Project Report

How does an individual's propensity to buy affects macro-trend movements in a codependent cryptocurrency market characterised by the herding phenomena? A study on the joint behaviour of the most popular digital currencies.

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Abstract: Complex financial systems exhibit universal market failures that are unaccounted for under traditional finance theory and modelling. In this paper a novel approach to modelling financial phenomena is applied to both analyse and predict extreme price changes, market bubbles, in the cryptocurrency market. Individual's propensity to buy was identified as a main driver of price changes, leading to big price swings driven by relatively small changes in overall level of belief. The model performed well at identifying relative price direction, allowing it to be used as an early price deviance indicator.

Keywords: ABM; cryptocurrency; financial markets

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1. Introduction

Financial markets exhibit some universal behavior across different types of instruments. Spikes in market activity, volatility and market bubbles are some such occurrences that can be seen independent of the type of market. The classic efficient market hypothesis, defined by perfect information and rational agents, struggles to explain such phenomenons.

Historically general equilibrium theory has been used to analyse market behaviours. Within this framework each agent is assumed to perfectly optimize his/her objective function under full information and rationality. While this approach is able to derive analytical solutions it fails to account for the complexities of financial systems due to unrealistic expectations such as convergence to equilibrium prices, perfect information, and rationality, while ignoring the emergent characteristics of agents' interactions and their diverse strategies [1]. Furthermore, models based on historical prices such as the Capital Asset Pricing Model [2] fail to incorporate emerging phenomena, such as the creation of bubbles in novel markets.

Two fairly recent examples of overwhelming optimism are the DotCom bubble of the late 90s and early 2000s and the housing market bubble of 2007, which highlight the importance of a model to predict these events. The price buildup is often driven by widely shared belief in the rise of asset prices, leading to excess demand and a self fulfilling prophecy [3]. Hence, understanding such emerging phenomena and in particular the way how individual decision making can lead to such macro effects is of crucial importance in predicting future price fluctuations in financial markets. Specifically, the novel and highly volatile cryptocurrency market serves as an excellent example of such emergent phenomena, where the irrational drivers of bubbles are amplified due to increased uncertainty [4,5].

Traditional investment vehicles typically have some fundamental value, conversely cryptocurrency's value is only tied to two main drivers – public interest and investor demand [6]. Thus, this paper aims at accurately understanding the price movements of the market and the subsequent arisal of bubbles through such subjective dynamics. In particular, it is hypothesised that individual-level decision making and the dynamic spreading of information through shared connections act as main drivers for understanding and predicting the price movements of a market such as cryptocurrencies. As a result, this paper analyzes how an individual's propensity to buy affects macro-trend movements in a codependent cryptocurrency market characterised by the herding phenomena.

The model discussed in this paper analyses the two most popular digital currencies - Bitcoin and Ethereum. An Agent-Based-Modelling (ABM) approach is found to be particularly appropriate to unveil macro-level price trends, driven by a market characterised not only by herding behaviour and individual beliefs, but also by highly correlated price movements. Additionally, instead of artificially set parameters, the model is calibrated to real world data. Furthermore systematic changes to the individual propensity to buy will allow the exploration of shocks such as the aforementioned arisal of bubbles, as well as help in predicting future adjustments in the price of highly volatile assets.

The paper will proceed with the following sections: firstly a brief explanation on blockchains will be provided, followed by a complete literature overview. Next, the model dynamics will be discussed in detail followed by an analysis and results section. Finally, a conclusion will be provided including recommendations for further research.

2. Literature review

2.1. Cryptocurrencies and their relevance

Digital currencies remain shrouded in mystery for a lot of people, to what makes them so different a basic understanding is required. Bitcoin being the first of its class is a good example, it uses the blockchain protocol to validate information without the need of a trusted party. At its core the blockchain is a network of computers voting on the validity of the "blocks" of data [7]. If accepted, blocks are appended to a "chain" stored using cryptographic functions that make it easy to tell if any past transaction has been altered. Each time a block of data is added, the integrity of all previous data is confirmed by the whole network. To cheat one would need to take control of the majority vote - the extreme cost of this gives legitimacy to the network [8].

While Bitcoin's goal is to act as a payment system by validating transaction information [7], nothing is stopping us from using the blockchain for any data validation. Ethereum, for example, uses the blockchain to legitimise any contract between two agreeing parties without the need of a third-party involvement [9]. This creates the possibility of decentralized financial products without a middleman involvement and the fees that are associated with it. This paper will now focus on how to specifically apply an ABM in the context of such a market.

2.2. Agent based models for financial market modelling

In recent years, agent-based models (ABM) have gained a lot of traction in the pursuit to reproduce and comprehend the stylized facts underlying the functioning of financial markets [10]. As ABM follows each agent across time and maps daily events to micro-level decisions and reactions of the agents, the macro-system evolution can be investigated as time evolves [11]. Additionally, the ABM is able to capture two crucial determinants of investors' behavior, namely herding behavior, which can arise as a byproduct of interactions between individual agents and their learning dynamics [12] and asymmetric trading, which reflects the phenomena that individuals tend to make investment decision based on a probability that changes depending on whether a daily stock price return is positive or negative.

Most papers focus on models, where two types of agents are present at any point. More precisely, the fundamentalist agents utilize the intrinsic value of the stock and external economic factors as a measure proxy and decide to participate in the market if and only if the stock is below the benchmark fundamental value [13]. On the other hand, the financial market is also characterized by noise traders or chartists, who focus on exploitation of price fluctuation rather than on stock's fundamentals and thus are capable of destabilizing the market, which in turn results in market bubbles and crashes [13].

