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# The Role of Cognitive Biases in the Fluctuation of Traditional and Modern Financial Markets

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## ABSTRACT

Behavioural economics is overlooked when talking about economics but it is a key part of our everyday lives. Cognitive biases are the foundation of behavioural economics and they dictate every decision we make. In this paper, I examine the role our inherent cognitive biases play in the fluctuation of traditional and cryptocurrency markets. I first lay the groundwork by establishing what behavioural economics is and explaining common biases as well as explaining what financial markets are in general. I then use the dot-com bubble as a case study to analyse the existence of these biases in a traditional market by comparing fluctuations during the dot-com bubble to the speculative bubble model. Following this, I introduce cryptocurrencies and analyse the cryptocurrency market over a time period and analyse trends to determine whether a bias exists. This is done using internet search data from Google Trends, as well as conducting a self-designed survey and a regression analysis of the resulting data. Results corroborate well with the existing literature and tentatively point to the existence of cognitive biases with regard to market fluctuations in both traditional and crypto assets. The alignment of my survey data with my research strengthens the premise that these biases not only exist but also contribute to the fluctuations of markets.

## Introduction

What does behavioural economics tell us about financial markets? How much of an impact do cognitive biases have on market fluctuations? Can they be discounted? Traditional theories in finance and economics rest on the assumption that humans are completely rational. Recent insights at the intersection of economics, finance and behavioural studies are, however, indicating that cognitive biases and emotions ultimately influence decisions.

This is the idea that behavioural economics aims to convey, that humans are irrational beings and their actions should be modelled accordingly. Despite being a relatively new sub-stream of economics, the field has gained significant traction and verification due to transformative research done by Daniel Kahneman, Robert Thaler and a larger community of adepts. Behavioural economics has created a new way of looking at investors' decisions and this paper aims to explore its influence in the markets today.

While many papers debate on the herd behaviour in the cryptocurrency market specifically and some on behavioural finance in traditional markets, consolidated data to present the importance and existence of these biases in both markets are rather absent. My paper aims to bridge the research gap and address the absence of such studies. It not only explains biases in the cryptocurrency market but also takes into account the traditional markets to enable readers to make a direct comparison. The paper establishes these biases using real-world trends and scenarios to aid the reader's understanding. It additionally contains a self-designed survey with 150 independent observations as well as regression analysis.

This paper explores biases in traditional as well as modern markets to establish a connection between price fluctuations in these markets and the biases. The first section of the paper gives an overview of behavioural economics in general, establishing significant research done in the field as well as providing an overview of key biases which are incorporated later in the paper. The following section, Financial Markets, talks about financial markets in general and what fluctuations essentially mean. The next section tackles financial bubbles and provides an understanding of a speculative bubble by explaining each stage as well as providing visual context. The dot-com bubble, a specific case study from the traditional market, is then analyzed. The final section undertakes the analysis of the cryptocurrency market. It explains what cryptocurrencies are and explores various biases which affect the value of the asset using internet search data from Google as well as a regression model based on survey data.

## Behavioural Economics

Behavioural economics, one of the newest disciplines of economics, is a direct contradiction to the concept of Homo economicus. "Thinking fast and slow" by Daniel Kahneman provided groundbreaking research on Behavioural economics and cognitive biases which shaped what we know about behavioural economics today. Kahneman proposed the dual system theory reshaped the way we think about decision-making. It states that the brain has two systems used for decision making: System 1 and System 2. System 1 primarily relies on mental shortcuts known as heuristics. The brain relies on this for making quick decisions based on previously known information such as comprehending simple sentences. System 2 on the other hand entails much slower responses involving reflection and analysis and is used for more complex tasks such as filling out a tax form. These two systems work in unison forming the dual processing system which determines the decisions we make. (Kahneman, 2011)

Investors, like any other humans, are irrational and biases such as heuristics (mental shortcuts), overconfidence and herd behaviour affect investor decisions and subsequently lead to fluctuations in the market. (Tversky and Kahneman, 1974). Traditional finance adopted the Efficient Market Hypothesis (Eugene Fama, 1970) which states that stocks always trade at their fair price making it impossible to trade over or undervalued stocks. In the real world, there are cognitive biases at play. "There is nothing as disturbing to one's well-being and judgment as to see a friend get rich" is a phrase quoted from Kahneman which perfectly summarizes the fear of missing out. It aims to explain that seeing your friend get rich could significantly hamper your sense of judgement and your well-being by causing you to indulge in an impulsive pursuit to get rich as well solely because your friend did. Kahneman suggests, that overconfidence is the most significant cognitive bias and cannot be discounted while assessing investor behaviour. Barber et al. (2019) hypothesized that overconfident investors performed worse in the market than ones who were not. The hypothesis was confirmed by their analysis of retail investor behaviour which was done using survey data from the National Financial Capability Study administered by the FINRA Investor Education Foundation. (Larry Swedore, 2019). This clear link between overconfidence and investor behaviour further supports the concept of behavioural economics and its link to the market.

