Evaluating Asset Bubbles within Cryptocurrencies using the LPPL Model

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## Abstract

The advent of blockchain technology has created a new asset class named cryptocurrencies that have experienced tremendous price appreciation leading to speculation that the asset class is experiencing an asset bubble. This paper examines the novelty and functionality of cryptocurrencies and potential factors that may lead to conclude the existence of an asset bubble. To empirically evaluate whether the asset class is experiencing an asset bubble the LPPL model is used. The LPPL model was able to successfully identify two of the four crashes within the data set signifying that cryptocurrencies are within an asset bubble.

JEL classification: G12, Z00, C60

Keywords: Asset Bubbles, Cryptocurrencies, LPPL model

Introduction:

One of the most googled terms of 2017 was "How to Buy Bitcoin." There has been an explosive interest in cryptocurrencies to the point where crypto exchanges have in many instances restricted the inflow of new users because of the overwhelming demand. The global cryptocurrency markets are witnessing trading volumes that are comparable to the NYSE (Chaparro, 2017). The exuberance of the asset class can be portrayed by the 2 billion dollar market valuation a cryptocurrency coin named Dogecoin achieve. The coin's name originates from a popular internet meme that parodies the comical appearance of a Japanese dog breed named Doge (Bach, 2018). With several cryptocurrencies having returns of over several thousand percents, such as Ripple which achieved 36,018% gain in 2017 (Wong, 2018), the questions that naturally arise if the cryptocurrency market is in a bubble.

Asset bubbles typically amplify the behavior of herding, moral hazard, and extrapolation to an extreme. Often, however, it is only with hindsight that these behaviors are identified. Identifying asset bubbles becomes problematic when a new revolutionary technology emerges as the valuation of the technology becomes extremely difficult because it is hard to quantify the degree of "disruption" the technology will induce (Cheah & Fry, 2015).

In 2009, a new technology was introduced under the name of Bitcoin. The inner workings of Bitcoin involved complex and groundbreaking cryptographic technology that aimed to disrupt the traditional fiat-based monetary system. Throughout history, the concept of currency has either taken the form of commodity money or fiat money. Commodity money derives its worth by a physical tangible good such as gold and offers a dual utility of being storage of value and a medium of exchange. A fiat currency also offers a storage of value and medium of exchange, but the currency itself has no intrinsic value; as its value originates from the backing of a central authorities' economic power and reputation. The advent of Bitcoin has introduced a new asset class called cryptocurrencies. This new asset class is not tangible and only exists virtually while having no centralized authority backing the intrinsic value. The value of cryptocurrencies originates in the additional level of convenience, convertibility, and security that is provided over traditional fiat currencies (Chiu, 2017). Blockchain technology has the capability of radically changing existing business structures as it combines the workings of computer science, information systems, and applied cryptography.

As alluring as blockchain technology has become, the technology itself is in its infancy and is far from being fully integrated within the current economic structure. Although the blockchain industry itself is still in its developmental stages, the current valuations provide a different perspective. This has brought forth the question of whether a speculative bubble exists within the cryptocurrency sector due to the meteoric rise of the currencies and the extreme volatility that has been accompanied. One of the most promising models that originate from statistical physics has been the log-periodic power law model. The log-periodic power law (LPPL) model seeks to predict the continuation and termination of a bubble.

The current academic literature has been able to find bubbles within the price action of Bitcoin successfully. Current research has primarily fixated investigating asset bubbles within Bitcoin as this is the largest cryptocurrency in regards to valuation. There has not been an extensive investigation into the cryptocurrencies outside of Bitcoin which are named Altcoins. As of 1/10/2018, Altcoins have reached a market capitalization exceeding $400 billion according to Coinmarketcap.com. The purpose of this paper will be applying the LPPL model to the aggregate cryptocurrency market including Bitcoin to determine if the asset class is in a significant asset bubble.