While such approaches might be successful in approximating the price evolution of conventional stocks, they cannot be applied with the context of this paper, as cryptocurrencies are not characterized by future cash flows that could be discounted to calculate intrinsic value [14]. Most of the recent research has focused on determining the price fluctuation of cryptocurrencies through supply and demand [15,16] rather than the alternative approximation of their fundamental value [17,18] yet no approach has been successful in becoming widely adopted, making cryptocurrency valuation very subjective [14]. Thus, this paper aims to utilise a novel approach at modelling through leveraging traditional techniques from ABM in finance, whilst incorporating subjective aspects of human behaviour into the agents decision making process. In particular an agent's investment decision has to be modeled through an individual personal belief in the future applicability and spread of the usage of currency as well as through social influence and herding arising from the current excessive excitement about the sector and these forces affect agent's views in an interchangeable manner [19].

2.3. ABM with herding behavior and network structure

The underlying heterogeneity of agents in ABM is reflected in the choice of their trading strategies. Nevertheless, the structural heterogeneity of the network of social relationships has received significantly less attention in the scientific community [19]. Network structures that are built on top of the ABM are a natural extension that can circumvent this issue. The advantage of networks lies in their ability to capture the fact that the agents' investment decisions are conditioned not only by the idiosyncratic factors, but also by the beliefs of the society, as well as of the agents' close connections and the interaction of these forces for each agent creates an aggregate effect on the macro-factors [19].

There are multiple network structures that could approximate the relationships occurring among individuals interested in investing in cryptocurrencies. Among these a small world network could be considered, where the geographical proximity is a decisive factor in probability to create a connection [19]. Indeed, despite geographical proximity not playing a decisive factor in the structure of cryptocurrency traders, the high connectivity of traders through globally accessible online platforms means that the small network phenomena prevails and hence, a network that incorporates this should be considered. Alternatively, a scale-free network, characterized by a power-law degree distribution and a small portion of individuals deemed as 'influencers', could be applied [19]. Although such networks may be more true to the real world intra agent dynamics they are generally not able to circumvent the N-dependence issue that arises in situations with a high number of agents [19].

As outlined by Cont and Bouchaud [20] [2000], the source of the N-dependence problem derives from the central limit theorem and represents the crucial size dependence of the system. In many cases, the interesting properties of fluctuations in returns such as their time-dependence structure and power-law distribution, progressively disappear as soon as the number of agents is enlarged, showing instead Gaussian fluctuations and a weak degree of temporal dependence [19,21]. Therefore, a simpler network, such as the random graph structure with homogeneous links and nodes is adopted. On one hand, this structure is proven to be resilient to N-dependence problems, as well as capturing the small-world phenomena, on the other however, it is inferior to other approaches in its ability to mimic some of the real-life human connections [19].

2.4. The effect of Transfer Entropy on the herding intensity

The models introduced above have not yet considered the possibility that the agents' investment decisions can be equally impacted by the herding tendencies observed in other stocks of the same sector through the transfer of information that is present among the two securities [22]. Multiple papers tried to replicate this phenomenon from a macro-perspective by investigating sector specific herding tendencies [23,24]. Such an effect is expected to play a role especially among cryptocurrencies, in which the sudden spike in interest for Bitcoin holdings lead to an increase in valuation and trading volume of other cryptocurrencies [25]. Moreover, some of these altcoins have only a limited use-case applicability and thus, their popularity could be described through the herding effect of speculators [25].

Formally, the concept of Transfer Entropy (TE) is utilized to measure the underlying relationship between two variables [26]. In other words, TE captures the amount of information that Y encapsulates about X, which is not already accounted for by X's own history and thus, describes an information transfer across different stocks (Sandoval, 2014). Within the context of the financial market, TE can be seen as a method that captures the fact that a speculative trading behavior for a stock X can be predicted on the basis of the speculative trading on stock Y, if the stock X displays a strong speculative influence on a stock Y [26]. TE can be summarized by a Markovian process of degree k, where k represents the number of past periods that are believed to be influential [26]. Backed by the empirical research on a short memory of the financial markets [27], this paper assumes only one previous trading day to be of importance.

3. Methodology

3.1. Model derivations

To study the research question at hand, a stochastic agent-based model is implemented, whose interpersonal relationships are captured with a random graph network structure with homogenous nodes and edges. More precisely, Erdos-Renyi graph is adopted, which chooses at random nodes that will be connected with a probability, $p^M(1-p)^{\binom{n}{2}-M}$ where 'n' and 'M' represent the number of nodes (agents) and edges (agents' relationships) respectively [28].

Since financial markets are characterized by a high level of complexity, it is essential to introduce certain assumptions that would enable for simplification and isolation of the processes that are under investigation. This paper assumes that at each time step agents face only two investment options, investing in Bitcoin and Ethereum, and individuals can choose to invest in both, one or none of the stocks. Following the approaches adopted in previous empirical research, each agent can hold at most one share from each cryptocurrency to allow for further simplification [24]. Finally, no movement of agents across the network is presumed as agents can trade with anyone in the market and therefore, the assumption is not expected to affect the results.

Depending on the investment decisions the individuals take at time step $t-1$, the agents will be assigned into one of the two compartments, buyers and sellers, at time t. While buyers do not currently own a share of stock, but are theoretically interested in buying one, the sellers hold at least a portion of a share and are hypothetically willing to sell their holdings depending on the market conditions. Such model specification can be summarized with an investment decision function that is dependent on the individual's internal state. In particular, on day t the potential buyer i makes a trading decision $\phi_{i,j}$ as shown in Equation 1.

$$\phi_{i,j}(t) = \{buy, stay\ inactive\}, \quad j = \{Bitcoin,\ Ethereum\} \tag{1}$$

given the respective microscopic transition probabilities P_{buy} and $P_{stayinactive}$ associated with each outcome. The individuals' transition between states derives from multiple forces affecting the agents simultaneously that have to be accounted for. This paper leverages transition probabilities developed by Alfarano and Milaković [19] [2009] and extends the formulas to fit the investigated research question.