Herd behaviour is one of the most significant biases in the realm of behavioural economics. Put forward by 19th-century psychologists Tarde and Le Bon, herd instinct or herd behaviour is another major cognitive bias. Herd behaviour refers to the concept where an individual follows the actions of the majority recognizing one's ignorance and assuming the other individuals are more informed. (Keynes 1930,1936,1937). An investor with herd instinct would undertake investments similar to the market majority. Herd instinct, when blown out of proportion, creates asset bubbles and then ultimately crashes, as described later in the paper. Chauhan et al. (2019) conducted an experiment using a mathematical model proposed by Chang et al. (2000) to show the effects of herding in the Indian stock market by analyzing large and small capitalization stocks. Large and small capitalization stocks both react differently to factors such as herding. Taking this into consideration, Chauhan et al. considered large and small capitalization stocks separately while analyzing price deviations and the results showed herding as a significant factor in large-cap stocks whereas not so much in small capitalization stocks. This further solidifies the claim that herding is a significant bias in financial markets, especially in stocks with larger market capitalization.

Fear of missing out – or FOMO – is a concept that usually runs parallel with herd behaviour and is usually the catalyst for it. It refers to the fear of an investor of missing out on opportunity leading them to act irrationally. Celik et al. (2020) conducted a study that collected data responses from 507 individuals and after analysis concluded that "FOMO tendency affects impulse purchasing". The study conducted provides relevant evidence for the high significance of FOMO in the market. Thus, it can be inferred that FOMO is another key bias in markets. Cognitive biases, as shown by the aforementioned evidence, play a key role in the fluctuation of markets. The background on behavioural economics given as well as specific examples of biases provided in this section will aid in comprehending references made to certain biases further into the paper.

## Financial Markets

This section explores and explains financial markets in general, laying the groundwork to understand fluctuations in them with regards to biases, which the paper analyses in depth in the following sections. A market is any structure that connects buyers to sellers. Financial markets essentially constitute a marketplace where assets such as stocks, bonds, and currency are traded. The stock market is a key type of financial market that allows investors to purchase and sell stocks which are essentially small parts of companies. The primary stock market is where stocks known as initial public offerings are listed. The secondary stock market is where previously owned stocks are bought and sold. Stocks usually trade at prices that differ from their actual value or intrinsic value and are thus often over or undervalued.

Fluctuations in the financial market are caused because of disparities in the fundamental value of a stock and its market value. Intrinsic value is a key factor that needs to be determined to establish the valuation of a stock.

Intrinsic value is effectively what an asset or stock is worth and can be measured by the means of different metrics, there is no standard method. If the intrinsic value is found to be greater than the current market value, the said stock is undervalued, and if the intrinsic value is lesser than the current market value of the stock, it is deemed overvalued. Intrinsic value is calculated using qualitative as well as quantitative factors. (Investopedia.com)

Qualitative factors include the company's business model, target markets and governance. Quantitative factors refer to financial ratios as well as complex mathematical models. Calculating the intrinsic value requires a certain degree of estimation as well as an assumption which automatically makes it relatively subjective. It is extremely important to have a reliable model in order to determine the most accurate intrinsic value. The ultimate goal is to determine whether a stock is under or overvalued.

There has been considerable contemplation over which price metric is the most effective. To help determine this, Pandey and Sehgal (2009) conducted a study to determine the effectiveness and efficacy of three metrics in calculating the value of an asset. They obtained data from the economies of the BRICS nations to conduct their analysis. They found that for Asian economies the most accurate multiple was the P/B ratio whereas the P/E ratio was more accurate in nations such as Brazil and South Africa. This analysis gives a guide to financial analysts in order to accurately determine asset values based on regions. The more accurate the intrinsic value of the asset, the more efficiently can you find out if a stock is under or overvalued and subsequently determine whether the market is in bubble territory.

## Bubbles

A bubble in a financial market is typically defined as a surge in the market value of a particular asset price or a great deviation from the intrinsic value, typically caused by irrational exuberance. The surge is usually followed by a crash, known as a bubble burst. In a bubble, the asset value shoots way over its intrinsic value and is traded at an inflated price until the crash. Bubbles can be caused by various factors, a significant number of them being cognitive biases. Every bubble begins with the expectation of excess returns from the investments (Garber, 1990).

Kindleberger (1978) described the typical stages of a bubble in his book, Manias, Panics and Crashes. The stages are as follows:

1. Displacement: This is the initial stage of a bubble, usually started due to a major changein the market such as deregulation, political changes, technological advancements etc. These changes usually act as a catalyst for a large number of investments.

2. Boom: Initially the prices rise slowly as seasoned investors start to invest. As soon as a large number of people begin to enter the market,the boom occurs and the prices start to skyrocket, massively overvaluing assets. An asset experiencing a boom attracts the attention of the mass media and individuals which may further encourage people to invest due to biases such as herd behaviour and FOMO and subsequently drive up the price further.

3. Euphoria: The euphoria stage is the peak of the speculative bubble model and is thepoint where the prices are the highest. At this stage, there is excessive optimism which is another cognitive bias. Irrational exuberance is also at its peak at this stage of the bubble. A theory referred to as the greater fool theory plays out at this stage. It states that investors may benefit from buying an overvalued asset since there will always be someone i.e., “the greater fool” who purchases the said asset, giving the seller a profit.

