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EXPLORING THE RISE AND FALL OF BITCOIN PRICES: TO WHAT EXTENT WAS OPTIMISTIC HERDING BEHAVIOUR IN BITCOIN MARKETS DISRUPTED BY THE INTRODUCTION OF BITCOIN FUTURES CONTRACTS?

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ABSTRACT

Bitcoin is a novel technology and global economies are in the very early stages of incorporating cryptocurrencies into their existing economic systems. Given the limited understanding of Bitcoin from a policy and economic perspective, this paper studies the extent to which futures trading accentuated Bitcoin's price collapse. This analysis is done through the lens of behavioral economics, specifically herding, which is the propensity of investors to disregard their private information and emulate the decisions of other investors.

A key finding from this analysis reveals that herding was present following the introduction of Bitcoin futures contracts when the market was experiencing extreme negative daily returns. This paper offers economic context for policy makers seeking to better understand the effects of derivative markets on Bitcoin's prices by way of the behavioral characteristics of its participants.

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Chapter 1

Introduction

The Importance of Economic Analysis in Emerging Cryptocurrency Technologies

> *"With e-currency based on cryptographic proof, without the need to trust a third party middleman, **money can be secure and transactions effortless**."*
>
> *– Satoshi Nakamoto, The Creator(s) of Bitcoin*

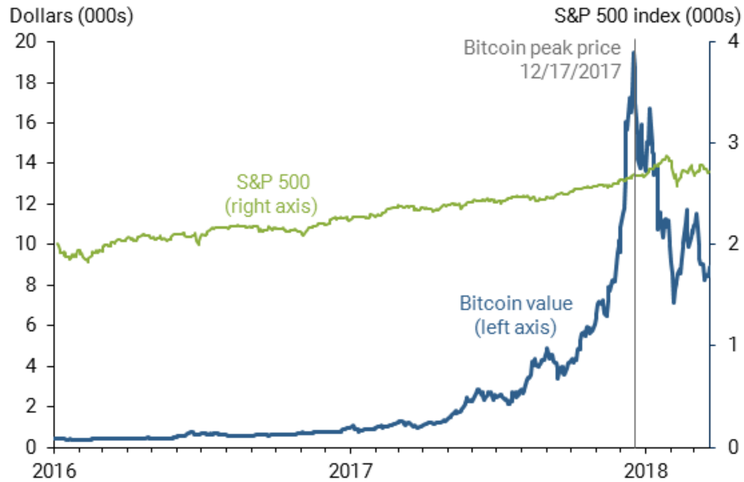
At the time of this writing, there were 17,583,587 Bitcoins in circulation, with a spot price of $3871.18 USD, leading to Bitcoin's market capitalization of $68,069,278,684 USD. Bitcoin's rapid gain in market valuation is an affirmation that it has captured the minds of futurists, entrepreneurs, scientists, revolutionaries, and ordinary citizens alike. Cryptocurrencies seek to disrupt, or end, the underlying systems governing financial services, market transaction protocols, and monetary policy tools. Bitcoin is the most popular instance of such a technology.

The successful integration of cryptocurrency technologies into global economic systems requires a responsible adaptation of their use, guided by appropriate and balanced regulation. Although regulation and government intervention is counter to Bitcoin's intentions, it is naïve to assume that governments and institutions will standby without interference. The echoes of the 2008 Financial Crisis serve as a reminder to regulators that no innovation in financial products or services that attracts significant public investment and euphoria should go unmonitored and unchecked. Given Bitcoin's ability to grow its market capitalization so quickly, regulators will likely continue to play a pivotal role in Bitcoin's journey, and regulation will inevitably affect

Bitcoin's price and derivatives offerings over time. The issue lies in the difficulty of regulating a technology that is not yet fully understood, and for which the ramifications of its mass adaptation are not clearly defined. For example, some consider Bitcoin a commodity, while others view it as a currency, and some are of the opinion that it is a new asset class in and of itself. If cryptocurrencies are to replace traditional currencies, as many intend to, then it is critical to understand the intricacies of its markets and the behavioral characteristics of its stakeholders (e.g. investors, users, optimists, and pessimists). Herein lies the intent of this paper, which is to further our understanding of the behavioral tendencies of Bitcoin's stakeholders in response to regulations, specifically with respect to the potential introduction of derivatives. This paper accomplishes this by using an empirical methodology for measuring herd behavior in markets from Christie and Huang (1995), and interpreting the model results through the lens of established theoretical and empirical literature from behavioral economics.

This paper is motivated by an economic letter composed by Hale et al. (2018) of the Federal Reserve Bank of San Francisco (FRBSF). Hale et al. (2018) propose a correlation between the introduction of futures contracts by the Chicago Mercantile Exchange and the steep fall of Bitcoin's prices. Hale et al. (2018) refer to the trend in Figure 1, where it is clear that Bitcoin was experiencing a rapid rise in prices between 2017 and 2018, but prices began a downward spiral following the introduction of futures contracts in December 17, 2018 on the Chicago Mercantile Exchange. They plot the performance of the S&P index to highlight the abnormality of Bitcoin's price movements in comparison to a traditional market indicator. To the authors, Bitcoin's sudden decline is not a surprising result, since previous literature has revealed the effects that short selling instruments, in this case futures, could have on an asset's underlying price.

Figure 1 Bitcoin Prices and S&P Stock Index



Source: Hale et al. (2018)

The case of Bitcoin is an opportunity to study the impact of derivatives markets on their underlying assets in a controlled setting. Since there was no regulated and secure way to trade Bitcoin derivatives before December 17, 2017, especially for institutional investors, the principal driver of Bitcoin's price was a function of its supply and demand from investors purchasing Bitcoin themselves either for speculative or transactional purposes. Hale et al. (2018) theorize that Bitcoin's massive bull-market was driven by optimistic investors continuously bidding up its price, with no downward price pressure from pessimists, who would have insisted that Bitcoin was overvalued. Futures contracts allowed pessimists the opportunity to express their opinions via formal market transactions; essentially, they could purchase contracts in which Bitcoin's spot price would be lower in the future than today. Hale et al. (2018) believe that these new signals from pessimists via futures contracts put downward pressure on Bitcoin's price, and so Bitcoin's ride had come to an end, and the decline began.

Although Hale et al. (2018) liken this to the introduction of credit default swaps to the housing market and its subsequent crash, they do not explore Bitcoin's price decline from the perspective of herding. This paper aims to fill that void and add to their work on the possible association between Bitcoin’s decline and the introduction of futures trading. The results of this analysis could prove useful for future regulations on derivatives offerings for Bitcoin.

Chapter 2

Literature Review

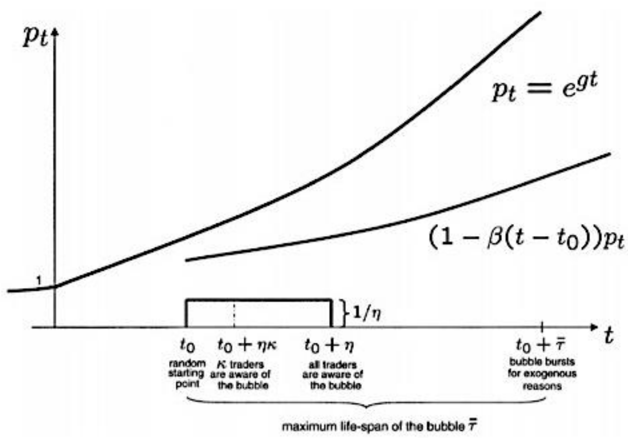
Theory from Behavioral Economics & Finance

A foundational understanding of relevant principles from behavioral economics and finance is critical to parsing the implications of the experimental results presented later in this paper. Considering Bitcoin's major price correction, it is attractive to classify its rapid growth and decline as a bubble; however, this statement is not fully accurate and Bitcoin's story is more complicated. Brunnermeier (2001) identifies the occurrence of a bubble as when an asset's price is inflated above its fundamental value. He further explains that an asset's prices are determined endogenously and are not set exogenously (Brunnermeier, 2001). As Hale et al. (2018) concede, it is difficult to determine Bitcoin's fundamental value. However, Bitcoin's fundamental value could be broken down into its transactional value and its speculative value. Transactional demand is driven by the actual use of Bitcoin to purchase goods and services, while speculative demand is driven by investors trading Bitcoin in order to sell their currency for profit in future time periods (Hale et al., 2018). The novelty of Bitcoin's technology makes it difficult for it to be adapted quickly into mainstream transactions for goods and services. It is far easier for speculative demand to remain active since investors may hold beliefs of future increases in value. Bitcoin was a proving ground for distributed and decentralized currency; however, its future transactional value depends on the number of users on its network willing and able to pay the transaction fees necessary for Bitcoin miners to maintain the network (Huberman, Leshno, Moallemi, 2017). Given these points, the possibility that Bitcoin's price will once again break its peak price cannot be fully discredited.

Nevertheless, Bitcoin's steep price growth and decline is a reflection of investors' beliefs and market decisions, which could be described as rational or irrational. Traditional financial theory points to the efficient markets hypothesis (EMH), which states that asset prices immediately reflect all available and new information, making technical or fundamental analysis futile for exploiting undervalued assets (Malkiel, 2003). Under this traditional view, investors are rational, and are all equally aware of an asset's true value. Rational investors, according to Barbaris and Thaler (2002), must satisfy two checks: they must correctly update their beliefs as new information is discovered, and their choices must be consistent with Savage's notion of Subjective Expected Utility (SEU). The authors further position behavioral finance as an alternate explanation to the less than rational behavior seen in financial markets, which traditional theory cannot fully account for (Barbaris and Thaler, 2002). More on irrational behavior models will be discussed later on.