Firstly, the decision depends on the idiosyncratic component α_j representing an individual's belief in the currency. The distribution function in use should reflect the fact that the agents' beliefs are random rather than clustered around a constant. In particular, it can be assumed that agents' belief, at and after the calibration period, were such that some agents have a very high belief in cryptocurrency assets, whilst others do not believe the asset will be successful at all. At the same time, the mean confidence in the asset should be defined in a way that the agents entering the market are characterized by a sufficiently high degree of confidence, which is an essential attribute for an agent to have in order to be considered susceptible to buying a cryptocurrency. Hence, $\alpha_j \sim Uniform(0.2, 0.9)$ was found to be the most appropriate distribution to accurately capture this initial behaviour. Moreover, α_j is a central variable of interest for the research question at hand and therefore, various aggregate shocks will be introduced throughout the analysis to understand how varying individual propensities affect the macro-trend movements in the market.

Furthermore, each agent is directly impacted by the investment decisions taken by other connected agents. Thus, the probability to buy a stock at time t increases as the percentage of agent's neighbors holding the given stock $n_j(i,j) \in (0,1)$ at time $t-1$ increases and can be viewed as a micro-herding effect that occurs in the network. At the same time, the agent's decision is influenced by the overall sentiment of the market and thus, the probability to buy will increasing in proportion to percentage of all agents holding a stock $\lambda_j \in (0,1)$ at time $t-1$. Such definition of λ_j allows for investigation of the herding behavior on macro-level. Additionally, not only is the herding phenomena occurring in the current currency of interest considered but also the herding of agents λ_l and neighbors $n_l(i,l)$ in markets for other cryptocurrencies through transfer entropies $TE_{l \to j}$. Finally, it is essential to guarantee that the utilized probabilities will be within the desired range, $P_{buy\,j} \in (0,1)$. Therefore, each probability measure is scaled by the most extreme value that could hypothetically arise for the most confident agent in the market situation, where everyone holds both stocks.

Such definition of measure allows for the final derivation of transitional probability that can be summarized as shown in Equation 2.

$$P_{buy\,j} = \frac{\alpha_j + \lambda_j * n_j(i,j) + TE_{l \to j} * \lambda_l * n_l(i,l)}{1 + \max(\alpha_j) + TE_{l \to j}} \quad \text{where} \quad l = \textit{the other cryptocurrency} \tag{2}$$

and the corresponding probability to remain in the current state is defined as $0 \leq 1 - P_{buy\,j} \leq 1$. On the other hand, the seller's decision $\phi_{i,j}$ at time t is derived as shown in Equation 3.

$$\phi_{i,j}(t) = \{sell, hold\}, \quad j = \{Bitcoin, Ethereum\} \tag{3}$$

where transition probabilities between the two states are denoted as P_{sell} and P_{hold} respectively. It is assumed that P_{hold} of the seller is directly proportional to the probability to P_{buy} of the buyer. More precisely, while the transition probability for a potential buyer surges with the increasing idiosyncratic beliefs and/ or herding tendencies of other agents, these forces have the opposing effect on P_{sell} of a potential seller. At the same time, a price increase from the time period result, will likely result in some additional fraction of the potential holders to consider selling the asset, due to a willingness to sell at the new, increase price level. Consequently, the return observed yesterday, $\frac{P_{t-1}-P_{t-2}}{P_{t-2}}$,should negatively effect the probability to hold stock and therefore, the probability of the seller to hold onto the stock P_{hold} will extend the P_{buy} in Equation 3 to give the final probability shown in Equation 4.

$$P_{hold\,j} = \frac{\alpha_j + \lambda_j * n_j(i,j) + TE_{l \to j} * \lambda_l * n_l(i,l)}{1 + \max(\alpha_j) + TE_{l \to j}} - \frac{P_{t-1} - P_{t-2}}{P_{t-2}} \quad \text{where} \quad l = \textit{the other cryptocurrency} \tag{4}$$

while the probability to sell a stock P_{sell} will be defined as complement to P_{hold}.

It should be noted that the inclusion of the latest price movement might result in probabilities outside of the desired range $[0, 1]$.Therefore, a simple assumption is applied to these cases, where the values will be adjusted to be equal to the limits of the probability ranges. The combined individual decisions of the agents' impact the daily stock prices through aggregate excess demand or supply that is present in the market at time t and the relationship can be modelled linearly with as shown in Equation 5 derived by Wang [29] [2014].

$$\log\left(\frac{P_{t+1,j}}{P_{t,j}}\right) = \zeta_j * \sum_{i=1}^{N} \phi_{i,j}(t) \tag{5}$$

where ζ_j captures the linear effect of aggregate market forces on the prices. Since ζ_j is unknown and dependent on the type of stock in question, its numerical value will have to be approximated using a calibration algorithm.

Once the daily stock price gets adjusted according to the demand and supply, each agent updates their market perceptions and re-evaluates the amount to purchase or sell. It is assumed that the agent that expressed a willingness to buy is prepared to pay at most yesterday's closing price. If the price has increased since yesterday, the agent is now able to buy only $\frac{P_t-1}{P_t}$ of a stock. Alternatively, in case the price has decreased, the agent is eager to purchase a whole stock and no more. On the other hand, sellers remain unaffected by the price volatility. This can be reasoned by the fact that agent who is determined to sell due to low personal belief in the cryptocurrency, low herding phenomena occurring in the market or due to both forces intervening, will always want to dispose his stock and will not consider keeping a $1 - \frac{P_{t-1}}{P_t}$ portion of a stock in case the price drops, since the utility obtained by the agent from selling a stock at lower price than anticipated is still higher than keeping a stock and risking to lose a higher part of a profit if the individual tries to sell later on.

