 1272.0      |
| DigixDAO           | 715  | 0.007 | 0.093 | -0.726| -0.038| -0.001 | -0.038| 0.785 | 0.787    | 17.0     | 5950.3      |
| Dogecoin           | 1570 | 0.005 | 0.100 | -0.440| -0.025| -0.004 | -0.025| 2.210 | 8.032    | 159.6    | 1621924.5   |
| EOS                | 276  | 0.015 | 0.149 | -0.320| -0.051| -0.007 | -0.051| 1.683 | 5.469    | 50.0     | 37409.3     |
| Ethereum           | 970  | 0.009 | 0.079 | -0.728| -0.027| -0.001 | -0.027| 0.510 | 0.234    | 15.6     | 6396.5      |
| Ethereum Classic   | 618  | 0.011 | 0.155 | -0.373| -0.032| -0.004 | -0.032| 3.233 | 14.674   | 303.9    | 2352930.3   |
| ICON               | 158  | 0.020 | 0.149 | -0.321| -0.067| 0.003  | -0.067| 0.592 | 1.032    | 5.5      | 69.3        |
| IOTA               | 294  | 0.008 | 0.108 | -0.314| -0.057| -0.001 | -0.057| 0.468 | 0.820    | 6.1      | 149.4       |
| Komodo             | 422  | 0.025 | 0.300 | -0.749| -0.052| 0.000  | -0.052| 5.601 | 15.366   | 286.4    | 1429157.4   |
| Lisk               | 727  | 0.013 | 0.158 | -0.810| -0.042| -0.004 | -0.042| 1.517 | 3.410    | 33.5     | 29522.3     |
| Litecoin           | 1801 | 0.005 | 0.077 | -0.402| -0.019| 0.000  | -0.019| 1.291 | 4.845    | 67.0     | 314227.5    |
| Maker              | 151  | 0.081 | 0.892 | -0.248| -0.040| -0.007 | -0.040| 10.896| 11.928   | 145.1    | 130694.2    |
| Monero             | 1412 | 0.007 | 0.082 | -0.315| -0.033| -0.001 | -0.033| 0.794 | 1.628    | 14.1     | 7845.7      |
| Nano               | 377  | 0.029 | 0.161 | -0.306| -0.069| 0.009  | -0.069| 1.024 | 1.771    | 9.6      | 881.3       |
| NEM                | 1098 | 0.011 | 0.109 | -0.303| -0.038| 0.000  | -0.038| 1.706 | 4.807    | 62.7     | 167350.2    |
| NEO                | 571  | 0.015 | 0.131 | -0.407| -0.044| -0.004 | -0.044| 1.228 | 2.897    | 23.8     | 11048.5     |
| OmiseGO            | 263  | 0.018 | 0.125 | -0.256| -0.049| 0.001  | -0.049| 0.741 | 1.876    | 11.3     | 909.3       |
| Ontology           | 26   | 0.002 | 0.134 | -0.423| -0.079| 0.030  | -0.079| 0.259 | -1.075   | 5.3      | 10.6        |
| Cryptocurrency | Obs. | Mean | S.D. | Min | Q25 | Median | Q75 | Max | Skewness | Kurtosis | Jarque Bera |
|----------------|------|------|------|-----|-----|--------|-----|-----|----------|----------|------------|
| Populous       | 265  | 0.014| 0.130| -0.691 | -0.060 | 0.007 | -0.060 | 0.833 | 1.182 | 13.5 | 1278.5 |
| Qtum           | 314  | 0.010| 0.129| -0.364 | -0.054 | -0.004 | -0.054 | 0.751 | 1.970 | 11.8 | 1216.8 |
| RChain         | 179  | 0.020| 0.162| -0.376 | -0.060 | 0.000 | -0.060 | 0.876 | 2.270 | 12.0 | 758.1 |
| Ripple         | 1703 | 0.006| 0.092| -0.460 | -0.023 | -0.003 | -0.023 | 1.794 | 6.120 | 97.9 | 649986.5 |
| Siacoin        | 950  | 0.013| 0.124| -0.385 | -0.046 | 0.000 | -0.046 | 0.814 | 1.932 | 11.1 | 3178.3 |
| Status         | 279  | 0.011| 0.147| -0.250 | -0.058 | -0.006 | -0.058 | 1.161 | 3.705 | 26.9 | 7268.1 |
| Steem          | 715  | 0.010| 0.145| -0.345 | -0.061 | -0.011 | -0.061 | 1.857 | 4.312 | 44.5 | 53628.9 |
| Stellar        | 1337 | 0.007| 0.096| -0.307 | -0.032 | -0.003 | -0.032 | 1.061 | 3.867 | 35.2 | 61194.9 |
| Stratis        | 599  | 0.016| 0.110| -0.290 | -0.051 | 0.005 | -0.051 | 0.663 | 1.401 | 8.3 | 895.2 |
| Tether         | 1128 | 0.000| 0.025| -0.499 | 0.000 | 0.000 | 0.000 | 0.650 | 8.397 | 535.5 | 13338912.4 |
| TRON           | 202  | 0.030| 0.204| -0.318 | -0.061 | -0.004 | -0.061 | 1.196 | 2.751 | 14.7 | 1399.9 |
| VeChain        | 224  | 0.021| 0.147| -0.496 | -0.063 | 0.000 | -0.063 | 0.706 | 0.861 | 6.1 | 115.0 |
| Verge          | 1256 | 0.029| 0.262| -0.600 | -0.071 | 0.000 | -0.071 | 5.800 | 9.460 | 193.8 | 1924531.2 |
| Wanchain       | 11   | -0.013| 0.081| -0.135 | -0.071 | -0.006 | -0.071 | 0.112 | 0.052 | 2.0 | 0.4 |
| Waves          | 670  | 0.006| 0.087| -0.520 | -0.036 | 0.001 | -0.036 | 0.382 | -0.073 | 7.7 | 613.7 |
| Zeash          | 521  | 0.002| 0.124| -0.719 | -0.043 | -0.005 | -0.043 | 1.826 | 6.131 | 95.2 | 187758.5 |
| Zilliqa        | 68   | -0.012| 0.088| -0.207 | -0.081 | -0.001 | -0.081 | 0.184 | -0.027 | 2.6 | 0.6 |
Methodology