4. Distress: At this stage in the bubble previous biases like overconfidence and over-optimism turn into over pessimism. Seasoned and educated investors recognize that they are at the peak of the bubble and begin selling at this stage to uneducated investors and earn their profits. Determining exactly when a bubble burst is due is highly challenging so investors have to be very cautious since once a bubble bursts, it does not reinflate.

5. Revulsion: This is the final stage of a speculative bubble which ultimately leads to the bubble crash. At this stage panic hits and investors try to sell their assets for as muchprofit as possible. Every investor realizes that the bubble has reached its peak and will soon crash at a different stage. Seasoned and professional investors usually are the firstto sell making a decent profit. Slowly everyone begins to sell and the prices crash. Sometimes panic in one sector can offset panic in another sector or country. This phenomenon of everyone’s panic selling could be characterized as one of the results of FOMO. The price plummets and the bubble has burst.

Each stage of the speculative bubble can be attributed to different cognitive biases. To further explore this, the next section contains a case study and detailed analysis of the dot-com bubble.

## Case study: The Dot-Com Bubble

The dot-com bubble was a bubble which lasted about two years and which occurred in the technology market in the late 1990s. The valuation of any internet-based company skyrocketed and these tech companies dominated the NASDAQ index. During this time, the advent of new technology caused irrational exuberance, excitement and over-confidence in the market. As the name suggests, any company having the suffix “.com” was invested in by people, speculating massive returns. The NASDAQ became 5 times higher from 1995 to 2000.

There is debate over when the dot-com bubble emerged. According to Delong and Magin (2006), the idea that the bubble emerged before 1998 is incorrect. Two key points for why the dot-com bubble emerged before 1998 are the Netscape IPO and Greenspan’s irrational exuberance speech which are refuted by Delong and Magin (2006) in their paper on the grounds that these events did not show clear signs of exuberance in the actual market. In their paper, Govetto and Walcher (2009) consider 1995 as the beginning of the dot-com bubble since that marks the rise of Netscape’s IPO which went from 28$ per share to 71$ per share. In line with Govetto and Walcher (2009), this paper considers the beginning of the bubble as the year 1995.

We compare the model of a speculative bubble with the NASDAQ from 1995 to 2005 to examine whether the dot-com bubble aligns with the model and will analyse the biases involved that caused the 1990's bubble.

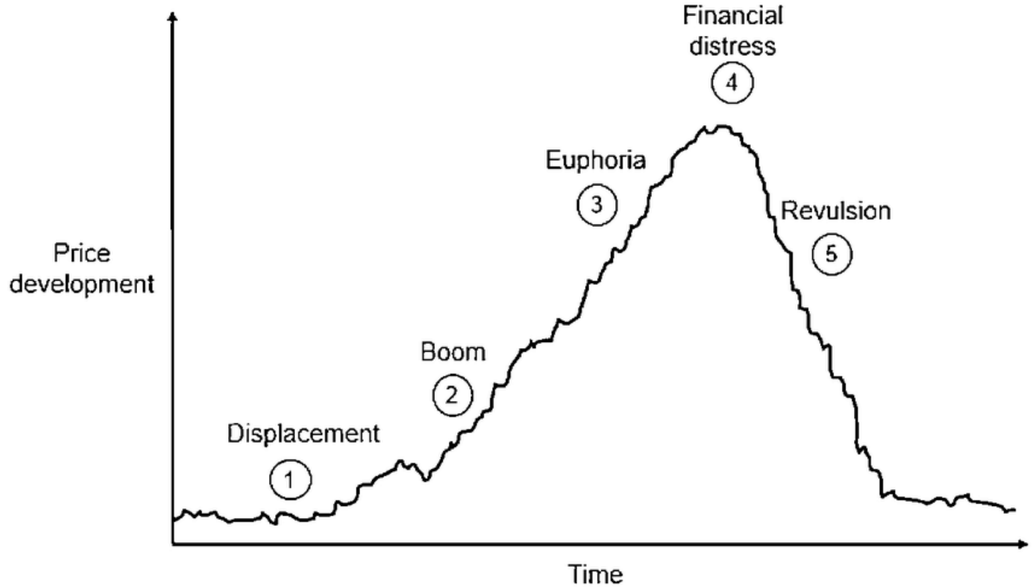


Fig.1 - Kindleberger–Minsky bubble pattern, (Kindleberger and Aliber 2005)