Finally, after all the expectations of agents are adjusted according to the above rule, the agents need to start interacting in order to proceed with the exchange of shares. In cases when demand and supply are not in equilibrium, it is presumed that only the agents who act fast will succeed in making the desired transaction, while the more hesitant individuals might fail to find anyone left who would be willing to undergo the stock exchange. Thus, within the framework of the model, agents that represent the interested buyers will be activated at random and will initiate the buying from a randomly chosen seller for as long as there are sellers left in the market. Once there are no more remaining agents in at least one of the two groups, the stock market closes for that specific day and no more transactions are undertaken until the next trading day.

3.2. Model limitations

One of the most prevalent shortcomings of the approach implemented can be considered the assumption that each agent can hold at most one share of a stock. It is expected that in reality, many portfolios of active traders will contain multiple shares of the same stock, especially in cases when investors hold strong beliefs about its future performance. Nevertheless, introducing such an assumption into a model guarantees that the shares available in the market will not get eventually concentrated in the hands of few, very active traders. This would prevent investigation of the central research question of the paper, since the model would be defined solely by the handful of active agents and idiosyncratic propensities would not play a role in determination of share exchanges anymore.

Secondly, the successful simulation of stock market functioning can be guaranteed only in situations, when the model initiates with almost equal number of total potential buyers and sellers. A situation in which there is only a limited number of sellers will always result in excess demand irrespective of individual beliefs or herding while a constant excess supply is expected to prevail in cases when the model initiates with a very large number of sellers. This is due to the fact that even if the probability to buy/sell is very low, the overall number of people who choose to become an active trader each day will be significantly higher compared to the active traders with an opposite internal state, given the huge initial number of agents in one of the groups.

Moreover, the presumption that each agent can participate in trading at most once a day can be quite restrictive too. For many traders and especially for day traders, who buy stocks to profit on short term intra day price deviance, such supposition is violated. A potential improvement could be achieved by introducing an additional category of agents for the day traders and allow these individuals to trade more frequently on a daily basis. However, given the fact that there is no publicly available dataset that would provide information on the number of day traders and the average number of their daily transactions, combined with the fact that it is essential to moderate the complexity of the model, the paper abstains from such approach.

Lastly, it is expected that the underlying stochastic nature of the model will introduce a high variance into the model's outcome. Therefore, multiple simulations are performed and the mean outcome will be utilized for result interpretations to mimic the real life scenario as close as possible.

3.3. Data and model calibration

The model described works using the prices of the cryptocurrencies. Using the investpy library, the data gathered consists of the daily price of both Bitcoin and Ethereum over the period of 1 st of April 2017 to 1st of May 2021. During that time period two bubbles can be observed, in 2018 and 2021. However, for simulation purposes, the calibration will be performed up until 16 th of December 2017 in order to capture the momentum of the first bubble. As described in the methodology the inputs into the model and therefore measures of calibration will be the daily log price difference as the aim is to understand how this affects customers the probability of customers to buy or sell their stock.

When modeling financial data, the most widely adopted calibration procedure is Markov Chain Monte Carlo (MCMC) as described by Jacquier *et al.* [30] [2007], Grazzini *et al.* [31] [2017]. This approach allows us to compute the maximum likelihood estimates, hence, finding the parameters of the model which best fit the observed data. However, as portrayed in the latter paper, the computational power needed for such a calibration procedure is demanding and as this is not the main insight this paper seeks to provide, a simpler MSE calibration technique is used.

Using MSE, ζ_j - the daily stock price response to changes in aggregate demand driven by individual actions is calibrated. The optimal level of ζ_j is jointly calibrated for both coins of interest, where Ethereum's optimal level is calculated based on the Bitcoin's level which is calculated first. Finally an optimal level of ($\zeta_i = 0.0009$, $\zeta_j = 0.0006$) was identified. The complete results of the calibration for Bitcoin are summarised in Figure 1 and the results for Ethereum can be found Figure 2.

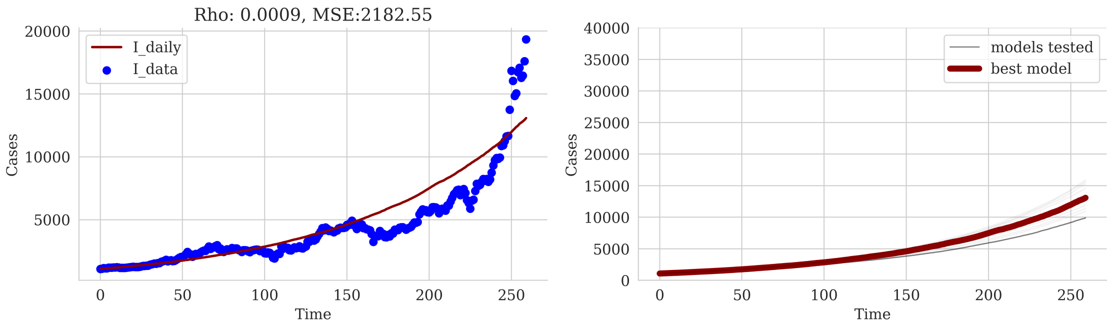

Figure 1. Calibration of the Bitcoin prices using MSE.

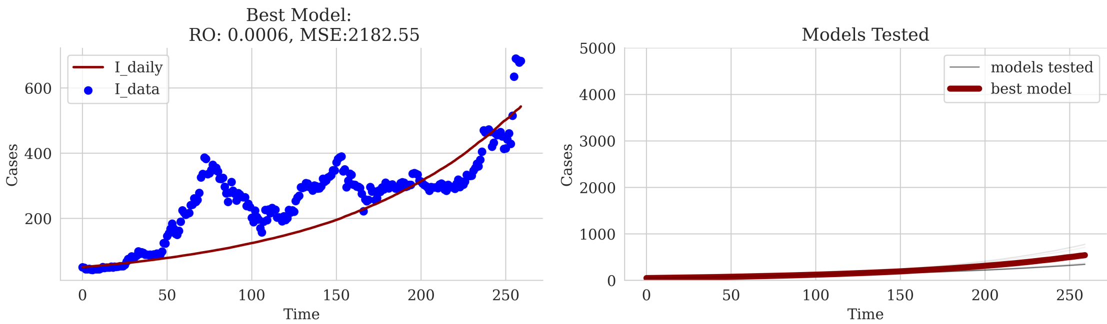

Figure 2. Calibration of the Ethereum prices using MSE.

