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The Application of Behavioural Heuristics to Initial Coin Offerings Valuation and Investment

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Abstract

Blockchain projects have seen a rush of investment in the form of Initial Coin Offerings (ICOs) in 2016 and 2017, yet little is understood about how to valuate these projects. This research explored the application of behavioural heuristics to ICO valuation and investing. Identified were six variables that may impact investment decision making due to key behavioural biases. These variables - coin value, market capitalisation, ease of understanding, market sentiment, maximum ICO bonus level, and pre ICO social media levels - were analysed using Pearson's Correlation against return on investment (ROI). The data was collected from numerous ICO websites and Twitter. Fundamental analysis was taken from Coincheckup due to it being a major source of information for many retail investors and using a well-defined methodology. Sentiment data was collected from Twitter and assessed using Crimson Hexagon's social sentiment analysis tool. Ease of understanding was evaluated using AWS Blockchain business canvas. All information was compiled into a single dataset and the top 47 projects in terms of ROI were utilised for this research. Ease of understanding was found to be significantly correlated with ROI. Ease of understanding was then combined with fundamental analysis to develop a hybrid model of evaluation for cryptocurrency projects. This model substantially outperformed fundamental analysis alone, with a 33.6% improvement on ROI. In conclusion, current methods of fundamental analysis for blockchain projects are an inadequate method for capturing their full potential future value. Investors lacking appropriate tools and with limited knowledge and experience - along with the relatively recent advent of cryptocurrencies - are being influenced by behavioural factors such as ease of understanding. It is therefore important that investors and entrepreneurs alike take such factors into consideration.

Keywords: *blockchain, behavioural economics, behavioural heuristics, ICO, cryptoeconomics, tokenomics*

JEL Classifications: *D02, D71, H11, P16, P48, P50*

1. Introduction

Before any business launches an ICO, they have two economic concerns: their cryptoeconomics and their tokenomics. Any factor that is likely to affect these economic concerns needs to be considered during the development phase. This research will argue that behavioural heuristics, rules of thumb that investors may utilise will impact price action in secondary markets. Where applicable, evidence from stock investing, venture capital investing and crowdfunding will be provided. It will clearly state why these heuristics may be particularly powerful in the cryptocurrency market, how these behaviours manifest, and how investors can take advantage of this information to improve their returns.

1.1 Cryptoeconomics & Tokenomics

The success of a blockchain comes down to its ability to incentivise the users of that network. To incentivise users, Blockchain projects use a randomised reward mechanism secured via cryptography. This is Cryptoeconomics.

Tokenomics is directly related to the liquidity of the system. Its function is to find the optimum point at which the short-term financial utility of a token intersects with the long-term utility of a token. This will directly impact the number of tokens there should be in the system. In the short-term, when there is a very limited application for the tokens, there needs to be a financial incentive

incentive for an individual to invest. However, if the price were to continually increase, there would be limited incentive for an individual to use that token on the network rather than speculate on it as an investment. If behavioural heuristics play a role in the formation of token price, then they need to be incorporated into your tokenomics to ensure the long-term success of a blockchain project.

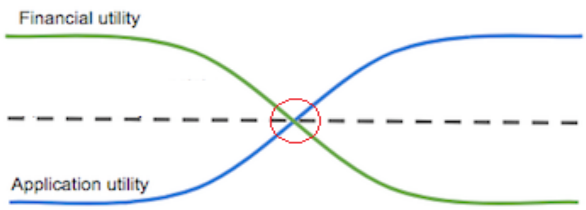

Figure 1. A graphical depiction of the intersection of application utility and financial utility as time progresses

2. Literature Review

2.1. Heuristics

Tversky and Kahneman [1], leaning on decades of psychological research, suggested that in complex decision-making situations individuals will use heuristics to ease the cognitive complexity of the task. Whilst these heuristics are a necessity in order to navigate the complexities of life, they are inherently prone to errors and biases.

There are four key general heuristics:

2.1.1. Affect, as argued and tested by Finucane et al [2]:

This is a reliance on the initial feeling experienced, or our intuitive judgement. As the decision we are presented with increases in complexity, our reliance on this initial intuitive judgement increases. Our reliance on it is also increased when presented with time constraints.

2.1.2. Representativeness

This is our tendency to assume individual characteristics to be representative of the whole regardless of whether those characteristics actually relate to the whole.