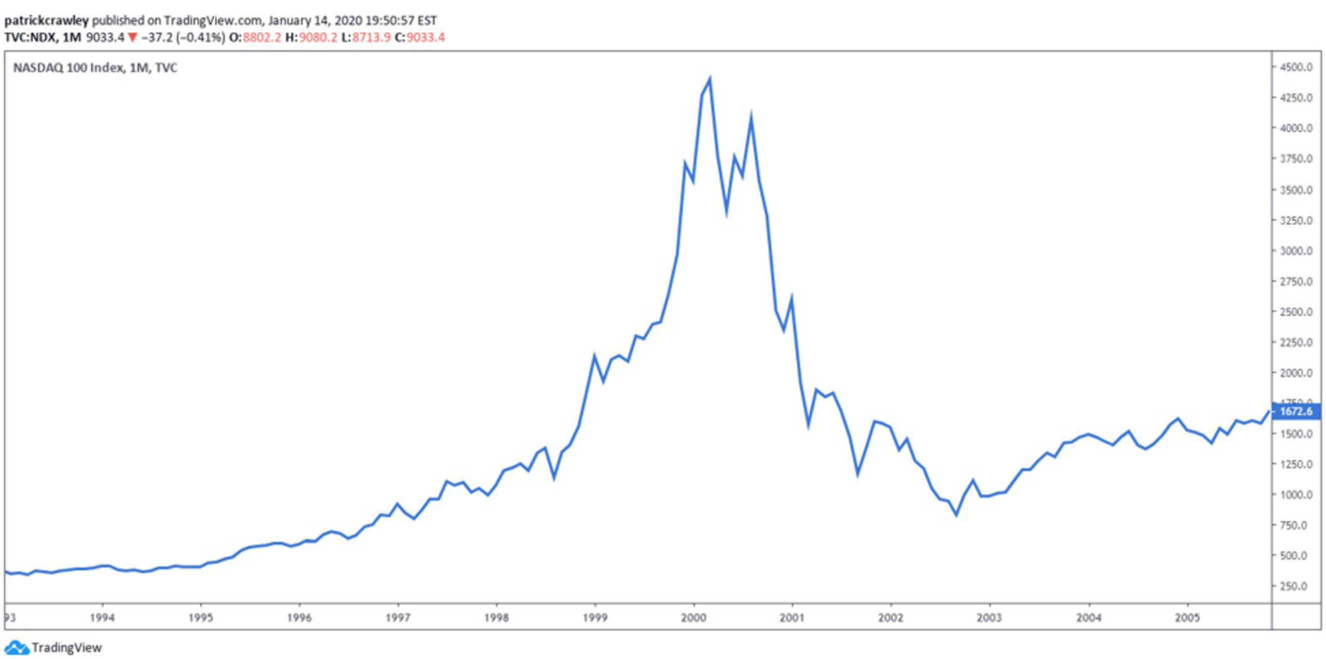


Fig.2 - NASDAQ100 before, during and after the Dot-com bubble, (Trading View)

As clearly visible above, Fig.1 and Fig.2, the model as well as the NASDAQ during the dot-com bubble resemble one another indicating the dot-com bubble has very closely followed the stages of a speculative bubble as indicated in the literature. The displacement, the point where the price starts to rise, occurs in 1995. In that year, Craigslist, Inc., eBay Inc, Match.com, L.L.C., and MSN was founded. On August 9, 1995, Netscape began trading. The stock reached a high of $75 from $28. ("Netscape IPO: 20-Year Anniversary: Read Fortune's 2005 oral history of the birth of the web," Fortune, August 9, 2015.) This new age of e-commerce and tech companies was the catalyst that created the foundation for the next stages of the bubble. The displacement caused caught the attention of investors in the market who saw it as an opportunity to make very large profits and invested irrationally. The cognitive bias over-optimism and overconfidence, as discussed by De Bondt (1998), played a key role and caused speculators to expect massive returns in this new age of stocks.

The boom stage of the bubble occurs from 1995 to 1999. Professional investors begin to invest in the stocks which causes the price to rise, this attracts media and other investors' attention as mentioned above which causes them to invest as well. People begin flooding into the market and as a result, the NASDAQ in 1998 opened at 1574.10 points, a 50% rise in two years. This was largely the result of the cognitive bias herding explained by DeBondt and Forbes (1999). New investors witnessed these tech stocks being heavily invested in and as a result of the idea of going along with the crowd i.e., herd behaviour, ended up investing in heavily overvalued stocks as in those who have strayed largely from their intrinsic value. This further drove up the valuation as seen in the graph.

The euphoria stage occurred during the dot-com bubble from 1999-2000. At this stage, people were overly optimistic and overconfident in the fact that their investments in these dot-com companies would yield large returns. The overconfidence and over-optimism bias constitutes this stage in the dot-com bubble, causing uninformed investors to wait on future returns. The NASDAQ peaked in march 2000 with 5132.52 points, a four-year increase of approximately 390%.

The final stages of the dot-com bubble, distress and revulsion, occur from 2000 until mid-2002 as seen in the graph above. Panic sets in and investors begin selling as soon as they get a hint of being in a bubble. The cognitive bias FOMO plays a key role in this stage. As people begin selling, the fear of being left behind or missing hits and panic selling occurs ultimately the value of these stocks plummeted massively, including blue-chip stocks. At this stage, all investment capital had dried up.

In October of 2002, the NASDAQ closed at 1114.14 which was over a 78% loss in value from March 2000. (Lombardi letter - Whitefoot, 2017) The market crashed as a result of this and the bubble burst, now assets are expected to return to their fundamental value. (Koehn, 2019). The dot-com bubble is a single case study that shows the impact of cognitive biases on these traditional markets and how they can cause or assist in the emergence of bubbles in the market. As shown above, cognitive biases have a key role in traditional market fluctuations.