The remaining variables are fixed as follows. The network is initiated using 500 agents, with 140 agents holding Bitcoin and another 140 holding Ethereum. Such initiation of the model guarantees that the number of potential buyers and sellers will be almost in equilibrium and guarantees that the system will not remain stuck in excess demand or supply throughout the simulation. The relatively large network size is utilised as a means of keeping limited execution times whilst still being able to understand well the dynamics of the different groups of agents. Furthermore, the random graph is initiated with a probability of 0.035 to ensure the full connectedness of the network. Finally, the calculation of the transfer entropy's reveals levels of 0.23 and 0.14 for the transfer entropy on of Ethereum on Bitcoin and vice versa. These relatively low numbers of the effect of one currency on another can be explained through some quite apparent differences in the price movement, in particular during the calibration period.

4. Results

This section will be structured as follows. Firstly, the results of the calibration and success of the incline period will be measured. Next, the sensitivity of the model to systematic changes in the idiosyncratic component after the calibration period will be discussed. Thirdly, different shocks based on real-life events resulting in a change in the individual propensity to buy will be incorporated in the model. Finally, the various other components of the model such as the effect on herding and transfer entropy will be evaluated by applying different networks of various levels of degree centrality in order to study the success of effectively incorporating such individual level behaviour together with the individual propensity to buy.

As can be observed from the graphs in Figure 1 above, it seems that the model dynamics performs quite well at capturing the incline, i.e. the creation of the initial cryptocurrency bubble. In particular it succeeds at describing the somewhat more smooth surge of bitcoin, whilst struggling to capture the up and down behaviour of Ethereum. This behaviour is to be expected as the model is not exposed to additional shocks after the initial one, whereas real markets are exposed to "micro" shocks regularly. It can further be observed that the model is experiencing difficulties in measuring the sharp rise from EUR 10,000 to EUR 20,000 within a matter of days, with a tendency to either overshoot or underestimate this effect. This result highlights the difficulties to model the unpredictable magnitude of a bubble in such a market, where prices can nearly double in a matter of days as observed towards the end of the period.

Furthermore, since the system remains characterized by excess demand for most of the steps in the simulation, it would be reasonable to expect that the number of potential sellers would be increasing compared to the number of buyers as the market matures. On the contrary, the distribution of the two types of agents seems to be relatively stable with a maximum deviation from the mean of just 1.5 % as shown in Figure 3. The shortcoming observed is in line with the construction of the model, which cannot perfectly encapsulate the increasing/decreasing volume of stocks due to cryptocurrency mining or stock splits. At the same time, this failure to capture rises and declines in the number of stockholders means that the aggregate level of herding behaviour, measured as percentage proportion of agents holding a stock at time t, will remain more or less constant over time. As a result, whilst herding may have an effect on a given individual's probability to purchase, the model fails to capture an impact of herding behavior on the aggregate demand and supply in the market. However, a deeper analysis on the effects of herding at the individual level will be provided in Section 4.3. On the other hand, a model in which the number of holders is allowed to increase, would not be able to properly capture the strong effect on price of a large number of small individual investors and their particular beliefs in the market, because only a few large investors would remain. Hence, further research could aim to build a model accurately capturing both behaviours, or otherwise split the two in different models to properly understand the effect of both of these components.

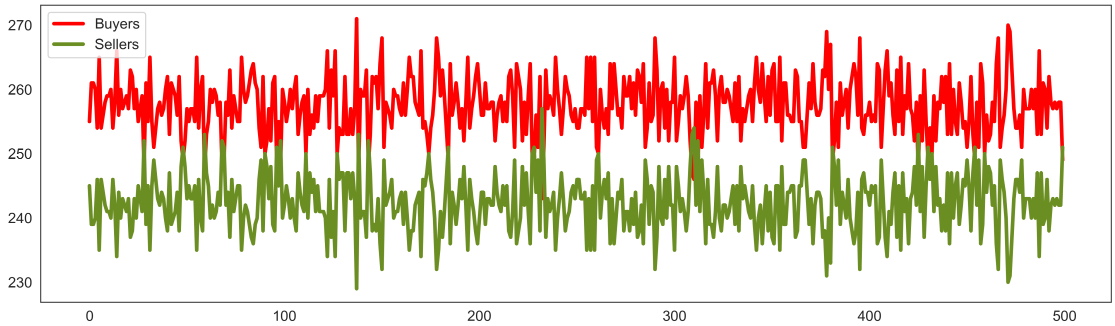

Figure 3. Number of buyers and sellers over time

4.1. *Model sensitivity to synthetic systematic shocks*

After a successful calibration that provided further insights on the benefits and shortcoming of the implemented approach, the model is exposed to numerous systematic shocks representing a universal shift in idiosyncratic attitudes of agents, α, due to new information arrival. The aim of the analysis is to understand the magnitude of impact of these beliefs onto the daily prices. Firstly, the investigation focuses on the situation of enhanced market attitudes towards the future potential of a given cryptocurrency. More precisely, after an initial calibration period of 260 days, situations of aggregate surges ranging from 10% to 40% are put under investigation and the main findings are summarized in Figure 4.