While the EMH completely discounts the possibility of bubble formation, Abreu and Brunnermeier (2003) present a model in which bubbles can persist even with rational investors, contrary to the EMH. Setting the context for their model, Abreu and Brunnermeier (2003) acknowledge that there are certainly a limited number of agents subject to irrationality in markets: however, the authors propose a model focused on rational arbitrageurs. They argue that rational arbitrageurs aim to maximize their returns by riding the bubble and form a diverse set of expectations on optimal timing for exiting the market. The resulting variance in exit strategies and market timing accelerates bubble growth, as no single arbitrageur wants to exit the market too early and risk sub-optimal returns. A relevant outcome from the model is that large scale synchronized action taken by the arbitrageurs is necessary to burst a bubble; however, they lack the incentive to make such a coordination effort if prices are continuously rising. With no incentives for joint action, except for possible synchronization events like news, the bubble will persist despite arbitrageurs' knowledge that the asset is over-valued.

Figure 2 Formation of Bubbles with Rational Arbitrageurs



Source: Abreu and Brunnermeier (2003)

The model in Figure 2 is Abreu and Brunnermeier (2003)'s illustration of bubble persistence starting at a time t_0 and ending at $\bar{\tau}$, where some exogenous event pops the bubble. The time $t_0 + \eta$ indicates the point when all traders have knowledge of the bubble's existence. The authors model investors' optimism by setting the growth rate of price, g, in $p_t = e^{gt}$, to be greater than the risk free interest rate, *r* (Abreu and Brunnermeier, 2003). This model is very relevant to Bitcoin's own price history, since optimistic sentiment in the value of new technology could not be checked by pessimistic pressure until the introduction of regulated Bitcoin futures. The introduction of Bitcoin futures could be a potential instance of a synchronizing exogenous event that leads arbitrageurs to coordinate their actions in a sell-off.

Barberis and Thaler (2002) set forth three limits to arbitrage, which can supply some additional context to the Abreu and Brunnermeier (2003) model. The first limit is the fundamental risk of decreases in asset value, which arbitrageurs typically balance by shorting a substitute asset. The second limit is noise trader risk, where asset price decreases can be further pressured down by unsophisticated investors, causing arbitrageurs to liquidate their positions. The third limit is implementation costs, which include transaction costs on trades, short sale limitations, and information acquisition costs to identify mispricing (Barberis and Thaler, 2002). In the context of Bitcoin, a trader may balance fundamental risk by diversifying across multiple cryptocurrencies. This may be challenging in practice for unsophisticated investors seeking portfolio diversification, as differences amongst cryptocurrencies can be difficult to parse without technical knowledge. A large number of unsophisticated and irrational investors would lead to higher noise trading, which in turn results in high volatility and unpredictability (De Long, Shleifer, Summers, & Waldmann, 1990). De Long, Shleifer, Summers, & Waldmann (1990) further explain that the unpredictability of irrational investors creates additional risk for arbitrageurs since the initial misunderstanding/mispricing of the asset may become more severe tomorrow than today.

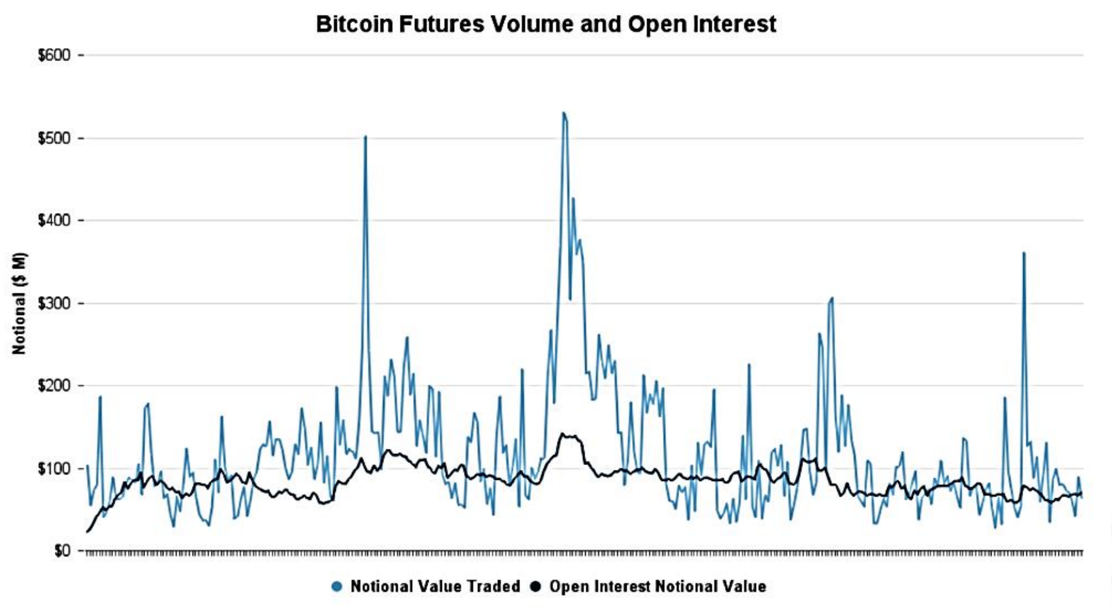
A central idea to this analysis is the formation of herds, and the impacts they have on asset prices. In an early work, Banerjee (1992) describes herds as every day occurrences where we make decisions to follow the lead of other peoples’ decisions. Banerjee’s model classifies agents who pay attention to the decisions of others as rational, since these agents are attempting to incorporate information they may not have that others have. He discovers that agents inadvertently form herds while incorporating others’ decisions, while ignoring their own private information. As a result, any given herding agent's information is less valuable to other agents because it does not reflect their own private information (Banerjee, 2002).

Park and Sabourian (2011) present a model where herding is driven by the nature of the underlying structure of information available to the investor. The authors show that herding causes large price movements, increases volatility, and decreases liquidity. In their model, herding results when an investor receives information that he believes was more likely to have been generated by extreme states. The authors call this a U-shaped signal. Likewise, contrarianism occurs when an investor receives information that he believes was more likely generated by moderate states. The authors call this case a hill-shaped signal (Park and Sabourian, 2011). The model is significant and relevant to the case of Bitcoin, because it highlights the negative impacts of mixed messages from information in speculating news articles or unsubstantiated regulatory announcements. Likewise, there must be some way to parse the true U-shaped signals that warrant investors shifting their beliefs to the extremes.

Futures & Financial Innovation in Markets

The key event of interest to this study is the introduction of futures trading for Bitcoin. Relevant literature on the impacts of futures trading on the price movements of their underlying assets can offer insights into Bitcoin's own price behavior. Futures contracts are financial derivatives that allow a buyer and seller to engage in the exchange of the underlying asset at a pre-determined time, price, quantity, and quality (Chen, 2019). The contracts themselves are standardized according to a set of rules determined by the issuing authority and are legally binding. On the first day of Bitcoin futures trading at the CME, more than $100 million in notional value was generated through the trading of more than 1000 contracts across all available maturities (McCourt, 2017). Figure 3 below shows the significant increase in the magnitude of futures trading in the 312 trading days leading up until March 15, 2019, relative to when they were first introduced in mid-December, 2017. The data show notional values reaching above $400 million on three occasions during this period, with the majority of other peaks averaging around $200 million. Figure 3 also shows the notional value of open interest during this period, where open interest is defined as the total number of contracts in existence that have not yet been liquidated (Grant, 2019). The key takeaway from the data is that the Bitcoin futures market is highly active, and the increase in the aggregate notional value of contracts shows that investors are becoming more comfortable with engaging in futures transactions. For more information on CME Bitcoin futures contract specifications and standards, see Appendix C.

Figure 3 Bitcoin Futures and Open Interest



Source: Bitcoin Futures Liquidity Report (2019)

From an investment strategy perspective, investors mainly purchase futures to either hedge their positions on the underlying asset to decrease risk or to profit from speculating on its future price. It is important to note that speculators do not need to hold any position in the underlying asset itself. As Hale et al. (2018) explain, speculators with pessimistic views on Bitcoin can purchase futures contracts listing Bitcoin's price lower than the current spot price. Upon expiration, contracts are financially settled through cash, please see Appendix C for more information on CME settlement procedures. There was no such regulated and mainstream mechanism to express pessimistic sentiment on Bitcoin via market transactions prior to the introduction of futures contracts on the CME, herein lies their significance to the case of Bitcoin.

Hale et al. (2018) also reference findings from Fostel and Geanakoplos (2012), who showed how financial innovation in the form of Credit Default Swaps (CDS) allowed pessimistic investors to bet against the underlying mortgage-backed securities (MBS) that grew to such immense popularity in the run-up to the 2008 housing bubble. The authors' data show that tranching and seemingly endless securitization of MBS led to sustained increases in their prices, while the introduction and popularization of CDS destroyed the market. They further explain that if the introduction of CDS had been timed earlier in the period of rising securitization, then the asset bubble would not have grown as large as it did, and the subsequent crash would not have been as severe (Fostel and Geanakoplos, 2012).

The discussion in Fostel and Geanakoplos (2012) has interesting parallels to Bitcoin's own demise; however, there are several differences to note. For one, there was no regulated securitization of Bitcoin in the period leading up to its price increases, rather it was mainly optimistic speculative demand from people willing to purchase it through Bitcoin's own network infrastructure. Additionally, the size of the Bitcoin market was nowhere near as large as the housing market when it has crashed. Furthermore, due to Bitcoin's unregulated nature, it attracted minimal institutional investment prior to the introduction of futures contracts, this may have changed ex-post. As the Chicago Mercantile Exchange noted, "Commodity Trading Advisors (CTAs), ETF providers, hedge funds, sell-side firms, proprietary trading firms and retail traders, among others all voiced strong interest in a bitcoin futures contract" (McCourt, 2017). As both the theoretical literature discussed previously and the forthcoming empirical literature show, institutional investors are observed to behave differently than individual investors in markets. This point is important to maintain for discussion of this paper's results later on.