## The Cryptocurrency Market

Cryptocurrencies are digital currencies that are essentially decentralized networks that work by the means of blockchain technology. Cryptocurrencies make intervention from banks unnecessary and make it essentially impossible to counterfeit as a result of the sophisticated software behind them. In recent years cryptocurrencies have become increasingly popular with new ones emerging all the time. The first cryptocurrency, bitcoin, was released in 2008 by a group of programmers. As of August 2021, there are currently 18.8 million bitcoins in circulation with a market cap of approximately 860 billion dollars. The creator of the cryptocurrency, in 2008, speculated that its price would be stable and non-volatile. However, recent fluctuations in the crypto market directly contradict this (Koehn, 2019).

Fluctuations in the crypto market have occurred since its release and part of the underlying cause of these fluctuations can be attributed to behavioural biases. This section of the paper explores the possible cognitive biases that may have caused the recent fluctuations in the market such as herding, FOMO, overconfidence as well as the impact of social media and Elon Musk on the crypto market. As established in the paper before, humans are not fully rational and investment decisions are affected by external factors like biases and emotions and this applies to the crypto market as well.

Koehn (2019) notes the analysis made by Cheah and Fry (2015) which showed the term "Bitcoin" was searched a lot more on the internet before peaks in prices or volatility. This reinforces the idea that external angles are at play in the price fluctuation of Bitcoin. Koehn (2019) assumes the intrinsic value of bitcoin as zero and concludes that herding behaviour, overconfidence and loss aversion can be found largely in the Bitcoin market as a result of the empirical herding analysis conducted. This study proves that cognitive biases are largely at play in the crypto market as well and the efficient market hypothesis is essentially moot.

Bouri et al. (2018) conducted a study to explore herding in the crypto market. Using 14 cryptocurrencies that occupied over half the crypto market and price data over a period of two years was used to analyse the effects of herding. Using the model suggested by Chang et al. (2000) the study was conducted, and the results showed anti-herding. This result was completely contradictory to the assumption. Given the fact that the model used above gave incorrect results as a result of assuming constancy in parameters, another model was used (Stavroyiannis and Babalos, 2017). The results of this model showed herding in different amounts over the period of two years, confirming the fact that it plays a significant role in the market value of cryptocurrencies. Herding factors have a significant effect on the value of assets and can cause emotional biases such as conformity, congruity and cognitive conflict, home bias, and gossip theories (Almansour, 2017; Balcilar et al, 2012).

Herding plays an integral role in determining prices in the crypto market (Calderón, 2018). Almansour (2020) conducted a study to analyse the presence of three behavioural biases in the crypto market: herding, heuristics and prospect factors. Using questionnaires, data from all investors in the UAE crypto market was collected to analyse investor decisions. A regression model was used based on the hypothesis that all three factors had a significant effect on asset prices and the results showed that all three factors do in fact affect prices. These studies provide conclusive evidence and explanations for the large fluctuations in the market.

Apart from traditional biases such as herding, factors like social media also have an impact on crypto prices.

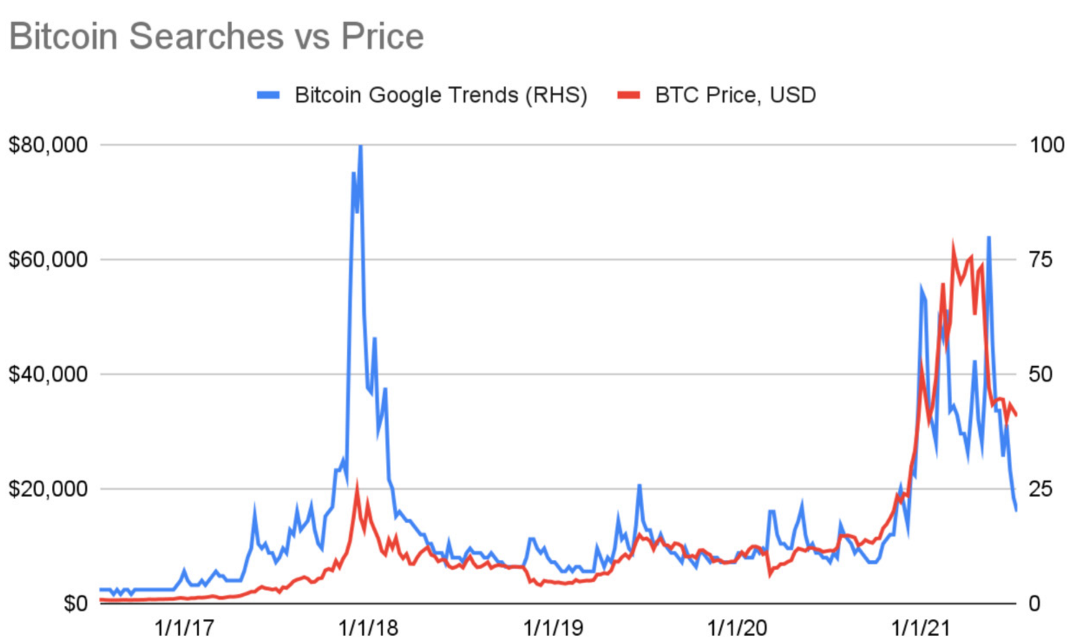


Fig.3 - graph showing correlation between Bitcoin Searches VS Price

Fig.3 shows a strong positive correlation between prices and google hits which indicates a clear relationship between the two variables and gives credibility to predictions for the price made using social media statistics.