To date few methods have been developed to test for empirical herding under prices settings. In the literature review section I have mentioned that direct observation on investors’ actions is the best approach to test for herding since the coordination mechanism and the potential tilting towards the social convention is exposed from the flow of information dynamics within individuals. Nonetheless, in cryptocurrencies market this is almost impossible due to its privacy, hence this study will follow prices as coordination mechanism. This limitation is not unique, in several financial settings analyzing stocks or exchanges rates almost impossible to get information of market participants. Given that herding cannot be measured directly from financial markets, the literature has developed different proxies for detecting herding behavior based on return’s regression tests. This study employs the methodology present in (Chang, Cheng, and Khorana 2000), which is an improvement from original methodology offered by Christie and Huang (1995). Christie and Huang (1995) suggested the use of Cross-Sectional Standard Deviation of returns (CSSD) to identify herding behavior in financial markets, it is defined as:

\[
CSSD_t = \sqrt{\frac{\sum_{i=1}^{n} (R_{i,t} - \bar{R}_{m,t})^2}{N-1}}
\]  

where is the observed stock return on a firm i (in our study it is described as c as presented in the data section) at time t, while is the cross sectional average of the returns in the aggregated portfolio at time t. The implicit indication of the CSSD it’s that it quantifies the average proximity of individuals’ returns to the mean, by extension, CSSD will always be equal or above zero, where a value tied to the lowest bound expresses a situation when all returns flow in harmony while a deviation from the zero mark represents dispersion. According to Christie and Huang (1995) it is possible to test for herding under market stress (large upswings and downswings) events by exploiting investors’ tendency to overturn their private beliefs in favor of the market consensus. This conclusion stems from a rational the Capital Asset Pricing Model [The CAPM relates risk of an investment and the expected returns given a market benchmark, which in stock market settings is for many cases the S&P500, deriving a measure of sensibility and asset is in comparison to the movements of the market. In this study I establish it as a base line to denote rationality in cryptocurrency markets. ] (CAPM) which predicts that the dispersion will increase with the absolute value of the market return since individual assets differ in their sensitivity to the market return. On the other side, if herding exists, individual returns will not differ greatly from the market results. Christie and Huang (1995) empirical tests is estimated as:

\[
CSSD_t = \alpha + \beta^L D^L_t + \beta^U D^U_t + \epsilon_t
\]  

where:

\[
D^L_t = 1 \text{ if market return on day lies in the extreme lower tail of the distribution, or zero otherwise}
\]

\[
D^U_t = 1 \text{ if market return on day lies in the extreme upper tail of the distribution, or zero otherwise}
\]