2.1.3. Availability

This is our tendency to make a decision based on the most salient information. This results in an overweighting of more recent information and the most extreme factors

2.1.4. Anchoring and Adjustment

When making a judgement, decision-makers often use an initial value and adjust away from it accordingly. Often this initial value - the Anchor - can lead to a biased judgement.

Each of these heuristics can lead to a number of systematic biases which can impact investment decisions within the cryptocurrency market

2.2. Affect

Affect [3] is the reliance on a positive or negative feeling toward a stimulus. Lemmon and Portniaguina [4] found that forecasts of consumer confidence in "affect" predicted returns for the 25 years post-1977. They concluded that this was due to the increase in household investors, suggesting that when the expertise of the investor is low, behavioural biases played a larger role in an investor's ROI.

This is not dissimilar to the cryptocurrency market, which has a high percentage of household investors. Bollen [5] showed how social media data, namely Twitter, can be used to elicit sentiment. He found it can be accurately used to predict changes in the Dow Jones Industrial Average. Slovic et al. [6] refer to an "affect pool," or a collection of all the positive and negatively tagged associations. A similar approach is taken here with the ratio of positive to negative Twitter postings.

2.3. Herding

Some of the most salient information for investors is the most recent price action. A stock could be in demand and have seen its price rise in the previous period or investors could be selling that stock, resulting in a price drop. Researchers have found that market demand, rather than the expectations of fundamental value, influence demand [7]. Banerjee [8] was one of the first to look at herding behaviour. Using a simple model, he showed how using other peoples' information rather than one's own leads to an inefficient equilibrium. Further seminal work performed by Lakonishok, Shleifer, and Vishney [9] found correlated trading across subgroups of investors. Both of these studies focused on "Smart Money" institutional investors. These are investors who shouldn't be easily swayed by the actions of others. The cryptocurrency market has a large portion of individual investors. These are investors who are more likely to deviate from rational trading practices. Barber, Odean, and Zhu [10] showed that bias in individual investors is stronger and more persistent. This was supported by Merli & Roger [11], who built on LSVs model and included the measurement of individual herding on the trading records of over 87,000 investors from 1999-2006. According to Merli & Roger, the examination of an individual's heterogeneity, they could use poor past performance to predict the increased likelihood of herding in the next quarter.

In the cryptocurrency market, with its high percentage of individual investors (those most prone to biases), we would expect to see high levels of herding resulting in huge price swings due to overreaction. This is something that is very common in the market, so commonplace it even has its own term: "mooning." Kraft, Penna & Pentland [12] found strong evidence for a peer effect on the buying behaviour of cryptocurrency investors. They proposed one of three behavioural mechanisms for such an effect:

1. Traders explicitly copying buying trades – Herding
2. Buying due to momentum – Representativeness
3. Buying salient coins with recent price action – Attention

Using data from crowdfunding campaigns (a capital raising mechanism not unlike ICOs) Lu et al [13] found that early social media engagement and promotional activity correlated with the success rate of the project. Additionally, a number of studies have looked at Twitter volume and trading volumes and found positive correlations [14]. A similar correlation is likely between ICO success and ROI.

Another aspect of ICOs that may affect ROI is bonus levels. Adhami et al. [15] found that ICO bonuses were marginally correlated with ICO success. Behavioural economics suggests that ICOs with a particularly high bonus will dissuade later adopters and lead to a reduced ROI for investors.

2.4. Representativeness

This is the assumption that a sample is representative of the population. Two of the most common examples of this are the Gambler's Fallacy and Hot Hands Fallacy. These two fallacies are related to a belief in momentum. The same bias can be seen in trading behaviour. Barber, Odean, and Zhu concluded that "investors tend to buy stocks with strong past returns." Moment trading is a well-documented characteristic of the cryptocurrency market. Liu and Tsyvinski [16] found strong evidence of this, finding that "a one standard deviation increases in today's return leads to increases in daily returns by 0.33%." During a weekly timeframe, a one standard deviation increases leads to a 3.16% increase at week t+1. In real terms, this is a 5.55% ROI at the daily level and a 16.64% ROI at the weekly level. The particular significance of their finding is that traditional technical analysis methods of analysis were not significant, or they had no discernable pattern. They concluded that cryptocurrencies did not behave like a traditional asset, a store of value such as precious metals, or as a currency; instead, they had their own characteristics and market-specific factors. Whilst their paper focused on the top three cryptocurrencies - Bitcoin, Ripple and Ethereum - and looked at trading rather than ICOs, it is reasonable to believe that these market-specific factors will be present in ICOs as well. Tversky & Kahneman [17] noted that these reasoning errors are most severe as uncertainty increases, which could explain the large deviations in price. Whilst this research will not examine momentum directly, it will explore a few factors that could lead to increased demand and subsequent momentum. Chief among those will be the Size Effect.