Background:

<u>Cryptocurrencies</u>

For the last few thousands of years, physical tokens have been used as a means of payment and store of value. There are, however, great limitations with the current monetary system in regards to the transferring of money between two parties. The transferring of money is an incredibly complex system that requires a third-party verification to serve as the middleman; to ensure that both parties obtain the agreed amount of money and that it is properly recorded within a ledger. Bitcoin introduces a new technology called blockchain that can greatly improve the current monetary exchange system through properly and securely digitalizing the entire process. Blockchain provides a global ledger that is available to every participant within the respective network, and the collective network verifies each transaction (Hayes, 2017). The security of this system is essentially impenetrable, and this allows for the velocity of a monetary unit to greatly increase – ultimately leading to greater economic efficiency.

The internet is powerful in that enables the spread of information. Unfortunately, the internet can't perform the function of disturbing value such as assets, money, contracts, and votes due to the dilemma of "double spending." Double spending is the problem that users have to ability to make a digital copy of the original item and send this copy as if it was the original digital item. This dilemma would allow for individuals to "double spend." To further understand this key concept, a digital currency wouldn't be feasible since an individual could take the digital currency and send the digital currency to two separate parties at the same time. The sender of the digital currency made a copy and sent it to the two other parties while still retaining the original. Because of this dilemma digital currencies were not plausible until the introduction of the blockchain. Blockchain created a decentralized database where the order of transactions is unanimously agreed upon by everyone involved (Franco, 2015). A blockchain is a decentralized transaction and data management technology that allows its public depository of records to be incorruptible and irreversible. The most basic way to conceptualize blockchain is as a distributed public ledger that contains every single transaction that has been carried out in history. Furthermore, the blockchain is publicly available to everyone involved in the system, and the encryption involved far exceeds any current firewall security system that is utilized by banks or another financial intermediary (Lakhani, 2018).

The concept of blockchain technology came into existence with the introduction of Bitcoin. In 2008, a few weeks following the collapse of Lehman Brothers an anonymous individual under the pseudonym Satoshi Nakamoto released the first decentralized digital currency known today as Bitcoin. Bitcoin operates under the process of validating entries, safeguarding these entries, and finally preserving the historical record. Every bitcoin account has a private key and electronic signature that accompanies each transaction as a verification and security protocol. The verification process is completed once is it established that the sender has actual ownership of the currency and there is a sufficient amount of his account. This is done through an elaborate process involving cryptography where several computational codes are solved. Once the transaction is verified, it becomes a "block," this block is then broadcasted to the massive global ledger that is interconnected with millions of computers around the world. The transaction is distributed using a peer to peer network that is operated by volunteers called "miners." These miners collectively at any given time have a computational power that is 10 to 100 times the capacity of Google (Tapscott, 2016). The miners are responsible for solving a complex computational problem that involves verifying, clearing and storing the block and finally linking it to a preceding block, therefore creating a chain of blocks. The block containing the transaction becomes linked to the blockchain that holds the historical data of every transaction that ever took place. Once the block becomes linked, a specific time stamp is established that completes the transaction. This timestamp is an important characteristic as it ensures that double spending is impossible within the system (Price, 2017).

The miners are the reason the system can function in a decentralized manner, and their work input allows for the global ledger to exist. The efforts of the miners are compensated with Bitcoin every instance a miner verifies, processes and link the blocks to the blockchain. This current blockchain system offers the most advanced level of encryption that is possible. To attempt to hack the system and alter existing data would require the altering of every blockchain in the history of commerce that has been created on millions of computers simultaneously—a task that is almost impossible (Swan, 2015).

The technology behind Bitcoin has been dispersed to other cryptocurrencies called Altcoins. Altcoins are Bitcoin alternatives and use the same or a similar technological foundation. Currently, there are three designations for altcoins. The three designations rely on the hashing algorithms functions and are categorized into SHA-256 alternate cryptocurrencies, Scrypt alternate cryptocurrencies and other **(**Bonneuau et al., 2016)**.** The SHA-256 was originally developed by the NSA and is the protocol that is used by Bitcoin. The Scrypt hashing function provides the same degree of encryption, but the difference lies in the mining capabilities, which is a very technical component and is outside the scope of this paper.