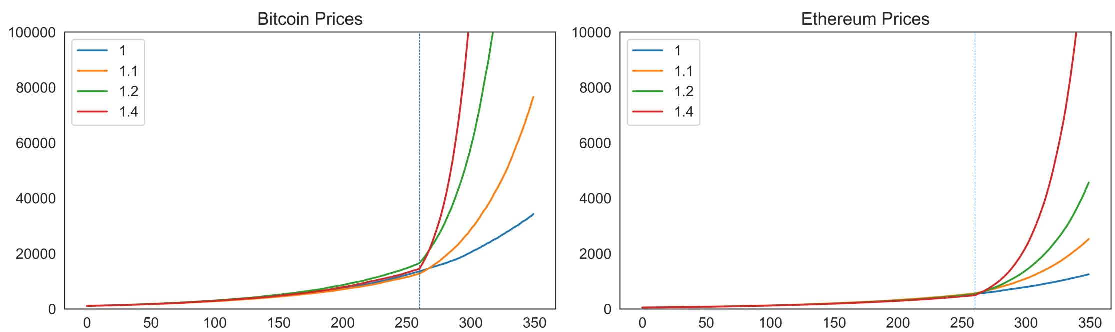

Figure 4. Sensitivity of price as a response to positive shocks in alpha.

As can be observed from the graphs, even a relatively minor positive shock can trigger an exponential surge in prices and thus, can dramatically increase a probability of formation of the price bubble due to an intensified excess demand present in the market. More specifically, even a 10% surge in aggregate beliefs results in more than 86.8% (69.5%) upturn in prices for Bitcoin (Ethereum) in 30 days following the systematic shock. On the other hand, a universal shift of attitude of 40% or more can create a drastic exponential growth of the returns, which can be as high as 399.5% (214.3%) in the subsequent month. On top of that, the observed effect seems to be stronger for Bitcoin than for Ethereum, and thus, it can be argued that the greater bubble currently present in the Bitcoin market stems, at least partially, from the higher relative impact of agent's beliefs on the market conditions. This result is in line with the fact that Ethereum is an asset with a potential fundamental value through its more diverse range of applications and is thereby less sensitive to changes in the individual propensity.

Similarly to what has been observed with positive shocks, the tumbling idiosyncratic beliefs are able to cause sharper price declines for Bitcoin than for Ethereum. The results are summarised in Figure 4. As a direct consequence of this finding, it can be noted that a universal drop in attitudes amounting to 10% triggers a considerable price correction for both currencies that however, results in contrary outcomes. More precisely, the prices of Ethereum remain to rise at a lower rate, 6.2% return in a month, while those of Bitcoin start to plateau and finally decrease, achieving -1.9% monthly return. At the same time, if the agents were to lose 40% or more of their confidence, the whole market value of Bitcoin could be wiped out in less than 100 days. The same effect would need a significantly longer time span to take place in the market for Ethereum.

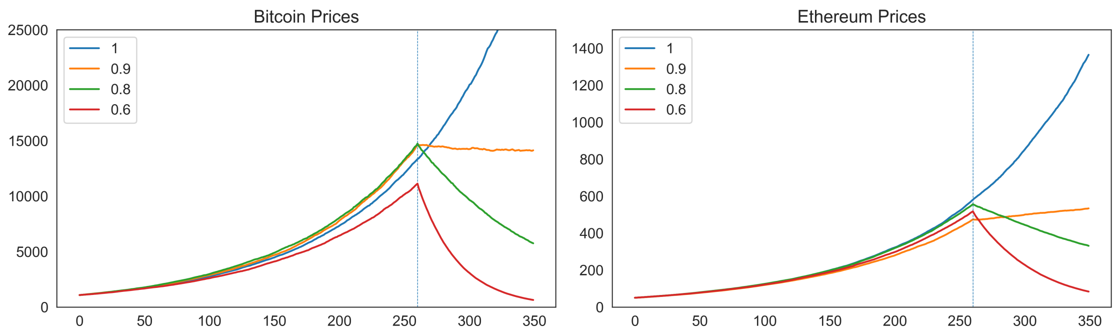

Figure 5. Sensitivity of price as a response to negative shocks in alpha.

The simulation results obtained from the model provide strong support to the hypotheses that the introduction of the systematic shocks to the idiosyncratic beliefs can significantly impact the aggregate market condition. Consequently, the developed model could be successfully used in prediction of the future prices of cryptocurrencies, if data mapping the real-time micro-level attitudes of agents towards the future potential of Bitcoin and Ethereum could be retrieved.

4.2. Replication of historical market shocks

Once the model sensitivity towards the individual propensity to buy has been understood, specific shocks are utilised in order to remodel some of the real-life events in the past. Such shocks can be subsequently leveraged to understand the movements of the cryptocurrency market in response to upcoming changes in the belief in the asset, such as the recent crackdown of China on the crypto market. In particular, four different shocks are introduced to the currencies, aiming at somewhat accurately predicting the ups and downs in the market in 2018. Firstly, an initial decline of 10% in the Bitcoin market only is utilised in order to represent the initial halt and onset of the crash of the bubble in early December 2018. An additional adjustment for both Bitcoin and Ethereum was introduced in January, signifying large-scale governmental crackdown and the final onset of the bear market that would last for about two years. The overall loss of confidence of about 30% and 33% respectively is utilised to signify the strong decline in individual belief that actually occurred. At the same time, not actually changing the distribution of alpha itself allows for investors with an initial high belief to remain interested stakeholders despite the observed downturns, whilst allowing for other investors to fully stop investing in the coin.

Furthermore, a return of belief, and subsequent stabilisation of the market is introduced, with an initial higher return of confidence to reflect a slight uptick, followed by a small correction and the final stabilisation of the market. While a successful model should ideally be able to capture such stabilisation to the market through incorporating a shift in the aggregate demand resulting from a higher number of potential buyers and lower number of sellers remaining in the market, the design of the model does not allow for such a correction to occur. Hence, further research should aim at trying to realistically model a market in which the number of buyers and sellers in the market are initialised not to be equal to each other but rather can fluctuate beyond the equilibrium outlined above. Finally the resulting price movements over 20 simulations as a response to the changes in idiosyncratic beliefs in the market are plotted in Figure 6.