This dichotomy was developed to capture differences in investor behavior upon extreme upswings or downswings in comparison to what it is expected to be “normal”, expressed as the 90% or 98% percent of the distribution. Nonetheless, this methodology have two main drawbacks, firstly, it is too sensitive to outliers and secondly, it is completely arbitrary what is considered as “extreme” since the 1% and 5% rule might not fit good for all distributions. Consequently this study will followed an extension to Christie and Huang’s model proposed by Chang, Cheng, and Khorana (2000)\footnote{Chang, Cheng, and Khorana (2000) stated that Christie and Huang (1995) approach “requires a far greater magnitude of non-linearity in the return dispersion and mean return relationship for evidence of herding than suggested by rational asset pricing models”}, which is based on the Cross-Sectional Absolute Deviations defined as:

\[
CSAD_t = \frac{1}{N} \sum_{i=1}^{n} |R_{i,t} - \bar{R}_{m,t}|
\]  

where:\n
\[
D^L_t = 1 \text{ if market return on day lies in the extreme lower tail of the distribution, or zero otherwise}
\]

\[
D^U_t = 1 \text{ if market return on day lies in the extreme upper tail of the distribution, or zero otherwise}
\]
The CSAD is a measure of dispersion that takes the absolute difference between the individuals return and the average market returns, which makes it far less sensitive to return’s outliers. Figure 2 illustrates the CSAD measure for the full sample, in which it is noticeable a structural break in the first quarter of 2017 characterized by a level disruption and a higher degree of dispersion. Chang, Cheng, and Khorana (2000) demonstrated “that rational asset pricing models predict not only that equity return dispersions are an increasing function of the market return but also that the relation is linear”. Moreover, they rely on the following intuition: “if market participants tend to follow aggregate market behavior and ignore their own priors during periods of large average price movements, then the linear and increasing relation between dispersion and market return will no longer hold. Instead, the relation can become non-linearly increasing or even decreasing...” This model has been recently employed by several papers, for instance, Arjoon and Shekhar (2017) examined herding in the context of frontier market, Chiang and Zheng (2010) found herding behavior in advanced stock markets, Demirer, Lee, and Lien (2015) empirically tested for herding commodity financialization settings and Balcilar, Balcilar, Demirer, and Hammoudeh (2013) who studied for herding in Gulf Arab stock markets. Following the line of the aforementioned papers, this study starting with a reference model specified as:

$$CSAD_t = \gamma_0 + \gamma_1|R_{m,t}| + \gamma_2R_{m,t}^2 + \varepsilon_t$$

The model exposed in equation 3 aims to detect significant dispersion of returns during markets stress. Hence, a statistically significant negative coefficient of i.e. indicates that herding is likely to be occurring, whereas a significant positive implies a presence of adverse herding. On identification of herding Kabir and Shakur (2018) highlights what Wohar and Gebka (2013) stated about a possible situation when investors “overemphasize their own view or focus on views dominant among subset of actors (who may herd jointly moving in and out of positions) excessively ignoring market information, it results in increased dispersion in returns across assets leading to adverse herding”. It is important to clarify that as many other author that had been studying herding behavior (Arjoon and Shekhar; Chiang and Zheng; Economou, Katsikas, and Vickers 2016) this model employs Newey and West (1987) clever solution to account for heteroscedasticity and autocorrelation consistent standard errors in regression coefficients, besides the inclusion of lagged dependent variables (to guarantee that effects are not a consequence of autocorrelation dynamics.