According to the study conducted by Mai et al. (2015) social media has a significant influence on bitcoin prices. “A positive shock of bullish posting predicts positive bitcoin returns on the next day, and a positive shock of bearish posting predicts negative returns on the next day.” Additionally, the paper finds that disagreement on online platforms predictsthe occurrence of trading and that limiting the tweets from the users with the maximum followers showed the predictive relationship to be more significant. This further shows herd behaviour as users with maximum followers show the most significant relationship and thus can be inferred that the said followers adopt herd mentality and make decisions based on these posted messages. Although this research is limited since it only analyses twitter data over 4 months, it gives a clear indication of the overarching trend.

The final analysis on Bitcoin prices is that of the effect of Elon Musk. Elon Musk is arguably one of the most influential individuals in the tech world and is the CEO of Tesla, SpaceX and The Boring Company. In recent years Musk had made comments on Bitcoin which havecaused major fluctuations in the market. This can be classified as an effect of cognitive biases. Tesla stated that they had invested $1.5 billion worth of bitcoin. After this, it wenton to state that payments would be accepted in the form of bitcoin after which Bitcoin reached an all-time peak of $58,000. Following this, in April 2021 Tesla sold 10% of its Bitcoin stock to check for liquidity but the action caused panic in investors nonetheless. Subsequently, Musk stated he won’t be accepting Bitcoin as a form of payment any longer due to its high energy consumption. After this, Bitcoin fell to nearly $30,000. These subsequent fluctuations in the market prove the kind of influence Musk has on individualsand his ability to affect such a large audience. Herd behaviour comes into play here as wellas some individuals make decisions largely based on Musk’s tweets. People are afraid to goagainst the majority and so opt for the “safer” route.

The above studies and examples show the presence of cognitive biases in the crypto market, proving that these biases cannot be discounted while determining the prices of assets as they have a significant impact on the market causing fluctuations as well as price bubbles.

## Research Methodology

The survey was created with the objective of finding evidence of cognitive biases, namely herd behaviour and FOMO in the cryptocurrency market. The survey designing took place over the course of one week during which I went through relevant literature which included surveys in order to gain an understanding of how a survey should be formatted. The extensive reading I did before authoring the sections above aided greatly in the creation of questions. The behavioural economics section of the paper outlines the various biases. Via my reading, I was able to conclude the most significant bias with regards to the cryptocurrency market was herd behaviour followed by FOMO. The first few questions of the survey address basic information such as gender, age and education level to ensure those factors are taken into consideration while performing regressions to gain a more accurate result. The following questions lean towards cryptocurrency and more specifically cryptocurrency in an individual’s friends and family circle. These questions served as the predictors of herd behaviour and FOMO. The survey was sent out via email, and WhatsApp links and posted on reliable platforms to obtain a wide range of responses. I was able to obtain 150 individual responses over two weeks time. After sifting through the responses and ensuring the responses were appropriate the survey data was made into numeric data via Microsoft excel and was then ready to be used in E-views to perform relevant regressions.

The link to the survey is in the appendix.

## Survey Data Analysis

In this section, I present findings from the survey I conducted in order to investigate the existence of herd behaviour in the cryptocurrency market based on my network of friends and family. I have tried my best to obtain responses from people with varying nationalities, ages and backgrounds in order to obtain more accurate and well-rounded results. This section of the paper aims to use data from the survey conducted to find evidence of herd behaviour in the cryptocurrency market. A link to the survey is attached in the appendix. I obtain 150 observations from this survey and use those to carry out my analysis of herd behaviour in the cryptocurrency market using OLS regressions.

I estimate regressions where $y = \alpha + \beta x$. Here, $y$ denotes the dependent variable and $x$ denotes the independent variable. The number of independent variables differs depending on the regression.

In the following tables I report and interpret the results of my regressions:

Fig.4 - Regression 1.

Dependent Variable: LIKLEHOODOFINV
Method: Least Squares
Date: 04/16/22 Time: 13:47
Sample: 1 150
Included observations: 150

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.091345 | 0.646239 | 7.878422 | 0.0000 |
| FRIENDVIEWS | 0.408838 | 0.274590 | 1.488904 | 0.1388 |
| FAMILYVIEWS | 0.880026 | 0.265431 | 3.315456 | 0.0012 |
| _FRIENDSFAMINVESTED | 2.314196 | 1.153570 | 2.006116 | 0.0468 |
| AGE | -0.043452 | 0.016577 | -2.621252 | 0.0097 |
| EDUCATION | 0.196424 | 0.321561 | 0.610846 | 0.5423 |
| GENDER | -0.817060 | 0.399587 | -2.044759 | 0.0428 |
| REGION | 0.100923 | 0.185802 | 0.543174 | 0.5879 |
| LOAN | -0.416489 | 0.515719 | -0.807590 | 0.4207 |
| PRESSURED | -0.271801 | 0.734754 | -0.369921 | 0.7120 |
| FOMO | 1.495161 | 0.536801 | 2.785319 | 0.0061 |
| FINANCEED | 0.494052 | 0.468162 | 1.055300 | 0.2931 |

| | | | |
|---|---|---|---|
| R-squared | 0.371910 | Mean dependent var | 4.453333 |
| Adjusted R-squared | 0.321845 | S.D. dependent var | 2.867515 |
| S.E. of regression | 2.361403 | Akaike info criterion | 4.633007 |
| Sum squared resid | 769.5187 | Schwarz criterion | 4.873858 |
| Log likelihood | -335.4755 | Hannan-Quinn criter. | 4.730857 |
| F-statistic | 7.428532 | Durbin-Watson stat | 2.051315 |
| Prob(F-statistic) | 0.000000 | | |