Relevant Empirical Literature

Numerous empirical analyses were conducted on various sections of global financial markets to detect and measure herding. The empirical methodology used in this paper follows that proposed by Christie and Huang (1995), and is discussed in detail in the research methodology section. In brief summary, Christie and Huang (1995) propose using the cross-sectional standard deviation (CSSD) to determine the propensity of individual equity returns to stray from market returns during periods of large price changes. Herding implies minimal propensity to stray, while large CSSD values indicate no herd consistent behavior. Christie and Huang (1995) define the 1% and 5% tails of the returns distribution as extreme swings in portfolio returns.

Interestingly, Christie and Huang (1995) found that there was little evidence of herding during periods of market stress as indicated by relatively positive and high values of CSSD.

Rather, their results were more in line with the predictions of rational asset pricing models, which suggest an increase in CSSD between a security's returns and average portfolio returns during periods of market stress (Christie and Huang, 1995). Additionally, the authors found lower CSSD values when returns were in the extreme 5% tails of market returns than in the extreme 1% tails. This indicates that rational asset pricing theory is more pronounced at the extreme 1% tails than at the 5% tails of market returns. Christie and Huang (1995) also extend their returns analysis from daily data to monthly data so as to not neglect herd formation or dissolution over longer time intervals. They find that CSSD values are higher for monthly price data than they are for daily data, and attribute this result to the increased time available for investors to make decisions, resulting in a higher likelihood of deviation of equity returns from the portfolio average (i.e. more dispersion and less herding). For the authors, this observation conveys that herding is more of a short-lived phenomenon.

Hwang and Salmon (2004), contrary to Christie and Huang (1995), assert that confining herding to periods of market stress assumes that herds cannot form during seemingly normal market scenarios. They cite a case of NASDAQ, which represents a portion of the stock market, experiencing large price movements, while the overall stock market did not reflect any notable changes. Hwang and Salmon (2004) argue that definitions of market stress are also subjective, which could result in varied results across different implementations of Christie and Huang's (1995) method. Additionally, they believe it is important to distill "spurious herding," which results from collective actions taken by investors based on changes in fundamentals, from the herding resulting from investors suppressing private information (Bikchandani and Sharma, 2001). To address this concern, Hwang and Salmon (2004) condition their model on changes in an asset's fundamentals, allowing them to distill spurious herding from overall herding observed in returns data. Additionally, Hwang and Salmon (2004) warn that the possible correlation between CSSD and time series volatility makes it difficult to distinguish herd effects from volatility effects (Hwang and Salmon, 2004). Applying their method to the US and South Korean stock markets, they found evidence of herding during both rising and falling markets. Notably, they assert that market crises actually serve as correctional events that drive market prices towards their efficient levels (Hwang and Salmon, 2004). Similarly, the authors attribute the tendency of herds to weaken before a market crisis manifests and pursue a "flight to fundamentals" to Christie and Huang's (1995) inability to detect herds during periods of peak market stress, i.e. the 1% tails of Christie and Huang's (1995) returns distribution. Essentially, Hwang and Salmon (2004) find that herding decreases before a market downturn. Please refer to Appendix A for more information on Hwang and Salmon's (2004) methodology.

Chang, Cheng, and Khorana (1999) expand Christie and Huang's methodology by three measures: they use the Cross Sectional Absolute Deviation (CSAD) with a non-linear returns parameter, differentiate herding between developed and developing markets, and analyze changes in herding following the liberalization of Asian markets. Including a non-linear returns parameter can reveal any additional interaction between the CSAD and market returns otherwise overlooked in the linear case, i.e. herding may be increasing at a decreasing rate or vice versa. Finally, the authors conduct their analyses for both a bull market and bear market case in order to detect any asymmetry in herding between those two scenarios. Using the CSAD, they found no herd consistent behavior in developed financial markets, namely the U.S., Hong Kong, and Japan, which is consistent with Christie and Huang's (1995) results. However, significant non-linear herding was detected in developing markets, specifically South Korea and Taiwan, which the authors attribute to investors basing their decisions on macroeconomic factors in lieu of complete firm specific information in these countries. The latter point is significant; nascent markets lacking complete and equally distributed information seem to cultivate herd behavior. Notably, CSAD values increased at a higher rate in an improving market than they did during declining markets, which indicates that herding decreased at a higher rate in up-markets than during down markets. Please refer to Appendix A for more information on Chang, Cheng, and Khorana's (1999) methodology.

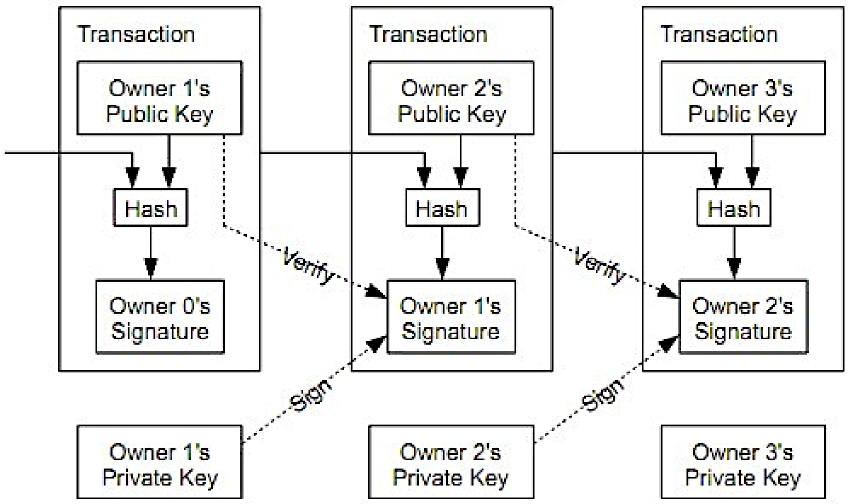
Caparrelli, D'Arcangelis, and Cassuto (2004) apply the methods from Christie and Huang (1995), Hwang and Salmon (2004), and Chang, Cheng, and Khorana (1999) to the Italian stock market. The authors studied price movements of 68 large-cap stocks and 83 small-cap stocks over a 13 year period. Using Christie and Huang's (1995) CSSD method, they found no evidence of herding during extreme market conditions (1%, 5%, 17% upper and lower tails of the returns distribution), which is consistent with Christie and Huang's (1995) observations. Next, the authors reformulated dispersion using the CSAD during both the bull-market and bear-market case, as prescribed by Chang, Cheng, and Khorana (1999). In this case, they found positive and significant coefficients for the linear parameter for both the bull-market and bear-market cases, where the linear bull-market coefficients were larger than their bear market counterparts. This indicates higher dispersion during rising markets than during falling markets. However, if the non-linear parameter is negative and significant, then we can say that herding is present, since the CSAD is increasing at a decreasing rate as market returns become more extreme. The authors do find negative and significant coefficients for the non-linear parameter, which indicates herding in large-cap and small-cap stocks, as well as the global portfolio consisting of both of large-cap and small-cap stocks. Finally, using Hwang and Salmon's (2004) approach, they found that herding is subject to significant variation over time, and the extent of herding is typically larger for small-cap stocks than for large-cap stocks. Herding tends to form more gradually in the small-cap subsample, while it develops more rapidly in the large-cap sample. They note the increase in herding in the Italian stock market beginning in December of 1998 of their sample, which has some consistency with Hwang and Salmon's (2004) finding that herding typically peaks at the end of bull markets and decreases before an imminent crash.

Tan et al. (2008) follow Chang, Cheng, and Khorana (1999), using CSAD to detect herd behavior in the Chinese stock market. As the authors explain, the Chinese Stock market is divided into two classes: A shares, which allow for individual investors to purchase stocks, and B shares, which can only be purchased by institutional investors. This is a valuable opportunity for research, since individual investors are generally less knowledgeable and more capital restricted than institutional investors. The authors exploit the difference in share class to distill differences in herd formation between the two groups, which can help outline key differences in their respective behavioral tendencies. Their key findings include that CSAD values tend to be larger for extended time intervals, such as monthly data, and are lower for weekly and daily data. Note that this is consistent with Chang and Huang (1995), where CSSD values were lower for daily returns data than for monthly returns data. Furthermore, CSAD values are notably higher for class B shares, which are purchased by institutional investors, than for class A shares, which are purchased by individual investors. The authors note that this could be attributed to the informational advantage that institutional investors have over individual investors, which allows them to stay somewhat ahead of the curve and reallocate their assets. Meanwhile, the individual investors may be far more sensitive to signals from others' trading behavior, and respond based on their observations of such information.

Bitcoin and Blockchain Technology

A brief note on how Bitcoin and Blockchain technology function is important to clarifying the important distinctions between Bitcoin, fiat currencies, and equities, as is necessary for later discussion. As outlined in its white paper by Nakamoto (2008), Bitcoin is a self-regulating, peer-to-peer transaction system that eliminates the need for financial intermediaries and counter-parties, shifting complete control and anonymity to its users. The Bitcoin network is comprised of a globally distributed set of nodes, also known as miners, which expend time and energy to crack cryptographic puzzles, called proof-of-work, to mine more Bitcoin. Nodes are incentivized to mine Bitcoin by being awarded small amounts of it when they solve cryptographic puzzles, as well as through transaction fees. The puzzles must be solved in order for a transaction to be processed and added to the transaction chain. The network is virtually secure from attack since copies of the transaction ledger are distributed and stored remotely on all nodes in the system, and nodes have to agree on one version of the transaction chain. The likelihood that an attacker could race an honest network node and modify the Blockchain decreases exponentially as the length of the Blockchain increases (Nakamoto, 2008). In effect, as transactions are processed and added to the existing chain, the network actually becomes more secure. Bitcoin achieves decentralization, privacy, and security using Blockchain technology. A model of Bitcoin's Blockchain is shown in Figure 4. Figure 4 illustrates how transactions are sequentially processed and linked together in a chain by nodes on the network. Each user has a unique private key, which is a randomly generated number, and a corresponding public key.