The Size Effect is the assumption that smaller firms outperform larger firms. Initially observed by Banz [18], the literature on whether this is actually evident is mixed. Some suggest that over time, the effect disappears [19] Others show seasonal variation [20]. What is apparent is that the effect is not linear [21]. The effect could be due to investors erroneously believing that smaller capitalisation firms have more room to grow. By looking at the market capitalisation of ICOs, we can see whether a size effect is present in the cryptocurrency market. The ICOs in the lower percentile would therefore be correlated with larger ROIs.

2.5. Availability

The availability heuristic states that the most recent or salient information has a stronger influence on our decision-making. One aspect that affects the salience of information is familiarity. The familiarity bias is most clearly demonstrated by the Home Bias. This is an investor's preference to invest in their own country [22]. Very simply, investors tend to stick to what is familiar and therefore easier to understand. This is also evident in investors' decisions towards industries of expertise.

Zacharakis & Meyer [23] determined that one of the key markers for venture capital (VC) investment is market familiarity and competition. They note that this could lead to the behavioural bias of only investing in a company or product the VC can immediately understand. In the cryptocurrency market, the traditional method of evaluating an ICO is very similar to that of a VC evaluating a startup. Traditionally this would involve looking at the team, the potential market they are entering, competition, quality of the product, and the business plan. For a blockchain startup, this would be their whitepaper and timeline. Coincheckup, a highly popular website for cryptocurrency platforms, uses a similar VC-style model to evaluate and weight the quality of blockchain startups. It looks at the team, potential market, competition, and quality of the product. Additional factors that determine VC involvement include a preference for smaller emerging markets [24] and a preference for niche markets [25]. These factors could explain the rapid expansion of capital into the blockchain space.

Brennan & Cao [26] point out that when investors have limited information, researchers tend to see return-chasing behaviour, i.e., only buying when risk-adjusted returns are high. This behaviour is extremely prevalent in the cryptocurrency market. This behaviour would suggest a lack of expertise in the market. This is likely to lead to stronger effects from biases such as familiarity. In the cryptocurrency market, ICOs that have a product that is easy to understand, or one that is similar to a product an investor may already know, can take advantage of this bias. By analysing the whitepaper, researchers can ascertain the complexity of the product and the degree to which it is easy to understand, or its similarity to a well-known product. Shehhi et al [27] found that ease of understanding played a role in an investor's choice of which cryptocurrencies to mine.

2.6. Research Questions

Considering the research from behavioural economics and the work that has already been done on the cryptocurrency market, I propose the following research questions to be explored:
Q1) Will ICOs with large bonus levels dissuade later investors because of a fear they have already missed out?

Q2) Will higher ratios of positive sentiment, or pre-ICO social media levels, or coin size, or market capitalisation, be correlated with higher ROI in ICO investing due to behavioural factors such as Affect, Herding, and the Size Effect?
Q3) Will the ease of understanding of a blockchain project be correlated with higher ROI due to familiarity?
Q4) Would a hybrid Behavioural and Technical Model of ICO rating be correlated with higher ROI than a Technical Model alone?

3. Methodology

The cryptocurrency market is relatively new. Whilst Bitcoin has been around since 2008, it was only with the launch of Ethereum in 2014 and the subsequent "altcoins" that began using the ERC20 Ethereum platform that a market began to form. 2016 saw a boom and the formation of a true marketplace, with a huge increase in ICOs - from 39 total until 2016 to 256 in 2016 alone. As such, getting reliable data is extremely difficult; no single repository for the industry currently exists. The data in this research was collated from several sources. The data was taken from tokendata.io and cross-referenced with data from icostats, icobench, and icodata, along with the websites for the respective ICOs.