In this regression, the dependent variable is the likelihood of an individual investing. The regression was carried out to estimate how the likelihood, measured on a scale of 1 to 10, of an individual investing in cryptocurrency, is dependent on various parameters (in order) such as their friends' views, family members' views, the percentage of friends and family who have already invested, age, level of education, gender, region of origin, whether or not they have a loan or mortgage, whether or not they have been pressured into investing, whether or not they have experienced FOMO (fear of missing out) and whether or not they have had specialized financial education.

Based on the results of this regression one can clearly interpret that friend's views, family's views and % of friends and family invested are clear predictors of the likelihood of an individual investing. This hints at the existence of herd behaviour in the market. FOMO is another significant indicator of herd behaviour and is also another cognitive bias, further strengthening the premise of these biases existing in the cryptocurrency market. The results are robust to controlling for other factors like age, region of origin and financial education. Interestingly, there seems to be a negative correlation between gender and the likelihood of investing where female respondents are almost 10% less likely to invest than male respondents.

Fig.5 - Regression 2.

Dependent Variable: SELFINVESTED
Method: Least Squares
Date: 04/15/22 Time: 03:40
Sample: 1 150
Included observations: 150

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.183477 | 0.044501 | 4.123021 | 0.0001 |
| FOMO | 0.278890 | 0.078873 | 3.535964 | 0.0005 |

| | | | |
|---|---|---|---|
| R-squared | 0.077899 | Mean dependent var | 0.286667 |
| Adjusted R-squared | 0.071669 | S.D. dependent var | 0.427050 |
| S.E. of regression | 0.411462 | Akaike info criterion | 1.075044 |
| Sum squared resid | 25.05656 | Schwarz criterion | 1.115186 |
| Log likelihood | -78.62830 | Hannan-Quinn criter. | 1.091352 |
| F-statistic | 12.50304 | Durbin-Watson stat | 2.117169 |
| Prob(F-statistic) | 0.000543 | | |

In this regression, I investigate whether FOMO impacts whether an individual is invested in cryptocurrencies or not. The dependent variable here is whether or not an individual has invested and the independent variable is whether or not an individual has experienced FOMO. While this setup would have prompted for a Probit/Logit specification instead of the Classical Linear Regression Model, this basic regression still reveals a strong positive correlation between the fear of missing out feeling and the decision to invest in cryptocurrencies. This further shows the existence of biases in the cryptocurrency market.

Fig.6 - Regression 3.

Dependent Variable: OWNVIEWS
Method: Least Squares
Date: 04/16/22 Time: 13:53
Sample: 1 150
Included observations: 150

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.064545 | 0.062116 | 1.039114 | 0.3005 |
| FAMILYVIEWS | 0.321168 | 0.072553 | 4.426690 | 0.0000 |
| FRIENDVIEWS | 0.368265 | 0.069735 | 5.280896 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.362199 | Mean dependent var | 0.240000 |
| Adjusted R-squared | 0.353522 | S.D. dependent var | 0.856714 |
| S.E. of regression | 0.688832 | Akaike info criterion | 2.112157 |
| Sum squared resid | 69.74987 | Schwarz criterion | 2.172370 |
| Log likelihood | -155.4118 | Hannan-Quinn criter. | 2.136620 |
| F-statistic | 41.73979 | Durbin-Watson stat | 1.974121 |
| Prob(F-statistic) | 0.000000 | | |

In this regression, I investigate whether an individual's own views on cryptocurrencies are impacted by their friend's and family's views. The dependent variable here is an individual's own views and the independent variables are friend's and family's views. With the help of these results, I interpret that family and well as friend views are very significant predictors of an individual's views. 35% of the variation in an individual's views is dependent on friend and family views. I also observe that friends' views influence an individual's own views slightly more than their family's views. This regression further verifies the existence of herd behaviour. The p-values for the variables are almost 0 meaning that the coefficients obtained are statistically significant.

Fig.7 - Regression 4.

Dependent Variable: SELFINVESTED
Method: Least Squares
Date: 04/15/22 Time: 03:35
Sample: 1 150
Included observations: 150

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.101125 | 0.040743 | 2.482021 | 0.0142 |
| _FRIENDSFAMINVESTED | 1.102012 | 0.160620 | 6.861006 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.241311 | Mean dependent var | 0.286667 |
| Adjusted R-squared | 0.236185 | S.D. dependent var | 0.427050 |
| S.E. of regression | 0.373226 | Akaike info criterion | 0.879981 |
| Sum squared resid | 20.61610 | Schwarz criterion | 0.920123 |
| Log likelihood | -63.99857 | Hannan-Quinn criter. | 0.896289 |
| F-statistic | 47.07341 | Durbin-Watson stat | 2.232302 |
| Prob(F-statistic) | 0.000000 | | |

In this regression, I investigate whether an individual has invested or not depending on the % of their friends and family invested. I interpret from this regression that whether or not an individual has invested in crypto or not depends 24% on the % of friends and family invested. Herd behaviour is once again verified via this regression. The p-value is almost zero making the coefficient statistically significant and thus reliable.