Figure 4 Bitcoin Blockchain Model



Source: Nakamoto (2008)

A user's public key is essential to validate that they indeed initiated a transaction or are the recipients of a transaction. Suppose a user wishes to purchase an item and sends the seller some amount of Bitcoin. The sender uses his private key to sign off and encrypt the transaction, which is broadcasted to the network. The only way to decrypt the sender's transaction is to validate that the public key corresponds to its private key, which is the work of the network nodes (Berentsen and Schar, 2018).

It is clear that Bitcoin offers many favorable characteristics as a means of exchange; however, there is no shortage of skepticism about its adaptation. As Huberman et al. (2017) show, without sufficient congestion, i.e. transaction volume on the Bitcoin network, nodes' expected return on processing transactions decreases, resulting in their departure from the network. As the number of active nodes decreases, the network security decreases, and users will be less willing to transact, which threatens to further decrease transaction volume. The latter exemplifies a technical challenge for maintaining Bitcoin's long term success. Numerous public figures in government and financial services have denounced Bitcoin, and expressed a lack of confidence in its ability to effectively address the requirements of scalable currency. Notably, the Reserve Bank of India, India's central bank, has banned its use, citing that there are various risks associated in dealing with virtual currencies (Reserve Bank of India, 2018).

Undoubtedly, government regulation and opinions expressed by officials and leaders in industry will impact Bitcoin's price. The essential point is that this market is not nearly as ordered in terms of clarity of information and future regulation as are other markets, like conventional fiat currencies. To this point, there is still much debate on the classification of Bitcoin into an existing asset class, like currencies or commodities. An investigation of Bitcoin's public ledger by Baur et al. (2018) shows that a third of Bitcoin is held by investors who never use it to transact for goods and services, while a much smaller segment of users actually use it as they would a traditional currency. The authors have several classifications for how they define an investor versus a normal user, see Appendix C for more information.

Chapter 3

Research Methodology

Christie and Huang's Approach to Detecting Herding

This paper follows Christie and Huang (1995)'s method of using the Cross-Sectional Standard Deviation (CSSD), also referred to as dispersion, as a proxy measure to detect changes in investor herding during periods of market stress, i.e. time instances with abnormally high or low price movements. Following literature from behavioral economics and social psychology, Christie and Huang (1995) define herding as an investor's tendency to suppress his/her private beliefs and make decisions based on observations of others' actions. In theory, as Christie and Huang (1995) postulate, the result of such behavior should manifest itself in the form of market consensus, where the deviation between individual returns and overall average market returns should be relatively small. Determining the CSSD for each time interval (e.g. daily, weekly, monthly) in the time series is a simple and intuitive method for quantifying how an individual asset's returns move relative to the average returns of the portfolio.

Christie and Huang (1995) believe that herds are most likely to form during periods of abnormal market conditions, which for the purpose of their analysis were defined as extreme price movements of the equities included in their portfolio. The fundamental idea is that during periods of market stress, investors enter a panic mode and adopt a belief that the market must have information they themselves do not, leading them to condition their decisions on observations of other investors. Likewise, when the market is undergoing abnormal price movements, Christie and Huang (1995) expect the herd mentality to proliferate, resulting in lower dispersions. The authors concede that their hypothesis is contrary to the predictions of rational asset pricing theory. Under rational asset pricing models, extreme market events result in increased dispersion between individual equities and the market/portfolio's returns since each security has a unique sensitivity to market events (Christie and Huang, 1995). Christie and Huang (1995) define dispersion using the following formula, which again, is simply the cross-sectional standard deviation of individual equity returns relative to the portfolio at time *t*.

Cross Sectional Standard Deviation

$$\boldsymbol{S_t = \sqrt{\frac{\sum_{i=1}^{n}(r_{i,t} - \bar{r}_t)^2}{n-1}}}$$

*, where **(i)** indexes an equity in the portfolio, and **(t)*** indexes time.

To detect herd formation during periods of market stress, Christie and Huang (1995) regress dispersion on extreme market returns. The effects of extreme market returns on dispersion are isolated through dummy variables for abnormally high or low returns, which are classified as either the top or bottom 1% or 5% of the returns distribution. The following describes their model.

Dispersion (S_t) Regressed on Market Returns – Equation (1)

$$\boldsymbol{S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t}$$

α Represents the average dispersion in portfolio returns between the two extreme tails

$\boldsymbol{D_t^L = 1}$ If portfolio returns on day *t* are in the <u>lower tail</u> of the returns distribution

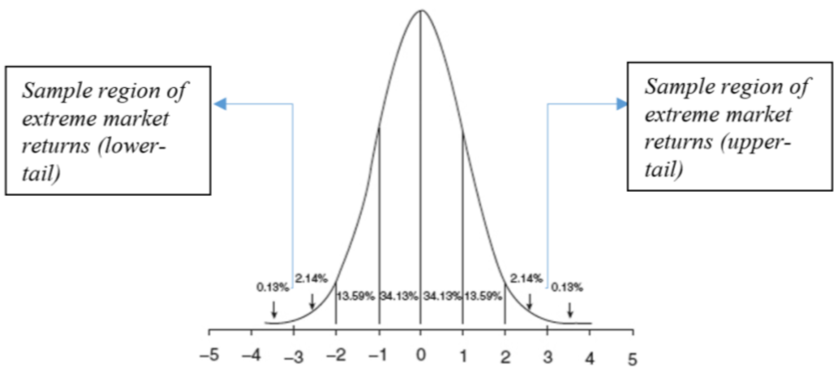
$\boldsymbol{D_t^L = 0}$ Otherwise

$\boldsymbol{D_t^U = 1}$ If portfolio returns on day *t* are in the <u>upper tail</u> of the returns distribution

$\boldsymbol{D_t^U = 0}$ Otherwise

Negative values for $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ imply $\boldsymbol{S_t}$ decreases when returns are extreme, which is indicative of herding since dispersion between individual equity returns and market returns is decreasing. Rational asset pricing would expect $\boldsymbol{\beta_1}$ and $\boldsymbol{\beta_2}$ to be positive, since it predicts that dispersion should actually increase during periods of market stress.

Figure 5 Standard Illustration of Normal Distribution



Source: Salkind (2010)

Visually, as shown in Figure 5, Christie and Huang (1995) are interested in capturing the effects of returns in the extreme tails (1% and 5% criterion) of the returns distribution on dispersion.

In context of Christie and Huang's (1995) hypothesis, the regression in equation (1) should produce negative coefficients for both dummy variables. This would indicate a decrease in dispersion, i.e. an increase in herding, when price returns are abnormally low or high. Positive coefficients would reflect the opposite case, which supports the rational asset pricing theory that dispersion increases, i.e. herding decreases, with abnormal price movements. Lastly, it could also be the case that herding manifests itself asymmetrically, such as when one coefficient is negative and another is positive. This could happen when herding increases during extreme negative price movements (i.e. $\boldsymbol{\beta_1}$ is negative), while decreasing during extreme positive price movements (i.e. $\boldsymbol{\beta_2}$ is positive), or vice versa. Christie and Huang (1995) further investigate the asymmetrical case by comparing their estimates for dispersion with those predicted by a rational asset pricing model. This step is beyond the scope of this analysis; however, it is interesting to note that Christie and Huang (1995) found convincing evidence in favor of rational asset pricing as the magnitude of market downturns increases. In any case, the magnitude and directionality of the herding coefficients is the most important output from this analysis, and reveal key insights about investor behavior during market stress.

Adaptation of Christie and Huang's Method

Although for the purposes of their analysis Christie and Huang (1995) use price data on conventional equities, their methodology can still offer valuable tools to identify herd behavior in the cryptocurrency market. Limitations caused by this adaptation are discussed in the next section.

Similar to Christie and Huang (1995), this paper is interested in isolating the effects of extreme price movements on herding in the Bitcoin market. In addition, this paper also seeks to isolate the effects of herding before and after the introduction of Bitcoin Futures on December 17, 2017, which coincides with Bitcoin's peak price. Isolating the effects of extreme market returns before and after futures will reveal differences, if any, in investor herding during Bitcoin's bullish phase and its subsequent bearish crash phase. Again, this is made possible by the subsequent decline of Bitcoin's value following the introduction of futures contracts.

These regressions are conducted individually on three portfolios: a pure cryptocurrency portfolio, a pure fiat currency portfolio, and a mixed portfolio consisting of both cryptocurrencies and fiat currencies. The purpose of constructing multiple portfolios is to identify any possible links between investor behavior in fiat currency markets and cryptocurrency markets, and make an effort to quantify any relationship between the two. Additionally, applying this methodology to a conventional and well understood asset like fiat currencies can offer some level of standardization, since cryptocurrencies are relatively nascent. Likewise, since the same regression is run on all three portfolios, the only changes in model coefficients should be driven by the nature of the respective market being investigated.

Additionally, Christie and Huang (1995) find significant differences and valuable insights from running their regressions on both daily and monthly price data on the same portfolio, since herd behavior is shown to change as the period of observation changes. Since cryptocurrencies are relatively young, monthly price data is limited and results in numerous regression issues and limits test power. An additional issue encountered was multi-collinearity resulting from limited observations of the dummy variables following the introduction of futures. To solve for this and still achieve variation in time intervals, daily and weekly price data are used instead. Multi-collinearity was addressed by redefining the upper 1% tail following the introduction of futures using the price data specific to that period.

The regression of dispersion on market returns during periods of stress is identical to that outlined previously and in Christie and Huang (1995). However, the regression used to test for changes in herding before and after the introduction of futures is different, and involves two additional dummy interaction variables that allow for time-splitting. This is noted in equation (2) on the next page.