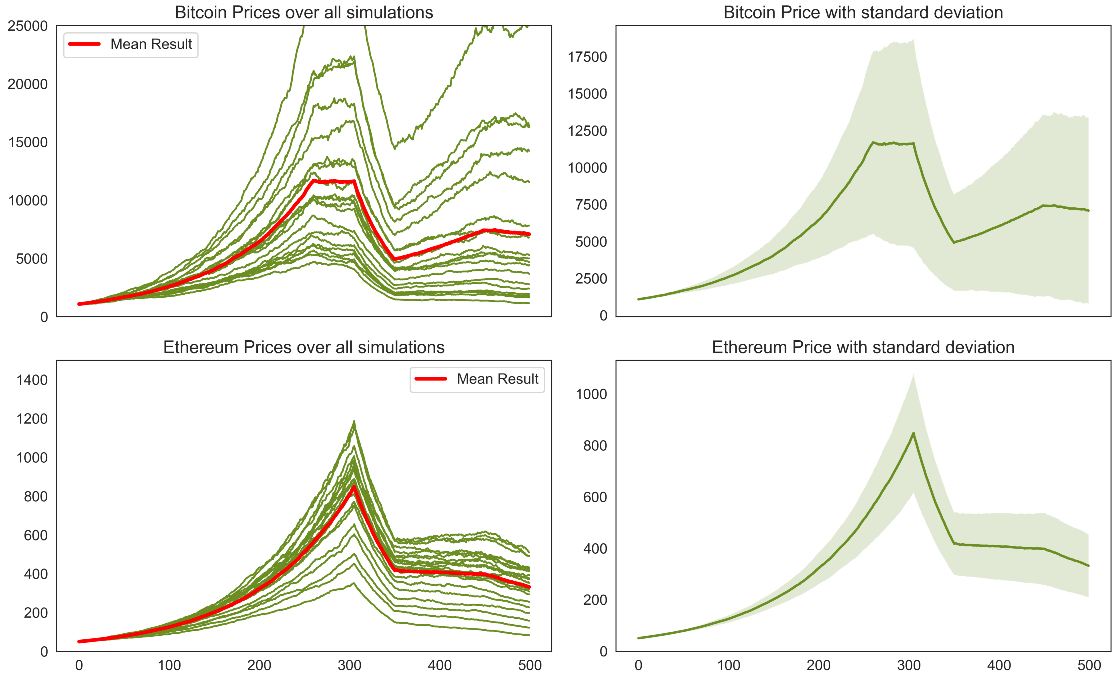

Figure 6. Price simulation as response to idiosyncratic beliefs in the market.

As shown in the graph, the introduction of the shocks seem to quite well predict the various price movements in the desired manner. In particular, the Bitcoin price seems to plateau for a while in December before witnessing a strong and rapid decline in January together with Ethereum, and finally stabilising roughly at a price of EUR 8,000. This stable level observed is somewhat higher than the actual level of Bitcoin at the time at around EUR 6,000. Indeed, as was observed in the incline, the model fails to accurately capture the strong and quick magnitude of the price movements that are so highly characteristic of the cryptocurrency market. On the other hand, a stronger reduction in the level of alpha would lead to a far steeper decline in the curve, bringing down the price to nearly zero. This further signifies the issues of models to predict accurately the exact prices of such a highly volatile market. At the same time, the models ability to showcase the overall movements of the price do provide evidence for the usefulness of the model to predict the arrival further bubbles and subsequent crashes, despite the underestimation of its magnitude. In particular, this model can serve as the basis for predict future emerging phenomena, including bubbles and price corrections through the estimation of alpha in real-time by understanding changes in peoples sentiment.

Finally, it can be observed that Ethereum does not seem to be strongly impacted by the initial decline in alpha of Bitcoin. This can be attributed both to a very low transfer entropy of Bitcoin on Ethereum in the calibration period, but also to the limited changes in the mean herding behaviour, not allowing for transfer entropy to develop its full effect on the price of the other coin.

While the shortcoming of the model to accurately incorporate the herding effect into the effect on prices may be seen as problematic, the model is still able to strongly predict the movements of prices overall. Indeed it is likely that the overall direction of price movements can be predicted well through the individual propensity to buy, whereas herding is better able to predict the magnitude of the price shifts. At the same time, while the overall effect on price cannot be observed, it is expected that the herding effect has an impact on the individual level probabilities to purchase a stock. Hence, this paper will subsequently aim to understand the differences in the individual probability to purchase a cryptocurrency for selected agents to properly grasp the effects of herding on the individual. Additionally, networks of varying degree distributions will be utilised in order to capture these behavioural changes as the network dynamics are adapted.

4.3. *Graph sensitivity analysis*

One of the defining components, which heavily influences model results, is the underlying graph structure. In the base analysis Erdos-Renyi graph is implemented, which assumes that each node has an equal probability to create an edge with another node independently of all other edges. Such an approach fails to account for the average low path length and higher clustering coefficient that could allow for a higher variation in micro-herding effect through an increased variance in the degree distribution. Therefore, it is essential to understand how the model behaves on the network that resembles more closely the real, human networks. As an alternative, Watts and Strogatz small world network could be considered given its ability to circumvent the aforementioned issues of a random graph. Nonetheless, this structure still lacks yet another essential property generally observed in real networks, the degree distribution, which is usually Power law as opposed to Poisson or Binomially distributed. Therefore, to account for this additional characteristic the Barabási-Albert model is adopted in the further analysis, as it incorporates two additional mechanisms, more precisely, network growth and preferential attachment, both of which induce the emergence of a scale-free network characterized by the power law degree distribution.