Data regarding the top ICOs sorted by their respective ROIs was collected and categorized using the business/ICO name, ICO date, ICO price in USD, current price in USD (as of June 2nd 2018) and ROI in USD. ROI was given as a multiple of initial investment. The top 51 ICOs by ROI were kept with the exception of Aeternity (phase 2) - this data was an extension of the phase 1 ICO. Later in the process, three more ICOs were removed: Ethereum, Nxt, and Metal. This was because it was discovered that they did not meet the requirement of a fully public ICO. This final cull left us with a dataset of 47 ICOs.

3.1 Fundamental Analysis Data

Coincheckup was used to collect data on the team, advisors, brand/hype, product, coin, social engagement, communication ability, business transparency, and/or Github data. These are key variables used as industry standards for evaluating the fundamentals of an ICO project. Coincheckup uses this data to create an overall weighted score for that business. Coincheckup was used because it is currently an industry favourite. This research used the same information with a few changes. The approach was to look at information only available at the time of the ICO, so the below criteria under Coin Strength was not included in the analysis:

- Average trading volume in past 3 months against other assets' average volume.
- Average market cap in the last 3 months against other assets' average market cap.
- Value growth since trade start date against total market growth.

This reduced the weighting for coin strength to 6.9% for semi and centralised structures, and 8.1% for decentralised structures. The left-over weighting from this reduction was redistributed evenly across all categories to keep the ratios intact. The revised weighting was used to give an overall score for that business/ICO. This was a given as a percentage and used to represent the overall strength of that business/ICO. Using Pearson Correlation, the ROI for the ICOs was compared to their weighted score. This gave us the correlation for a solely fundamental model. This was used later to compare against a hybrid model.

3.2 Behavioural Variables

The key general heuristics were used to categorise several key biases. These biases were explored to see how they may manifest in the cryptocurrency market.

The following were identified as potential triggers for a behavioural response:

- ICO bonus levels – Loss Aversion
- The ratio of positive to negative information from Twitter data – Affect
- Pre-ICO social media levels (Twitter) – Herding
- Ease of understanding the whitepaper/product/similarity to a well-known product – Familiarity Bias
- Small market cap – Size Effect

3.3 Behavioural Variable Data Collection

1) Max ICO bonus levels were taken from the whitepapers of the respective ICO along with the ICO rating website. Building upon Adhami, Giddici & Martinazzi's [15] work, the research will explore whether a large maximum ICO bonus discourages potential investors.

2 & 3) Affect and pre-ICO social media levels were found using Twitter data using a similar approach to that of Bollen [5]. Affect was found using Crimson Hexagon's Sentiment Analysis tool for keywords in the crypto space. This was used to elicit market sentiment at the time of an ICO. Pre-ICO social media levels were found using the "$" tag for the respective ICO for the two months prior to the launch, along with a number of keywords for the industry. Sentiment data was binned into three-month periods from January 2016 to June 2018.

4) The ease of understanding was evaluated using Amazon's web service template for evaluating the applicability of a blockchain project. The score was given based on the ease of completing the various sections. The scores for each section were averaged to give an overall 'ease of understanding' score for that project. The score was given out of five.

5) Coin value and market cap were taken from the token data source.

3.4 Behavioural Data Analysis

Pearson's Correlation was used to identify whether any of these biases were present and whether they correlated with the ROI of the top 50 performers. For significance levels, one-way ANOVAs were used. Once the correlating variables were identified, they were combined with the data from the fundamental analysis and used to create a new Weighted Behavioural Algorithmic score. This score was then compared against the ROI of the top 50 performers to see whether it has a stronger correlation, and therefore whether we could use the algorithm to better predict potential high performers.

3.5 Review

The main issue faced during this research was the difficulty of getting high-level data. There is no single repository for cryptocurrency data, so the data provided was taken from multiple sources. Due to this necessity, the research was restricted to a severely limited number of ICOs. A further limitation was the use of Twitter data alone as an indication of pre-ICO social media levels. Additional social media channels such as Telegram, Discourse, and Reddit are heavily used by blockchain projects. Whilst this paper will not be evaluating the causality of the behavioural mechanism, only its correlation to an investor's ROI, any follow-up work should include a causal link. For example, further work could build on the work of Frey, Herbst, and Walter [28], who found that as the number of active traders decreases, so does the level of Herding. By examining the number of active traders on the various crypto-trading platforms over time, researchers could seek to elicit Herding levels.