Dispersion (S_t) Regressed on Market Returns Before and After Futures Contracts – Equation (2)

$$\boldsymbol{S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \beta_3 (D_t^L \times Time) + \beta_4 \left(D_t^U \times Time\right) + \epsilon_t}$$

α Represents the average dispersion portfolio in returns between the two extreme tails

$\boldsymbol{D_t^L = 1}$ If portfolio returns on day *t* are in the lower tail of the returns distribution

$\boldsymbol{D_t^L = 0}$ Otherwise

$\boldsymbol{D_t^U = 1}$ If portfolio returns on day *t* are in the upper tail of the returns distribution

$\boldsymbol{D_t^U = 0}$ Otherwise

$\boldsymbol{Time = 1}$ If the time, t $t \geq December\ 17, 2017$

$\boldsymbol{Time = 0}$ Otherwise

This regression is only applied to the daily and weekly data for the pure cryptocurrency portfolio and the mixed cryptocurrency-fiat portfolio, since the futures contracts are specific to Bitcoin.

Assembly of Dataset

As outlined in the regression methodology, the primary goal of this analysis is to use the cross-sectional standard deviation as a proxy measure to detect herding. Given the nature of this regression, it is important to maximize the number of observations so as to allow for a sufficient number of instances where the market is experiencing extreme positive and negative swings in asset returns. In addition to having sufficient time series observations, it is also valuable to apply the regression to a standard portfolio of fiat currencies to compare to a pure cryptocurrency portfolio. Lastly, a mixed portfolio consisting of both cryptocurrencies and fiat currencies can help to control for any interactions between the two markets, despite their fundamental drivers being very different.

The pure cryptocurrency portfolio consists of daily price data for 19 cryptocurrencies chosen based on their market capitalizations. Price data were collected from coinmarketcap.com, which also provided information on market capitalizations. The cryptocurrencies are not weighted by their share of overall portfolio market capitalization. The cryptocurrencies included in the portfolio are Bitcoin (BTC), Ripple (XRP), Ethereum (ETH), Bitcoin Cash (BTC), Stellar (XLM), EOS (EOS), Litecoin (LTC), Tether (USDT), Cardano (ADA), Monero (XMR), Dash (DASH), NXT (NXT), Doge Coin (DOGE), Tron (TRON), IOTA (IOTA), NEM (NEM), NEO (NEO), Ethereum Classic (ETC), and ZCash (ZEC). It is assumed that a high market capitalization indicates investor and public confidence in the cryptocurrency, and their willingness to use it either for transactional and speculative purposes. Bitcoin is the oldest of these currencies, and so it has the most available price data. Some cryptocurrencies, for example Tron, were introduced as late as September, 2017, but quickly rose to prominence. In order to justify the cross-sectional standard deviation, only price data following April 1st, 2015 were used in the regressions. Around this time, most of the cryptocurrencies in the portfolio had been introduced, and thus can be used to calculate more convincing values of the CSSD.

The pure fiat currency portfolio is mainly constructed of globally dominant currencies, denominated in U.S. dollars, from high GDP countries; however, some low profile currencies were also included as an attempt to balance the portfolio and better reflect global price movements. Data were collected from the Federal Reserve Bank of St. Louis FRED exchange rate data. The currencies in the portfolio are the U.S. Dollar (USD), Japanese Yen (YED), British Pound (GBP), Swiss Franc (CHF), Canadian Dollar (CAD), New Zealand Dollar (NZD), Chinese Yuan (RMB), Indian Rupee (INR), Brazilian Real (BRL), and the Thai Bhat (THB). Although data were available since as far back as the year 2000 between all of the currencies in the fiat portfolio, the regression was also restricted to time periods after April 1st, 2015. This constraint maintains consistency with the time period used for the pure cryptocurrency portfolio.

The mixed fiat-cryptocurrency portfolio is a merged set of all the currencies included in both the pure cryptocurrency portfolio and the pure fiat currency portfolio. The purpose of creating a merged portfolio is to allow for regression outputs to show any effects that the fiat currency markets could have had on cryptocurrency markets. For example, since many cryptocurrencies are denominated in dollars and other major global currencies, a significant change in the price of a US dollar could affect the relative price of Bitcoin. Again, the regression was restricted to time periods after April 1st, 2015.

All raw price data across the three portfolios were collected as daily prices. Before applying the regression model, weekly price data were generated using STATA by finding prices at the beginning and end of 7 day periods. Weekly data were then stored separately for analysis. For both daily and weekly price data, returns were calculated using the following formula.

Returns Calculation

$$\boldsymbol{r_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}}}$$

*, where **(i)** indexes an equity in the portfolio, and **(t)*** indexes time.

Limitations of Available Data and Regressions

There are some key limitations of both the data used in this analysis and the regression models applied to understand it. The principal distinction between this analysis and that of

Christie and Huang (1995) is that the latter focused specifically on equities and this analysis focuses on cryptocurrencies. Equities, which represent ownership of small portions of companies, bear significant differences from currencies. One difference is that investors purchase equities for dividends and voting rights, while a currency actually allows for transactions between holders for goods and services. Moreover, this analysis is interested in cryptocurrencies, which themselves have several fundamental differences from conventional currencies. As mentioned earlier, Baur et al. (2018) find that a significant portion of Bitcoin is held by investors, not those using it for transactions, which differentiates it from a classical currency.

Furthermore, compared to Christie and Huang (1995), who use 26 years of equity price data for their daily NYSE and Amex data and 63 years of monthly data for NYSE firms, this analysis is restricted to a little more than 3 years of data. As discussed in the assembly of data section, cryptocurrencies are very young and the immediate consequence is a lack of significant historical data. A consequence of a limited time series is that there will be less observations of exceptionally high and low market returns for which the CSSD to be regressed upon. Another effect was multiple collinearity issues between the explanatory variables, which were periods of market stress, on CSSD. This was solved for by restricting the data in equation (2) to the 5% and 10% extremes in order to collect enough observations of extreme price movements. As mentioned by Hwang and Salmon (2004), the definitions of market stress are very subjective and can change over time as a market develops. This is important to keep in mind while comparing the results of this analysis to those discussed in the empirical literature review who also apply Christie and Huang’s method. Another important point that Hwang and Salmon (2004) consider is incorporating the effects of changes in fundamentals on herding. They incorporate the dividend price ratio, relative treasury bill rate, term spread, and the default spread to account for macro-economic impacts. This is difficult to emulate for Bitcoin since its fundamentals are difficult to estimate, and also because attempts to link its performance to macro-economic factors would be shallow due to the limited understanding we have to date on this relationship.

Some final effects on the results not captured could be new regulations, speculation in news media on Bitcoin, hacks of cryptocurrency exchanges, etc. These variables are not controlled for, and so can have possible explanatory impact on returns behavior throughout the time series.

Chapter 4

Herding Analysis Results

Dispersion and Market Stress Model Results

Table 1 Dispersion Regressed on Market Stress (Daily Price Data)

Panel A: Pure Cryptocurrency Portfolio

	1% Criterion			5% Criterion			10% Criterion		
Model Variable	α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
Coefficient	.0532375	.0272729	.3501702	.0488883	.0113108	.1274128	.0464311	.0102389	.0788908
t-statistic	42.93	1.77	16.99	39.93	1.93	21.70	34.77	2.35	18.88
P > $\vert t \vert$	0.000	0.077	0.000	0.000	0.054	0.000	0.000	0.019	0.000

Panel B: Pure Fiat Currency Portfolio

	1% Criterion			5% Criterion			10% Criterion		
Model Variable	α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
Coefficient	.0006797	.0107764	.013591	.0006049	.0073404	.0068246	.0004975	.0059672	.0057659
t-statistic	17.80	11.12	16.20	16.54	15.89	19.50	14.84	23.49	25.55
P > $\vert t \vert$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel C: Mixed Cryptocurrency and Fiat Currency

	1% Criterion			5% Criterion			10% Criterion		
Model Variable	α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
Coefficient	.0437154	.0439546	.2854483	.0392017	.0270396	.128772	.0364041	.0221904	.0835849
t-statistic	44.93	4.55	29.54	38.42	6.09	29.01	32.26	6.57	24.74
P > $\vert t \vert$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Regression coefficients are specific to equation (1) $S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t$, *see regression methodology section for additional information on model parameters.*

The results of running the regression from equation (1), which focuses on identifying changes in dispersion during periods of market stress, are shown in Table 1 and Table 2. Table 1 displays regression coefficients for daily returns data, while Table 2 shows the regression coefficients from weekly returns data.

To clarify, the 1%, 5%, and 10% criteria correspond to the upper and lower tail regions of the returns dispersions. A 1% criterion captures the most extreme upward or downward movements in market returns, while the 5% and 10% are relatively less extreme.

Beginning with Panel A in Table 1, which consists solely of cryptocurrencies, results show that all of the regression coefficients are positive across the 1%, 5%, and 10% criteria. Aside from the beta coefficients for the lower tail of the 1% and 5% criteria, all other coefficients are significant at the 95% confidence level. Notably, the coefficients for the upper tails of the distribution are all larger than those representing the lower tails. In all cases, the positive coefficients show that dispersions are increasing during periods of market stress; however, dispersion tends to increase much more significantly when the returns are positive and extreme, i.e. the upper tails. This is significant, for example, the ratio of the increase in dispersion during extreme positive returns to extreme negative returns in nearly 13:1, and falls to around 12:1 and 7:1 for the 5% and 10% criteria respectively. Lastly, a comparison of the coefficients between the three criteria show that dispersions increase as the market returns become more extreme.

Panel B studies the impacts on dispersion for the portfolio of fiat currencies. The results are similar to those form Panel A, and all of the coefficients are significant at the 95% confidence level. In comparison to their corresponding values in Panel A, the coefficients in panel B are much smaller, indicating that the magnitude of increases in dispersion for fiat currencies are smaller than for cryptocurrencies. An additional comparison of the constants in the regressions between Panel A and B show that, on average, dispersion is much lower in the fiat currency portfolio than the cryptocurrency portfolio.

Panel C addresses the interaction between cryptocurrencies and fiat currencies through a joint portfolio of returns data. Again, all coefficients are positive and significant at the 95% confidence level across the three market criteria. The magnitude of coefficients is far more comparable to that seen in the cryptocurrency portfolio than in the fiat currency portfolio. As also observed in Panel A and Panel B coefficients, dispersions in Panel C are the highest at the 1% criteria and decrease sequentially for the 5% and 10% criteria.