Since herding varies across time flows, it would be interesting to determine whether there are specific periods when herding behavior is manifested and when it is not, hence, this study will include a regime Markov Switching (MS) approach to identify regimes in which herding is exhibited. A Markovian switching herding model can be illustrated as:

$$\begin{align*}
\gamma_1,0 + \gamma_1,1|R_{m,t}| + \gamma_1,2R_{m,t}^2 + \gamma_1,kCSAD_{t-k} + \varepsilon_{1,t} & \quad \varepsilon_{1,t} = N(0, \sigma_1^2) & S_t = 1 \\
\gamma_2,0 + \gamma_2,1|R_{m,t}| + \gamma_2,2R_{m,t}^2 + \gamma_2,kCSAD_{t-k} + \varepsilon_{2,t} & \quad \varepsilon_{2,t} = N(0, \sigma_2^2) & S_t = 2 \\
\vdots & \quad \vdots & \vdots \\
\gamma_s,0 + \gamma_s,1|R_{m,t}| + \gamma_s,2R_{m,t}^2 + \gamma_s,kCSAD_{t-k} + \varepsilon_{s,t} & \quad \varepsilon_{s,t} = N(0, \sigma_s^2) & S_t = s
\end{align*}$$

Where is defined as the transition probability of the Markovian chain that can be illustrated as , hence, is the probability of being in regime at time given that the in the regime is equal to j. Therefore, know the model will be able to identify when exhibits herding or not, besides different magnitudes this behavior. A MS regression is a useful method to express adjustments which are more pronounced in high frequency data, moreover, it offers advantages to reveal patterns commonly hidden in data such as non-linearity. Regarding the amount of regimes, the definition is not a straightforward task, on this matter, Psaradakis and Spagnolo (2003) states that dynamic models with parameters that are allowed to depend on the state of a hidden Markov chain have become a popular tool for modelling time series subject to changes in regimes, nonetheless, the determination of an adequate number of states to characterize the observed data it is not conclusive. The MS models offer an advantage over the linear models due to their ability to reveal patterns beyond traditional
Figure 2: Actual and squared cryptocurrency market median returns and CSAD
stylized facts, which only nonlinear models can generate. In Psaradakis and Spagnolo (2003) view, a rule of thumb for autoregressive models based on AIC values do provide a good instrument to choose the correct state dimension.
Empirical results

Estimates of herding behavior

In this section, it has been presented the estimates for the models in the methodology. The first model is the standard (linear) herding model which is common in the literature, and we will herein refer to it as the static model because it has constant parameters. The second model is the Markov-switching (nonlinear) model which accommodates herding over multiple regimes.

Table 2: Regression estimates of herding behavior on the full sample

|                | Static | Regime 1 | Regime 2 | Regime 3 |
|----------------|--------|----------|----------|----------|
| Intercept      | 0.005* | 0.025*** | 0.025*** | 0.025*** |
| $\|R_{m,t}\|$ | 0.240***| 1.955*** | 4.5      | -0.385***|
| $R_{2,m,t}$    | -0.27  | -9.979** | -2.479   | 1.645*** |
| $CSAD_{t-1}$  | 0.430***| 18.998   | 6.29     | 8.403    |
| $CSAD_{t-2}$  | 0.220***| 9.098    | 0.193**  | 0.136**  |
| $CSAD_{t-3}$  | 0.277***| 12.227   | 3.855    | 6.669    |
| $R^2$          | 0.79   | 0.50     | 0.76     | 0.79     |
| $AIC$          | -4128.8| -6004.4  |          |          |

This table presents the estimated coefficients of equation 4: 

$$CSAD_t = \gamma_0 + \gamma_{s,1}R_{i,t} + \gamma_{s,2}R^2_{m,t} + \gamma_{s,k}CSAD_{t-k} + \varepsilon_t$$

for the existence of herding. In this specification the intercept is static, that is, it does not change across regimes, while other variables not. The numbers in second row are t-statistics, whereas ***, ** and * stands for significance at 1%