Outside of the technical engineering distinctions of Altcoins, there has emerged different subgroups within the Altcoin arena. The two main categories are split among currencies and utility tokens. Bitcoin is a cryptocurrency; the purpose of the coin is to act as a medium of exchange. Utility tokens greatly differ in that they act as quasi-securities since their purpose to provide a decentralized application. This decentralized application, however, utilizes its tokens (still considered cryptocurrency) to function as a stand-alone economy.

This class of cryptocurrency utilizes the blockchain trust in performing specified functions. Participants that are engaging with the specified function in the decentralized application pay for that service with the underlying cryptocurrency *(Digital Currencies,* 2015). Decentralized applications attempt to create the same services like Uber, Twitter, and Facebook. The distinguishing factor is that all the user information is decentralized. The decentralized component results in no single entity have access to your information, which is not the case with centralized applications such as Uber, Twitter and Facebook. To further illustrate the complexity and variation in the functionality and purpose of utility based cryptocurrencies it is helpful to examine Siacoin.

Siacoin is unique in that the tokens provide a service that aims to compete with the cloud storage industry. Siacoin uses the same basic principles Bitcoin utilizes; but rather than miners solving mathematical problems to be awarded a monetary gain, Siacoin has the miners provide their unused computer storage. Currently, there is a massive amount of latent storage on personal, and business computer’s hard drives and Siacoin aims to use that untapped storage to create a decentralized storage network. To use the Siacoin application, an individual would buy the Siacoin cryptocurrency to rent storage, while miners (providers) of storage would be paid in Siacoin. This Siacoin will act as another form of currency and can be exchanged for any other currency such as Yen, USD, etc. Outside of the added security component within Siacoin’s blockchain, the cost is significantly less than the current cloud storage average (Vorick, 2017).

Investors come into play as there is a belief that as the network grows the value of the currency appreciates due to the increased demand for the currency (Digital Currencies, 2015). This is the general underlying framework of most cryptocurrencies where there exists a blockchain solution that is far more efficient, safe or cost-effective.

Literature Review

Asset Bubbles

The exemplary case of an asset bubble that is repeatedly cited is the Dutch Tulip Mania Craze. The Dutch Tulip Mania focused on the insane price appreciation of tulip bulbs in Europe in the mid-17th century where certain tulips became more valuable than homes. The tulip example provides a very robust framework of what compromises asset bubbles. The fundamental value of the tulips was significantly below the market value; as the tulips provided no source of additional utility outside of an aesthetic perspective. The price appreciation was momentum based and thrived of individual's irrational exuberance. Asset bubbles that solely focus on a particular asset that far exceeds its historical worth with no technological innovation are far easier to identify and understand than "rational" asset bubbles. Rational asset bubbles focus on a revolutionary technology that can significantly affect how a current economy operates. The most recent example is the dot-com bubble; where the appeal of the internet's potential capabilities brought valuations that weren't sustainable in the long run (Bonneau, 2017). The NASDAQ which tracks technology and internet related stocks, towards the end of the 1990's had an average price to earnings ratio of 200. During the dot-com bubble, the funding among venture capitalist and initial public offerings surged from $3 billion to a staggering $60 billion in 1999

(Teeter & Sanderberg, 2017). This rate of growth is simply unsustainable, and that was made apparent as the NASDAQ fell a staggering 78 percent in the following 30 months erasing over $5 trillion in market value. The reoccurring theme among asset bubbles involving revolutionary technology is that market participants fail to critically understand the lengthy process of progression and adoption concerning technology. This hindsight creates valuations that would indicate the technology is fully operational and adopted, while in reality that is far from the case.