4. Research Findings

This research sought to explore which behavioural factors may play a role in the decision-making process of investors in the cryptocurrency market. Identified were six variables that may play a role due to key behavioural biases. This section shows the results of a Pearson's Correlation test along with a regression analysis of those variables.

4.1 Variable Outcomes

Table 1. Pearson's Correlation

	ROI (x)
ROI (x)	1
FA Score	0.159142633
Coin Value	-0.106236506
MarketCap	-0.168776981
Ease	0.3375918
Sentiment	-0.113042187
ICO Bonus	0.157188773
Pre-ICO SM	-0.08048759

Table 1 shows the Pearson's Correlation of the six behavioural variables - Coin Value, MarketCap, Ease of Understanding, Sentiment, ICO Bonus Level, and Pre-ICO Social Media Levels - along with Traditional Fundamental analysis. The Correlation showed no strong correlations amongst any of our variables. Interestingly, the fundamental analysis score, showed next to no correlation. This would suggest that the current methods of fundamental analysis for blockchain projects are inadequate. This finding supports that of Liu and Tsyvinski [16], who also found no correlation of traditional technical analysis factors in cryptocurrency markets.

The maximum level of correlation was ease of understanding with 0.3375918. A one-way ANOVA was conducted and found to be statistically significant $F(1,45)= 5.788$, ($P = .0203$), shown in Table 2.

Table 2. One-way ANOVA results

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	18400.81	18400.81	5.788246	0.020304*
Residual	45	143054.8	3178.995		
Total	46	161455.6			

Table 3 shows a low R Squared for the ANOVA; however, that is expected with the limited observations and the nature of the data.

Table 3: Regression statistics for ease of understanding

Regression Statistics	
Multiple R	0.337592
R Square	0.113968
Adjusted R Square	0.094279
Standard Error	56.38258
Observations	47

4.2 Main Findings

The data shows that fundamental analysis of blockchain projects is not correlated with ROI. Additionally, the data shows that behavioural factors do play a role - in particular, the ease of understanding of the project. The previous literature suggested six hypotheses to explore. Below are the detailed findings from the analysis of each of those questions.

Q1 regarding bonus levels showed no correlation with ROI. Previous research by Adhami, Giddici & Martinazzi [15] did find a marginal correlation with the success of ICOs. From this finding, it was suggested that larger bonus levels may dissuade investors. Further analysis showed that the highest average return for bonus levels was between 10% & 20% (Figure 2). Projects with higher bonus levels saw a rapid drop-off in average ROI. There was no difference between instances when projects that had a maximum bonus of 5% were included, and when the analysis was limited to those projects with a bonus of 10% & 20% alone. Due to the benefits of offering a slightly higher bonus level, the recommended maximum bonus level is between 10% and 20% for any ICO.

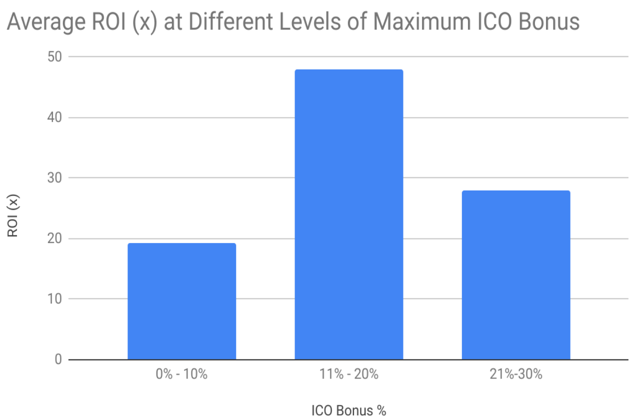

Figure 2. Average ROI per ICO Bonus level

Q2 was regarding the market sentiment at the time of the ICO. The results did not show any correlation. The approach taken here was to explore overall market sentiment. A finer analysis of the sentiment for a particular project in the months leading to its ICO may shed further light.

Q3 regarding pre-ICO social media levels was insignificant and did not correlate with ROI.

Q4, examining ease of understanding, proved significant. This suggests that the investor's decision to invest in a blockchain project is influenced by the ease of understanding the pertinent whitepaper. This is consistent with the assumption that in the absence of appropriate methods of fundamental analysis for blockchain projects, investors are relying on personal assumptions and feelings toward a particular project. As noted by Shehhi et al. [27], ease has been found to play a part in the decision of which cryptocurrencies to mine.