Table 2 reports the estimates for static model and a three regime switching models according to the specification seen in equation 3. The coefficients are were estimated using Newey and West (1987) methodology, to achieve heteroscedastic and autocorrelation consistent standard error estimates for the full sample, that is, the main 100 cryptocurrencies according their market capitalization. As I have explained before, under the assumption that dispersion and the absolute market returns are linearly related, we must center the attention on the coefficient associated with , since it captures herding behavior under market stress. In column 3 we can see that in the static model has a negative sign, nevertheless it is non-significant. The possible explanation is a high degree of variability that cancels the effect across the sample, for this matter it is useful to rely on the Markov Switching estimates that account dynamics in the parameters. Following the estimates of MS model for the first regime in column 3 it has been found a significant negative coefficient of suggesting herding behavior in cryptocurrencies market the full sample (or “portfolio”). Moving to the third regime, there is statistical evidence in favor of herding, nonetheless the magnitude is far lower than the first regime exposed above. Interestingly, there is also a second state where reverse herding is prominent in the market, seeing at column 3 a coefficient of , an evidence of market participants behavior characterized by performing contrary to market consensus, leading to a higher degree of cross sectional return’s dispersion in the cryptocurrency market.

The most striking result that stems from the MS model is the identification of periods where herding behavior has been found significant. From [Figure 3] it can be seen that by far the greatest amount of time cryptocurrency market exhibits dynamics opposite to what a rational asset pricing would expect. A further examination of the graph permits to identify a high probability of regimes 1 and 2 to fit the data, those two states as explained above had been found to a strong evidence in favor of herding, prominently on the first regime (light blue). In addition, the coefficients associated with the absolute cross sectional returns are significant and positive across all models (static and MS) suggesting an increasing linear relationship to dispersion values of CSAD.
Figure 3: Regime switching smoothed probabilities under symmetric herding behavior for the full sample
Estimates of herding behavior under asymmetric market states

This investigation began to test the presence of herd behavior in a sample of the first main cryptocurrencies filtered according their market capitalization. In the past section, it has been found that dispersion decreases when extreme returns are present in the market, nonetheless, it remains to distinguish between the directions in which returns goes. Regarding this matter, many of the recent empirical studies coincide in the important of distinguish between herding behavior under irregular market dynamics, in other words, account for asymmetric reaction in face of downswings and upswings in the market returns (Arjoon and Shekhar 2017; Chiang and Zheng 2010; Demirer and Kutan 2006; Economou, Katsikas, and Vickers 2016). In order to test whether crypto-investors react differently on days when the median returns are positive or negative, it has been created a dummy variable code as 1 when analogy with a 0 when . Then the directional herding is expressed as:

\[ H(\text{up, down}) = \begin{cases} (1 - D)R_m^2 & \text{if } R_{m,t} \geq 0 \\ DR_m^2 & \text{if } R_{m,t} < 0 \end{cases} \]  

(7)

Which leads to a new specification given by:

\[ CSAD_t = \gamma_{s,0} + \gamma_{s,1}D|R_{m,t}| + \gamma_{s,2}(1 - D)|R_{m,t}| + \gamma_{s,3}DR_{m,t}^2 + \gamma_{s,4}(1 - D)R_{m,t}^2 + \sum_{i=1}^{k} \gamma_{s,k+4}CSAD_{t-k} + \varepsilon_t \]  

(8)

Table 3 reports the regression estimates for herding under asymmetric conditions for the static and regime switching models as described in equation 8. In contrast with the model described in equation 5, this time it has been found that a four regimes fits better the phenomenon. The static regression estimate of the coefficient (column 5) confirms the existence of herding when market exhibits positive returns since parameters leads to enough statistical evidence in favor of this behavior. On the other side, contrary to our expectations, there is statistical evidence in favor of reverse herding under the existence of declining returns , this leads to the conclusion that crypto-investors do not follow the consensus when market returns decrease. The fact that when cryptocurrency markets faces extreme negative returns individuals do not “flight to safety”, on the contrary, it implies that the “HODL” strategy is consistent with the data.

Additionally, it has been estimated the parameters of the MS herding model under based on equation 8 in order to observe if the static model fails to capture potential unobserved dynamic structures of herding behavior over time. The column 4 in table 3 presents the estimates for herding under extreme declining market settings.
Figure 4: Regime switching smoothed probabilities under asymmetric herding behavior for the full sample.
Table 3: Regression estimates of herding behavior on the full sample under asymmetric states