The most appropriate method to understand the impact of the inherent network on the results is through understanding the alterations to the agents' idiosyncratic probabilities to switch their state caused by the alternative network implementation. Therefore, the average probability to buy for both Bitcoin and Ethereum for the most and the least connected agent are plotted over time to study this phenomenon and the results are summarized in Figure 7. A generalizable finding that is persistently found in both graph structures is that the agents with the highest number of connections are characterized by more volatile transition probability. The observed difference among the two types of agents is more drastic in the Barabási-Albert model, where the difference in the variance of probability to buy is about 360%. This is in line with the theoretical expectations since the model allows for a larger variation in the degree centrality. Thus, the most connected agents are expected to be negatively impacted by the micro-level herding that occurs due to an average low proportion of the agents' neighbors that will hold a stock at any time step, while the opposite effect is expected for the least connected agent. At the same time, such finding further confirms that the holders of a stock are more likely to exchange stocks among each other due to the presence of herding on an individual level.

Finally, while the graphs in Figure 7 do show some support for the effects of herding behaviour on the probability to buy, it is noteworthy to outline that the magnitude of the effect is somewhat smaller than that of the individual belief α_j. Indeed, examining the variation in the probabilities to buy of the most connected nodes for bitcoin, it is easy to see that the changes in the probabilities are largely driven by the shocks to alpha, with an effect of about 5% upon the introduction of a shock. The changes driven by herding on the other hand are only about 2.5%. This provides further support for the effect of the individual propensity to buy in modelling the cryptocurrency market and the crucial importance in understanding such changes in real-time.

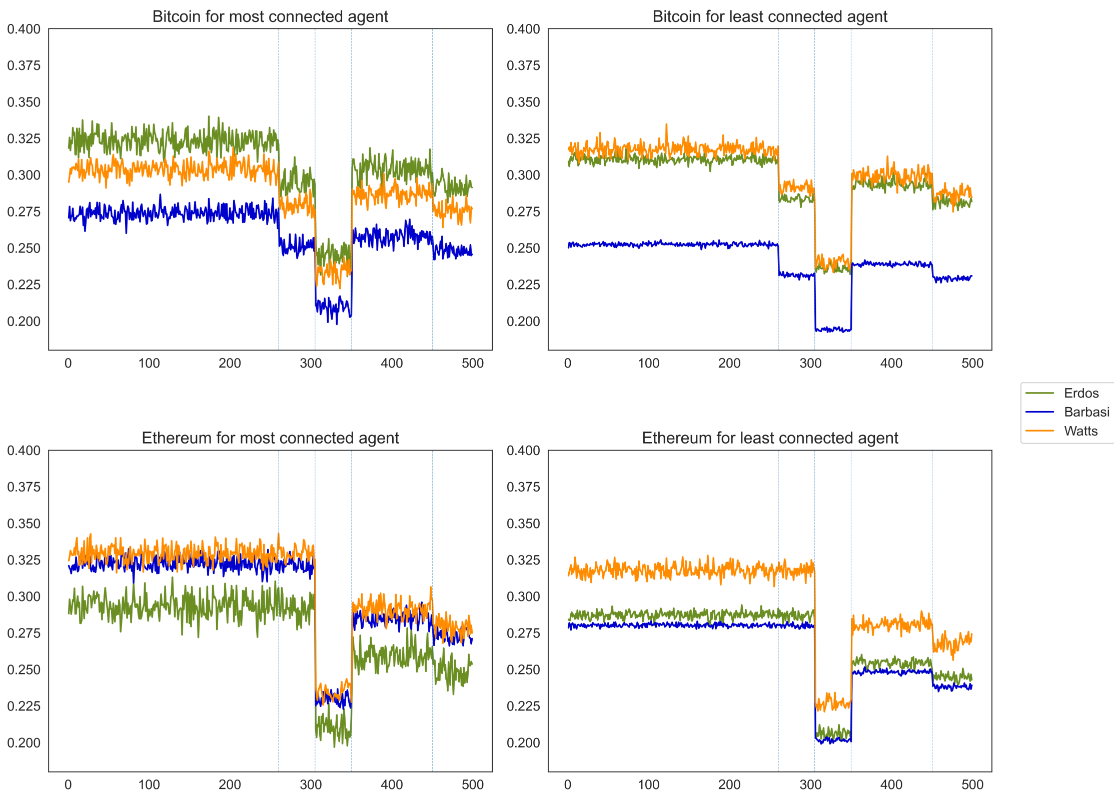

Figure 7. Probability to buy over time for selected agents.

5. Conclusions

The model presented in this paper aimed at investigating how the individual propensity to buy cryptocurrencies affects the market as a whole and manifests in macro phenomena such as bubbles, herding and codependent price movements. Strong evidence was found to suggest that personal belief is a major driver in a market defined by uncertain and incalculable intrinsic value and no large institutional investors. It is noteworthy that this is more true for Bitcoin rather than Ethereum, suggesting that the former is prone to more irrational investing and possibly that Etheruem's additional applications reduce uncertainty by providing more signals of fundamental value.

Thanks to the model's ability to extrapolate individual propensity to macro price trends, it was able to predict the general price movements of the cryptocurrency market induced by different levels of shocks. This lead to the conclusion that the approach can be successfully used to anticipate price changes driven by information shocks. Future work should aim to use twitter sentiment analysis to predict alpha in real-life and utilise this to get a price change indicator, which could potentially be used to provide advice on future investment decisions.

On the other hand, the accuracy of prediction was hampered by the failure to appropriately capture herding's effect on aggregate demand and supply. Despite this, herding did have an effect on an individual's probability to buy or sell a stock. Therefore, future improvement to the model would be to mitigate some of it's limitations such as the limit on the amount of stock one can hold or increase the number of buyers as the price rises. This will result in a better incorporation of herding effects and will improve predictive ability.

Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent Based Modelling
TE	Transfer Entropy

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