Observations from the weekly data, as shown in Table 2 below, reveal important differences that arise from changing the observation interval. Referring first to Panel A, dispersion coefficients across the lower tails of the 1%, 5%, and 10% returns distributions are negative, while the coefficients on the upper tail are positive. Negative dispersion coefficients indicate the presence of herd behavior; however, the coefficients for the lower tails are not statistically significant at the 95% level, which decreases confidence in indicating herd behavior during extreme negative returns for weekly data. Additionally, dispersion coefficients are larger than they were for daily data in Panel A from Table 1, indicating that dispersion is larger in week to week observations than day to day time intervals.

Panel B from Table 2 is very consistent with Panel B from Table 1. All dispersion coefficients are positive and significant at the 95% confidence interval across 1%, 5%, and 10% criteria. Additionally, as observed in Panel B from Table 1, dispersions tend to increase as the market undergoes more extreme price movements. Coefficients are again larger for the weekly returns data than they were for daily data in Panel B from Table 1.

Interestingly, Panel C from Table 2 consists of all positive coefficients on dispersion as well. Since Panel C data is a combination of both cryptocurrencies and fiat currencies, the effect of conjoining the datasets removed the herding observed in the lower tails of the cryptocurrency portfolio presented in Panel A. Additionally, dispersions are higher, as observed earlier, during periods of extreme positive returns in prices as opposed to when they are extreme negative returns. All coefficients, excluding the ones corresponding to the lower tail of the returns distribution are statistically significant at the 95% confidence interval.

Table 2 Dispersion Regressed on Market Stress (Weekly Price Data)

Panel A: Pure Cryptocurrency Portfolio

	1% Criterion			5% Criterion			10% Criterion		
Model Variable	α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
Coefficient	.1611568	-.107198	1.462245	.148596	-.061212	.4816058	.1440665	-.057776	.3205651
t-statistic	16.80	-1.13	10.92	14.63	-1.39	10.40	12.97	-1.74	9.20
$P > \lvert t \rvert$	0.000	0.260	0.000	0.000	0.166	0.000	0.000	0.084	0.000

Panel B: Pure Fiat Currency Portfolio

	1% Criterion			5% Criterion			10% Criterion		
Model Variable	α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
Coefficient	.00383	.0180301	.029289	.0034632	.0151371	.0179354	.0032066	.010694	.0148333
t-statistic	13.02	3.33	10.79	12.00	5.00	11.69	10.96	6.08	11.45
$P > \lvert t \rvert$	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel C: Mixed Cryptocurrency and Fiat Currency

	1% Criterion			5% Criterion			10% Criterion		
Model Variable	α	β_1	β_2	α	β_1	β_2	α	β_1	β_2
Coefficient	.1349299	.0449398	1.252943	.1204299	.0106379	.4091461	.1111828	.0063557	.2454023
t-statistic	16.95	0.70	11.33	14.42	0.34	11.45	11.54	0.25	9.51
$P > \lvert t \rvert$	0.000	0.485	0.000	0.000	0.737	0.000	0.000	0.806	0.000

Notes: Regression coefficients are specific to equation (1) $S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \epsilon_t$*, see regression methodology section for additional information on model parameters.*

Dispersion and Market Stress Before and After Introducing Futures Model Results

The next segment of results is derived from equation (2), which distinguishes herding during periods of market stress before and after the introduction of Bitcoin futures contracts. Table 3 below displays regression coefficients from daily returns data, while Table 4 shows the corresponding coefficients for weekly data. In comparison to Table 1 and Table 2, there are only two panels in Table 3 and Table 4 since the futures contracts were specific to Bitcoin and not the larger currency market. Please refer to the methodology section for more additional details.

Table 3 Dispersion Regressed on Market Stress Before and After Futures Introduction (Daily Price Data)

Panel A: Pure Cryptocurrency Portfolio

	5% Criterion				10% Criterion		
Model Variable	Coefficient	t-statistic	P > $\|t\|$	**Model Variable**	Coefficient	t-statistic	P > $\|t\|$
α	.0494809	39.92	0.000	α	.0471227	33.92	0.000
β_1	.0238865	3.60	0.000	β_1	.0200148	4.02	0.000
β_2	.1790304	30.19	0.000	β_2	.113435	24.47	0.000
β_3	-.0249599	-2.27	0.023	β_3	-.0223249	-2.67	0.008
β_4	-.1455689	-10.68	0.000	β_4	-.0873653	-9.14	0.000

Panel B: Mixed Cryptocurrency and Fiat Portfolio

	5% Criterion				10% Criterion		
Model Variable	Coefficient	t-statistic	P > $\|t\|$	**Model Variable**	Coefficient	t-statistic	P > $\|t\|$
α	.0392017	39.49	0.000	α	.0364041	32.84	0.000
β_1	.0321758	5.60	0.000	β_1	.0265974	6.44	0.000
β_2	.154345	31.40	0.000	β_2	.0992922	26.24	0.000
β_3	-.0114745	-1.36	0.175	β_3	-.0115686	-1.80	0.073
β_4	-.1074065	-10.89	0.000	β_4	-.0622367	-8.64	0.000

Notes: Regression coefficients are specific to equation (2) $S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \beta_3(D_t^L \times Time) + \beta_4(D_t^U \times Time) + \epsilon_t$, *see regression methodology section for additional information on model parameters.*

In reference to Panel A from Table 3, the dispersion coefficients before the introduction of futures are positive for both the lower and upper tails of the 5% and 10% criteria, while dispersion coefficients after the introduction of futures are negative. All coefficients are significant at the 95% confidence interval. The earlier observation indicates the presence of herd consistent behavior following the introduction of futures contracts trading when the market is experiencing extreme negative returns. As was observed in Table 1 and Table 2, the magnitude of dispersion is higher Panel A of Table 3 for the upper tails. Furthermore, Panel A of Table 3 affirms again that dispersions tend to be higher at the more extreme 5% criteria than at the 10% criteria.

Shifting to Panel B, the negative dispersion coefficients marking the period after the introduction of futures contracts still persist into the mixed portfolio of cryptocurrencies and fiat currencies. Except for the dispersion coefficients for the lower tail of the distribution after futures trading began, all other coefficients are statistically significant. The pattern of dispersion being greater for the upper tails of market returns than the lower tails, as well as for the 5% criteria as opposed to the 10% criteria still persist in Panel B.

Table 4 on the following page is the final regression in this analysis, and displays the results from using weekly data as opposed to daily time periods. An immediate distinction between Table 4, Panel A results and Table 3, Panel A results is that the dispersion is negative for the lower tail of returns distributions before the introduction of futures. This is in addition to the post-futures coefficients being negative as well. This indicates that herding was present in the lower tail prior to futures, and increased in intensity following the introduction of futures. There is an issue of statistical significance in Panel A, where only the constant and the dispersion coefficient corresponding to the upper tail of the returns distribution before futures are significant. This is potentially a reflection of lowered test power resulting from limited dummy variable observations for the lower tail of the distribution.

Table 4 Dispersion Regressed on Market Stress Before and After Futures Introduction (Weekly Price Data)

Panel A: Pure Cryptocurrency Portfolio

5% Criterion				10% Criterion			
Model Variable	Coefficient	t-statistic	P > $\|t\|$	**Model Variable**	Coefficient	t-statistic	P > $\|t\|$
α	.1512149	15.69	0.000	α	.1457705	13.28	0.000
β_1	-.0435051	-0.72	0.472	β_1	-.0318914	-0.71	0.480
β_2	.6015137	13.43	0.000	β_2	.374754	10.72	0.000
β_3	-.0277591	-0.34	0.734	β_3	-.036441	-0.59	0.556
β_4	-.2229564	-1.86	0.064	β_4	-.1036682	-1.14	0.255

Panel B: Mixed Cryptocurrency and Fiat Portfolio

5% Criterion				10% Criterion			
Model Variable	Coefficient	t-statistic	P > $\|t\|$	**Model Variable**	Coefficient	t-statistic	P > $\|t\|$
α	.1159551	17.76	0.000	α	.1090811	14.45	0.000
β_1	.0415188	0.77	0.440	β_1	.0108883	0.30	0.761
β_2	.5102748	16.21	0.000	β_2	.3375591	13.30	0.000
β_3	-.0305914	-0.49	0.624	β_3	-.0051471	-0.12	0.907
β_4	-.2297787	-3.34	0.001	β_4	-.1518549	-3.03	0.003

Notes: Regression coefficients are specific to equation (2) $S_t = \alpha + \beta_1 D_t^L + \beta_2 D_t^U + \beta_3(D_t^L \times Time) + \beta_4(D_t^U \times Time) + \epsilon_t$, *see regression methodology section for additional information on model parameters.*

Looking at Panel B in Table 4, the results are more consistent with those observed in the daily data since the only negative dispersion coefficients are those corresponding to the period after futures were introduced. Again, the negative coefficients indicate that herding increased in the period after futures. Furthermore, the dispersions in the upper tail are larger than those in the lower tail across both the 5% and 10% criteria. Additionally, the dispersion coefficients are also larger for the 5% criteria than they are for the 10% criteria, which reaffirms that dispersions are increasing as the intensity of market stress increases. With the exception of the dispersion coefficients corresponding to the lower tail before futures, and the coefficient for the lower tail after futures, all other coefficients are significant.

Chapter 5

Interpretation of Findings

This study was separated into two empirical analyses; the first analysis measured the effects of extreme market returns on herding, and the second analysis measured herding during periods of market stress with the extra consideration of the effect of futures trading on herd behavior.