The cryptocurrency markets have seen explosive levels of growth that greatly question the sustainability of the asset with regards to price action. Below in figure 1 is a visual representation of the top 10 ranked cryptocurrencies by market capitalization from January 2014 to January 2018. The growth of Bitcoin is spectacular with a 1782% within this time frame. The greatest amount of price appreciation, however, occurred within cryptocurrencies outside of the top 10 ranking cryptocurrencies by market capitalization. While Bitcoin experienced an insane price appreciation of 1782% within this four-year period, the entire cryptocurrency market grew from $10.7B to $600B from January 2014 to January 2018 (coinmarketcap.com) achieving an unbelievable growth rate of 59,900%. In figure 2 below is the growth of the cryptocurrency market from April 28, 2013, to January 11, 2018 index from a starting price of 100. The illustration was constructed from the data set used for the LPPL model, and the y-axis is log scaled to portray the meteoric growth and volatility of the asset class. It is undeniable that the technology behind cryptocurrencies is revolutionary. However a quick analysis of the growth rates within the industry immediately questions the sustainability and intrinsic value of such a market.

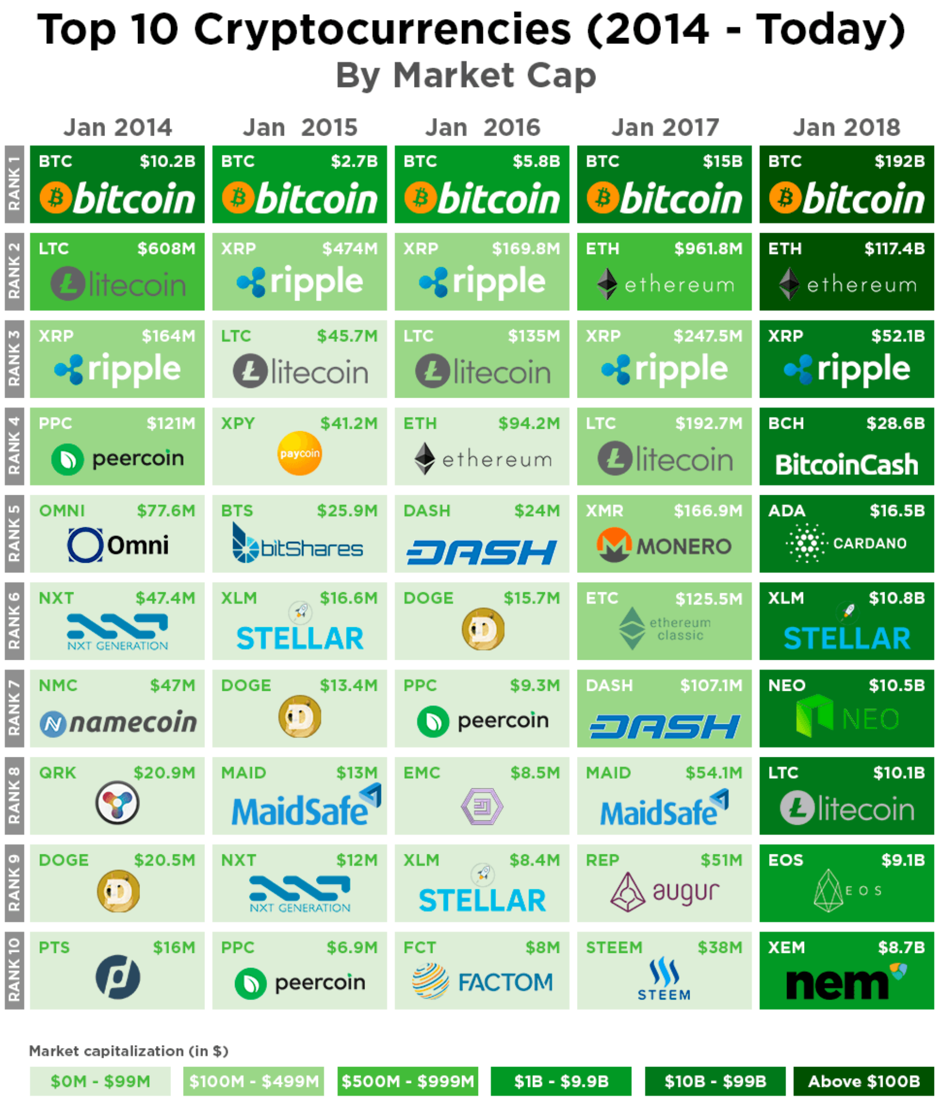

Figure 1

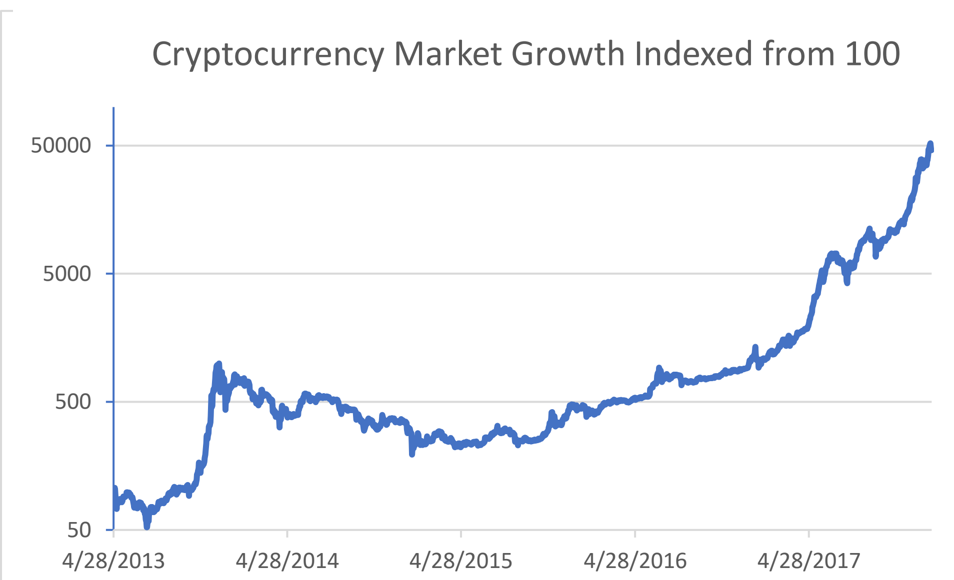

Figure 2

Potential Asset Bubble Factors in Cryptocurrencies

The actual theory behind the cause of the asset bubbles is still heavily debated among economist. Below are some of the main contributors within the cryptocurrency markets that may point to a potential asset bubble.

I. Illiquidity