An additional observation using the survey data was that 29 individuals said yes or somewhat in response to whether or not they have felt pressured to invest in or get into cryptocurrency. Out of these, 12 said yes or somewhat. this means that 41.38% of individuals that felt pressured got into or invested in cryptocurrency as a result. This is a significant percentage and thus proves the existence of the bandwagon effect or herd behaviour in the market. This conclusion drawn aligns with the regression results as well. The regressions carried out all point to the existence of herding behaviour in the market and show how factors like friends' and family's views are predictors of the individual's decision to invest. The results of the survey further align with the conclusions made in the previous sections of the paper regarding the existence of this bias.

## Discussion

The survey data provide evidence proving the extent of herd behaviour and FOMO in the market to a certain extent. Other studies have been conducted to investigate the same phenomenon through different methods. A study conducted by Taofik Hidajat in 2019 concludes that behavioural biases exist in the crypto market by analyzing past cryptocurrency trends as well as price graphs. The study explains not only herd behaviour but also other cognitive biases. The conclusions of this study align with the conclusions brought about by the survey which exhibits a clear existence of cognitive biases. Boxer and Thompson (2020) conducted an analysis of herd behaviour in cryptocurrency markets using a survey followed by a statistical analysis of the data. The data showed that the majority of respondents were male. This aligns with my survey data where females were almost 10% less likely to invest than males indicating that males may overall be more inclined toward the cryptocurrency space. The statistical analysis in their paper indicated that "People have a more positive attitude towards cryptocurrency when their social group of family, friends and peers view cryptocurrency positively." This is aligned with my survey data analysis which concluded that 35% of the variation in an individual's views is dependent on friend and family views. Boxer and Thompson (2020) also concluded that herd behaviour does exist in the cryptocurrency market, aligning with my conclusion.

An explicit effort was made to send out the survey to a range of individuals from various demographics to get a true picture of the market and not just a niche section. The respondents range in age from 15 to 72 with an almost equal distribution of males and females. This ensures that the data isn't bounded by generational differences or gender biases. Furthermore, the nationalities of the respondents include Asian, European, North American and Middle Eastern with an expected Asian majority. The region of origin may have been a limitation since the scope of my reach includes largely Asian individuals. The number of observations obtained was 150 which may have bounded the variation in responses. The number of responses was a significant limitation despite which I believe a large demographic was covered providing an accurate view of the market at large. Another limitation was the lack of respondents who were already invested in crypto. This made gathering data about the alignment of an individual's investments with a friend or family member's challenging. I acknowledge that there are additional factors that affect things like the likelihood of investing or whether or not one has invested which are not taken into account but I believe the parameters set by the survey take into account the major factors thus still giving credible results. I further acknowledge that these limitations may have caused discrepancies in the data but I believe at large the data holds significant credibility and accurately shows the existence of herd behaviour in the market. Calderón (2018) uses cryptocurrency market capitalisations and prices to conduct an analysis using CSSD, a method of measuring herd behaviour in markets as suggested by Christie and Huang (1995). The study conducted "suggests that investors frequently deviated from the rational asset pricing benchmark, and instead follow the consensus in market stress situations." this further aligns with the conclusions drawn from the literature review as well as the survey in the paper. This consensus among studies on herb behaviour in the cryptocurrency market proves as a clear indicator of the existence of this bias. Further scope exists to test other biases via surveys as well as investigate further herd behaviour using a more exhaustive array of questions and more responses. Furthermore, there exists scope to test the existence of herd behaviour using CSSD and other forms of regression analyses.

## Conclusion

Traditional financial theories such as the efficient market hypothesis do not take into account the various cognitive biases that influence our decisions. Human irrationality is a natural phenomenon and based on that no decisions can be purely rational. Behavioural studies are a key discipline addressing the presence of irrationality, aiding with the economic and financial analysis when the traditional assumptions are relaxed. Although research in the field of behavioural economics is progressing, still many inherent biases go unaccounted for. The only way to tackle the interpretation of investor decisions in the future is to consider traditional and behavioural economics. Further and more in-depth research is required in this new discipline of economics to help us effectively interpret as well as predict future market fluctuations. The dot-com bubble and the crypto market served as a traditional and modern market example respectively which provided a basis to establish the existence of these cognitive biases in both types of markets. Relying on the existing literature, a survey on crypto-investments and a regression analysis of my own, this paper concludes that biases are prevalent in every aspect of financial markets and mathematical models must take into consideration behavioural aspects of decision-making to draw solid conclusions. As long as human emotion exists, cognitive biases will remain a reality one should account for.

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Survey link: https://forms.gle/WXvWqd8SuQoMkki89

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