The results of the first analysis have many similarities to results from Christie and Huang (1995). With respect to the first analysis, herding was not detected during periods of market stress for the cryptocurrency, fiat currency, and mixed cryptocurrency-fiat currency portfolios. Furthermore, individual cryptocurrency returns actually deviated from their market portfolio to a much greater extent during periods of extreme positive market movements, consistent with the rational efficient market hypothesis. The primary conclusion from these results is that herding is not a concern during extreme price movements for Bitcoin. The failure to detect herd behavior at extreme conditions may be an implication of Huang and Salmon's (2004) criticism, where the authors detect herding during periods not characterized by market stress. A comparison between the daily and weekly data reveals that dispersion increases as the time interval increases. As Christie and Huang (1995) postulate, this could be a result of investors incorporating more information into their decisions, the effects of which materialize over longer periods. This result is consistent with results observed in Caparelli et al. (2004) and Tan et al. (2008), who also detect higher dispersions as the time interval increases. Essentially, investors are less likely to herd as the time period increases. As noted earlier, there is an indication in weekly returns data that investors are herding during extreme negative price movements. This coefficient is not statistically significant, possibly because there are not enough instances of extreme negative returns during this period to justify this relationship. However, it is noteworthy.

The results from the second analysis are more nuanced and important to answering the question about whether herding was the cause of Bitcoin's steep decline. Across both time daily and weekly data, the introduction of futures decreased dispersion for both the lower and upper tails of the returns distribution. Notably, herding was detected following the introduction of futures contracts for the pure cryptocurrency portfolio. This applied to both the 5% and 10% criteria. It is important to note that herding was only detected in the lower tail and not the upper tail of the returns distribution following futures trading. This suggests investors have a higher propensity to herd, following the introduction of futures, when the market is experiencing large negative price movements. Herding was no longer detected for the mixed portfolio case. With respect to weekly returns data, the model indicates that investors exhibited herd behavior when market returns were negative before the introduction of futures, and herding further increased after they were introduced. The issue is that these coefficients do not satisfy the 95% confidence level, however, the repetition of the trend towards herding during extreme negative price movements is interesting to note. Again, herding was not observed in the mixed portfolio, although it is clear that dispersions decreased following futures trading.

The daily data from Table 3 seem to be the most significant results to this analysis, both in terms of statistical significance, as well as in terms of offering a strong explanation of investor behavior in response to futures. Table 3 results showed that herding was present in daily returns data when returns were extremely negative. With respect to theory, initial price devaluations driven by futures trading from pessimists could have been exacerbated by investors' tendency to herd when market returns are extremely negative. In relation to Abreu and Brunnermeier's (2003) model, the evidence from this study suggests that futures could have been the exogenous event at time $\bar{\tau}$ that began Bitcoin's price decline. Taking from Banerjee's (2002) claim that herd behavior is rational, and setting that in the context of Abreu and Brunnermeier (2003), it is reasonable to conclude that rational herding could have accelerated Bitcoin's bear market following the introduction of futures contracts. As Banerjee (2002) also notes, as investors continuously incorporate others decisions into their own decisions, the inherent value of this information decreases over time, which is threatening to overall market health.

The challenge is that there should have been some level of herding observed during the period leading to its peak value, however the data do not indicate herding before futures. In effect, there could have been non-herd related market characteristics of investor decision making that led to Bitcoin's steep price increase. What this analysis can conclude is that herding was present when daily returns were extremely negative following the introduction of futures contracts. It is also significant that dispersions consistently increased when market returns were positive and extreme, which is in line with the rational asset pricing hypothesis. This is not necessarily a result of asymmetric distribution of information, since we should expect a poor information landscape to be defined by more herding, as Chang et al. (1999) observe in developing Asian markets.

Given the results of this study, it is not conclusive that herding was the fundamental driver of Bitcoin's steep price increases, although herding was observed for negative daily returns after the introduction of futures. This conclusion is made in the context of the limitations of Christie and Huang's (1995) methodology, as discussed in the limitations section. It is possible that herding could be observed to a greater extent when controlling for Bitcoin's fundamentals, such as changes to its technology or macroeconomic events, and during periods not characterized by market stress. It is also possible that herding could be more apparent when Bitcoin's time series is divided into a bull market phase and a bear market phase, as Caparelli et al. (2004) do for the Italian stock market.

Further research should incorporate the effects of transaction volume on Bitcoin's network, as well as price volatility to study how these varied from before and after futures trading began. Additionally, possible implications from news events and google search term popularity can serve as proxy measures of Bitcoin's popularity and propensity to attract investment. Lastly, it would be valuable to see how the mix of institutional and individual investors changed before and after the introduction of futures. While futures contracts allow greater participation from institutional investors, it would be interesting to model how institutional investment in actual Bitcoin, as opposed to derivatives, would affect the market. This investment is currently limited due to Bitcoin's limited history, market maturity, and developing regulatory landscape, among other factors.

Appendix A

Additional Information on Alternate Measures of Herding

Hwang and Salmon (2004)

The authors developed a new measure of herding using cross-sectional dispersions that incorporate factor sensitives of the equities being studies. Their approach is also able to discern herding caused by changes to the equities fundamentals from herding driven by the suppression of investors' own beliefs. They specifically study the US and South Korean stock markets. The herding parameter used by Hwang and Salmon (2004) is summarized and simplified in Caparelli et al. (2004), and is shown below.

$$H(m,t) = var\ c\left(\frac{\beta_{imt} - 1}{\sqrt{s_i^2 S^m}}\right)$$

Where:

$H(m,t)$ represents the herding parameter

β_{imt} represents the stock i's beta at time t, where β_{imt} is also classified as a parameter given by a Capital Asset Pricing Model (CAPM) in equilibrium. The CAPM is shown below:

$$E_t(r_{it}) = \beta_{imt} E_t(r_{mt})$$

s_i^2 represents variance in the beta of the stock

S^m represents variance in market

Low values of $H(m,t)$ indicate the presence of herding, while higher values are far less convincing about the presence of herd behavior. The information above is summarized from both Hwang and Salmon (2004) and Caparelli et al. (2004), please refer to their papers for more in depth discussion of methodology.

Chang, Cheng and Khorana (1999)

As mentioned in the paper, Chang, Cheng and Khorana (1999) use the Cross Sectional Absolute Deviation (CSAD) as a way to measure deviation of individual stock returns from market returns. To detect any important trends in asymmetrical herding, the authors split their regressions into the up-market and down-market cases. Similar to the CSSD, positive and significant CSAD values indicate herd consistent behavior. The authors' equation for the expected CSAD and model regressions are shown below.

Expected CSAD

$$\frac{\partial ECSAD_t}{\partial E_t(R_m)} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m| > 0$$

Up-Market

$$CSAD_t^{UP} = \propto + \gamma_1^{UP}\left|R_{m,t}^{UP}\right| + \gamma_2^{UP}\left(R_{m,t}^{UP}\right)^2 + \varepsilon_t$$

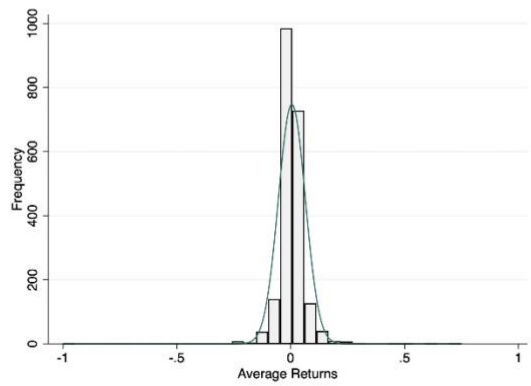
Down-Market

$$CSAD_t^{DOWN} = \propto + \gamma_1^{DOWN}\left|R_{m,t}^{DOWN}\right| + \gamma_2^{DOWN}\left(R_{m,t}^{DOWN}\right)^2 + \varepsilon_t$$

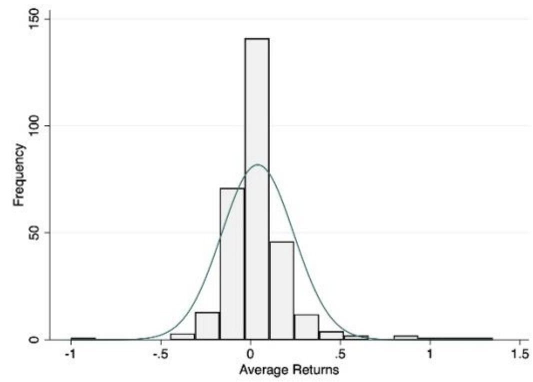
Appendix B

Distribution of Returns

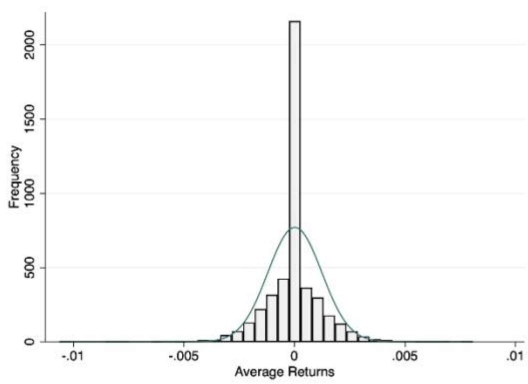
Crypto Portfolio Avg. Daily Returns



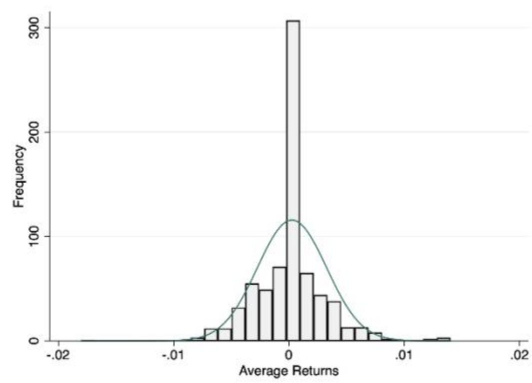
Crypto Portfolio Avg. Weekly Returns



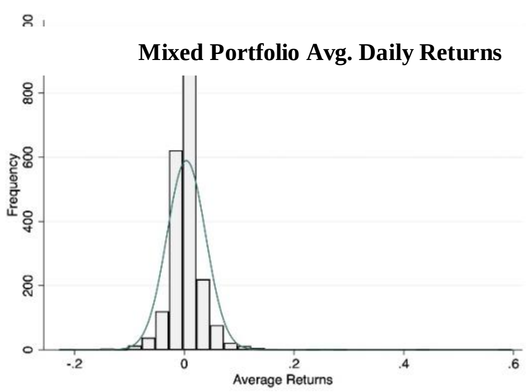
Fiat Portfolio Avg. Daily Returns



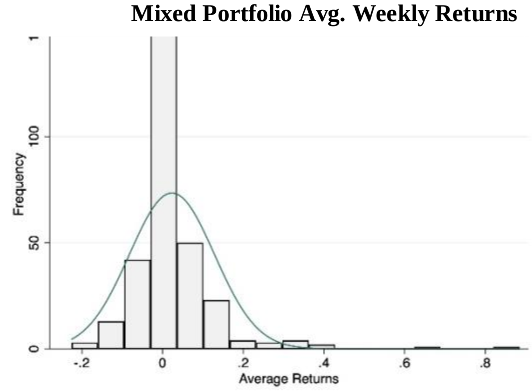
Fiat Portfolio Avg. Weekly Returns



Mixed Portfolio Avg. Daily Returns



Mixed Portfolio Avg. Weekly Returns



Appendix C

Futures Contracts and Additional Terms Specifications

CME Bitcoin Futures Contract Specifications (As of 3/31/2019)