Q5 regarding market cap: The amount the ICO raised was not correlated with ROI. This suggests that investors are not concerned with coin value and market cap at the time of ICO. This is contrary to what we see in trading behaviour in cryptocurrency markets, where there is a clear preference for smaller-valued coins and medium sized market caps.

Q6 sought to answer whether a hybrid model of fundamental analysis and behavioural analysis could outperform fundamental analysis alone. Looking at the top 15 in terms of ROI based on fundamental analysis, the average return was 52.63x. Based on ease of understanding, the average ROI was 64.53x. The fundamental analysis approach of investing in projects above a certain threshold, 77%, saw an average ROI 62.56. A hybrid model looking at traditional analysis scores of 77% or above and an ease of understanding score of above 3.0 gained an average ROI of 83.64x. This is a 33.6% improvement. In terms of ROI, this is a 3360% gain. This would support the hypothesis that a hybrid model outperforms fundamental analysis alone.

Table 4. Average ROI results

	AV ROI (x)
Top 15 TA	52.63
Top 15 Ease	64.53
FA Above 77%	62.56
Hybrid Model	83.64

5. Discussion

The analysis showed that of the six behavioural variables identified, ease of understanding was the only significant variable. When this variable was included in a hybrid model of analysis (inclusive of fundamental analysis), it outperformed the fundamental analysis alone by 33.6%. Investors taking this approach could see a massive increase in their returns. The next step would be to apply this model to another, larger dataset and see how it performs against new data. Machine learning techniques could hone in on the optimum levels to maximise ROI. This also highlights the importance of taking extra time when writing a whitepaper to ensure that it is easy to follow and understand. Whilst this can be difficult due to the technical nature of many blockchain projects, it is clearly important to investors and should not be over looked. A valuable approach could be to split the contents of a whitepaper into a high-level overview and a separate technical whitepaper. That way, investors can read the appropriate paper based on their level of technical sophistication.

Whilst the analysis showed a significant result, there were a number of limitations of the approach that must be addressed, the largest being the use of USD as our currency reference. Most of the ICOs presented in this study did not allow for USD investment. The investment was either in Ethereum or bitcoin. In some cases, it could have been that whilst there was a positive return in USD in terms of bitcoin or Ethereum, the returns could have been much less or even negative due to the substantial growth of both of these coins during the period of analysis. For example, Waves was included in our analysis with an ROI of 17x; however, in terms of bitcoin, this was a loss. Another limitation was how this research evaluated ease of understanding. Whilst the study used the AWS Blockchain Business Canvas as a template, the assessment of ease was subjective. Further studies could be improved by providing a more structured analysis. For example, points could be awarded for particular keywords, executive summary, or particular sections.

6. Conclusion

Cryptocurrencies do not fit typical fundamental analysis. These "coins" have no underlying assets; instead, their value comes from network values. It is a speculative market. The characteristics of such a market include short-term "narrow frame" investors, noise traders, and momentum chasing. We, therefore, cannot exclude behavioural factors when looking at price action. For startups that are planning to use an ICO as their funding vehicle, it is important that they take these factors into consideration when they are looking at their tokenomics - these will have a direct impact on the longevity of the project. For investors, it is important to understand the behavioural factors that may bias their investment decision. These findings are supported by the work from Hargrave, Sadhev & Feldmeier [29]. A key variable to consider is the ease of understanding of the whitepaper. Investors with limited knowledge and experience in blockchain find comfort and confidence in products that they can more readily understand. It is important for entrepreneurs not to underestimate the importance of their whitepaper to the success of their project. Additionally, investors can seek to maximise their returns by including this in their analysis. A final note is for entrepreneurs to limit the size of the bonuses offered for early involvement in an ICO. The recommendation from these findings is between 10% and 20%. Likewise, investors should be wary of projects offering particularly large bonuses. Further analysis is needed as to the extent of behavioural factors at play in the cryptocurrency market. Further research should seek to rectify the limitations of this research and build upon its findings. It is evident that this is a fledgling field; as the market becomes more sophisticated, the expectation is that better-educated investors will lead to behavioural factors playing less of a role. For now, however, investors and entrepreneurs alike cannot afford to ignore the significance of behavioural factors.

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