|                          | Static      | Regime 1     | Regime 2     | Regime 3     | Regime 4     |
|--------------------------|-------------|--------------|--------------|--------------|--------------|
| Intercept                | 0.007*      | 1.806        | 0.026***     | 10.958       | 0.026***     | 10.958       | 0.026***     | 10.958       |
| $D \times |R_{m,t}|$       | -0.916***   | -4.819       | -0.778***    | -2.885       | -0.017       | -0.037       | 0.480***     | 6.747        | -6.508***    | -3.95        |
| $(1 - D) \times |R_{m,t}|$     | 0.734***    | 7.384        | 1.251***     | 9.754        | 0.118        | 1.155        | -0.491***    | -24.813      | 4.314***     | 3.662        |
| $D \times |R_{m,t}^2|$   | 1.56        | 1.609        | 1.164        | 0.858        | -0.836       | -0.416       | -1.358***    | -3.487       | 25.960**     | 2.243        |
| $(1 - D) \times |R_{m,t}^2|$ | -1.169***   | -4.266       | -2.188***    | -7.63        | 0.376        | 1.303        | 1.372***     | 25.652       | -18.809*     | -1.895       |
| $CSAD_{t-1}$            | 0.427***    | 19.363       | 0.374***     | 7.101        | 0.252***     | 7.616        | 0.269***     | 12.634       | 0.372***     | 5.274        |
| $CSAD_{t-2}$            | 0.221***    | 9.36         | 0.259***     | 5.264        | 0.139***     | 5.326        | 0.200***     | 6.636        | 0.201***     | 2.619        |
| $CSAD_{t-3}$            | 0.277***    | 12.534       | 0.241***     | 5.569        | 0.289***     | 14.297       | 0.118***     | 3.99         | 0.220***     | 2.926        |
| $R^2$                   | 0.8         | 0.85         | 0.83         | 0.91         | 0.57         |
| $AIC$                   | -4219.5     | -6231.4      |

This table presents the estimated coefficients of equation 4: $CSAD_t = \gamma_{s,0} + \gamma_{s,1} D|R_{m,t}| + \gamma_{s,2}(1 - D)|R_{m,t}| + \gamma_{s,3} DR_{m,t}^2 + \gamma_{s,4}(1 - D)R_{m,t}^2 + \sum_{k=1}^{4} \gamma_{s,k+4} CSAD_{t-k} + \varepsilon_t$ for the existence of herding. In this specification the intercept is static, that is, it does not change across regimes, while other variables not. The numbers in second row are t-statistics, whereas ***, ** and * stands for significance at 1.
Even though herding behavior under increasing returns situations was significant at a 1% level in the static model with , the extension of the model of MS unveiled the true dynamics inside the data generating process. Particularly, there is an important difference between the aforementioned evidence of herding and the one visible in regime 3. Under a strengthen market situation, is has been found a very strong coefficient significant at a 10% threshold level that supports herding. Looking at Figure 4 it is clear that during the second semester of 2017 and the first days of 2018, the cryptocurrency market exhibited increasing level of cross sectional absolute deviations (or dispersion), with a substantial reversion from 2018 until the end of the sample. During that time, the model found that consensus was evident across investors as the prices started to rise.

Conclusions

This essay was undertaken to evaluate the pertinence of behavioral finance as a framework to explain price dynamics in crypto-markets taking as a central point a series of potential biases in decision making from the investors. Aiming to this objective, it has been reviewed literature on cognitive biases that has brought evidence of existence of anomalies, or deviations from what a rational could be expected in financial related environments. Among the diverse possible explanations of price movements from a behavioral perspective, the theory of herding which consists in a situation when individuals ignore their private information and instead follow the consensus is under prior consideration a good approach to start the discussion.

The apparent relevance of herding hypothesis to explain price movements demanded the task of finding an empirical model that led me to study the phenomena when only prices were the coordination mechanism. The former, and most relevant methodology to test for herding when only prices are available is attributed to Christie and Huang (1995), then is had been improved for Chang, Cheng, and Khorana (2000) among other authors, this study follow the same line.

The evidence from this study suggests that investors frequently deviated from the rational asset pricing benchmark, and instead follow the consensus in market stress situations. This findings have important implications, first, as I am concerned, this is the first study which analyzed the price puzzle from herding hypothesis, second, it unveils a signal that contradicts the circulated “noise” exposed in internet which asserts for the existence of informed people who are not sensitive to large price movements in cryptomarkets.

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