Contract Unit	5 bitcoin, as defined by the CME CF Bitcoin Reference Rate (BRR)
Price Quotation	U.S. dollars and cents per bitcoin
Trading Hours	Sunday - Friday 6:00 p.m. - 5:00 p.m. (5:00 p.m. - 4:00 p.m/ CT) with a 60-minute break each day beginning at 5:00 p.m. (4:00 p.m. CT)
Minimum Price Fluctuation	Outright: 5.00 per bitcoin = $25.00 Calendar Spread: 1.00 per bitcoin = $5.00
Product Code	CME Globex: BTC CME ClearPort: BTC Clearing: BTC
Listed Contracts	Quarterly contracts (Mar, Jun, Sep, Dec) listed for 2 consecutive quarters and the nearest 2 serial months.
Settlement Method	Financially Settled
Termination Of Trading	Trading terminates at 4:00 p.m. London time on the last Friday of the contract month. If that day is not a business day in both the U.K. and the US, trading terminates on the preceding day that is a business day for both the U.K. and the U.S..

Source: Bitcoin Futures Contract Specs - CME Group (n.d)

For more information on settlement procedures, position limits, exchange rules, etc., please refer to the CME Group's website, www.cmegroup.com.

CME Bitcoin Futures Daily Settlement Procedure (As of 3/31/19)

Normal Daily Settlement Procedure

CME Group staff determines the daily settlements for Bitcoin futures based on trading activity on CME Globex between 14:59:00 and 15:00:00 Central Time, the settlement period.

Tier 1: Trades on CME Globex

All contract months settle to the volume-weighted average price (VWAP) of outright trades between 14:59:00 and 15:00:00 Central Time, the settlement period, rounded to the nearest tradable tick. If the VWAP is equidistant between two ticks it will be rounded towards the prior day settlement price.

Tier 2: CME Globex Market Data

In the absence of trades during the settlement period, the contract month settles to the midpoint of the Bid/Ask between 14:59:00 and 15:00:00 Central Time, the settlement period.

Tier 3: Absence of Two Sided Markets

If there are no two-sided markets available during the settlement period in the Lead* month, then the settlement price will be the last trade price (or prior settle in the absence of a last trade price) adjusted to the Bid/Ask if one side is present. Deferred months will settle to the net change of the previous month, adjusted to the Bid/Ask if one side is present.

***The Lead month is the contract expected to be the most active.**

Final Settlement Procedure

Delivery is by cash settlement by reference to the Final Settlement Price, equal to the CME CF Bitcoin Reference Rate (BRR) on the Last Day of Trading.

Source: CME Bitcoin Futures Daily Settlement Procedure

Notes: This information is copied directly from the CME website, please refer to the site for more specific and up to date information regarding settlement procedures and regulations surrounding Bitcoin futures contracts.

Classification of Investor Types by Baur et al. (2018)

Active investor	More than two transactions and only sends Bitcoin in greater than USD$2000 transactions.
Passive investor	More than two transactions and only receives Bitcoin in greater than USD$100 transaction with no sending of Bitcoin; or has made only one receiving Bitcoin transaction of greater than USD$100.
Currency user	Makes more than one transaction, has made both sending and receiving transactions and sending transaction sizes are less than USD$2000.
Tester	Makes only one transaction of less than USD$100.
Miner	A user that has ever mined for Bitcoin as identified by a user receiving newly generated Bitcoin.
Hybrid user	All other users not categorized.

Source: Baur et al. (2018)

Notes: This information is copied directly from Baur et al. (2018), please refer to their paper for more clarification on definitions and additional information on their methodology.

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ACADEMIC VITA

MANAS RAJASAGI

EDUCATION

The Pennsylvania State University | Schreyer Honors College — **University Park, PA**
College of the Liberal Arts — *Graduation May 2019*
Bachelor of Science in Economics

PROFESSIONAL EXPERIENCE

Morgan Stanley — **New York, NY**
Summer Analyst | Finance Division — *Jun 2018 – Aug 2018*

- Collaborated with 4 Summer Analysts and 15 stakeholders from Wealth Management Finance and Technology to perform root cause analyses identifying key data security and accuracy issues concerning P&L and Assets Under Management reports in SAP Business Objects
- Contributed to developing a struggling relationship with a $2 Billion+ WM Client and Firm vendor by analyzing 10 unsuccessful Client submitted procurement proposals and creating 2 pricing analyses which senior procurement management presented to the Client
- Spearheaded R&D of 2 heat-mapped benchmarking analyses of language used by 9 competitor firms to communicate vendor sustainability requirements, which supported MS's efforts in amending sustainability language within future high spend RFPs and SOWs

United Looms – www.unitedlooms.com — **Chester Springs, PA**
Co-Founder & Strategic Partner — *Jan 2016 – Present*

- Invested $40,000 to develop a sustainable garment manufacturing business, providing 400+ foreign customers access to 100+ responsibly-sourced, artisanal Indian fabrics and multiple village-based supplier markets with high geographical, regulatory, and language barriers to entry
- Generated $20,000+ in sales-to-date through feedback-based sales and marketing strategies, with projected revenue growth of 50% over the next fiscal year through planned entrenchment into key existing customer segments and expansion into niche European markets
- Issued $10,000+ in microfinance loans creating 16 new jobs for artisans, fabric weavers, and workers to empower them to directly supply products to United Looms resulting in 30% cost savings for the company via vertical integration of production
- Cultivated strategic relationships with executives from India's largest microfinance bank, Bandhan Bank, and a prominent fashion house, Fabindia, to seek guidance on navigating financing, international supply chains, customer acquisition, and sales strategies

Start NYC — **New York, NY**
Lead Organizer & Company Liaison — *Jan 2017 – Nov 2017*

- Planned a 2 day program with notable, multi-million dollar valuation New York City fashion and e-commerce startups (Buzz Feed, Peloton, Bonobos, Proper Cloth) for 20 members of Innoblue, Nittany Data Labs, and the Schreyer Honors College
- Trained attendees in researching each industry, preparing resumes, questions, and networking skills to expand their professional networks and knowledge of innovative startups transforming various e-commerce markets

Community Kast **Bangalore, India**
Business Development Intern *Jun 2016 – August 2016*

LEADERSHIP & INVOLVEMENT

Innoblue Entrepreneurship Organization **University Park, PA**
President *May 2017 – May 2018*

- Led an executive board of 5 members to identify, plan, and execute 15+ events to drive collaboration, cross-disciplinary learning, and venture creation for Innoblue's 40+ members and Penn State's rapidly expanding entrepreneurship ecosystem
- Identified key tasks and goals for success in discussion with the executive board and delegated deliverables based on each board member's interests, skillsets, desire to take initiative, and ability to effectively execute specific projects
- Forged partnerships with other Penn State organizations (Nittany Data Labs, LaunchBox, HackPSU, Association for Computing Machinery) to train 200+ students in emerging technologies (blockchain, AI, cryptocurrency), ideation, business planning, idea pitching, and seed funding

PSU Quants **University Park, PA**
Vice President *Oct 2017 – May 2018*

- Collaborated with 6 executive board members to determine learning objectives, training plans, and increase membership by 50% in 6 months
- Sharpened data science skills through Data Camp training modules and explored use-cases, strengths, and limitations of different statistical regression models to better understand best practices for extracting insights from large datasets

Alpha Kappa Psi Professional Business Fraternity **University Park, PA**
Philanthropic Chair *Jun 2017 – Dec 2017*

- Engaged the brotherhood of 110 members to take on philanthropic involvement with a local food pantry and home for the elderly to support the community and strengthen the fraternity's philanthropic pillar
- Developed professional, networking, and interviewing skills through mock interviews, resume workshops, professional presentations, information sessions, and alumni outreach
- Corresponded with 2 developers to research market opportunities for adapting Community Kast, a robust and highly scalable mass communication mobile platform, for law enforcement, retail chains, and large communities
- Devised models of how potential consumers may interact with the product, and influenced the creation of the UI/UX interfaces based on researching multiple aspects of design and aesthetics

HONORS, SKILLS, & INTERESTS

- **Honors:** Dean's List (7/7), Schreyer Academic Excellence Scholarship, Department of Economics Honors Program, Chapel Executive Internship Scholarship, Distinguished Student Leader Scholarship
- **Skills:** Microsoft Office, Basic Programming (Python, HTML, CSS), Shopify E-Commerce, Squarespace, Conversational in Telegu
- **Interests:** Motorcycle Riding, Travelling, *Game of Thrones*, Spy Novels, Bollywood, Fashion Business & Strategy, TED Talks