In US equities there have been several instances of price manipulation within OTC markets. Over-The-Counter markets in the United States are not subject to regulation by the SEC. OTC markets are typically filled with small, illiquid stocks and are subject to manipulation. Because of the liquidity issues with the underlying OTC markets, there is a common illegal practice known as a "pump and dump." The basic premise involves a small group of individuals buying shares that are illiquid and then proceeding to spread false information about how promising the underlying asset is and how the asset will continue to appreciate in price. Since the asset has such low liquidity a small spike in demand will lead to massive price appreciation as inflowing demand significantly overshadows the limited supply. While this is occurring, the original group of participants who bought the shares will slowly unwind their position into the overflowing demand. In the end, the majority of the investors are left with an illiquid asset that continues to fall as the artificial demand ceases and investors come to realize the inaccuracies of the false information that originally prompted the hype. The opposite trend proceeds as investors rush to the exit their position and further contribute to the crash. Massoud et al. (2016) studied this activity within the OTC market and found that companies hire promoters to engage in continuously feeding the demand of the illiquid asset. This practice has seen to be prominent within the cryptocurrency space as several large online messaging groups have engaged in the illegal price manipulation (Williams-Grut, 2017).

Outside of questionable and illegal trading activities, there is also the extreme concentration of ownership within cryptocurrencies. Within the cryptocurrency sector, there is a term coined “whales,” about individuals who own large percentages of the total supply of a given cryptocurrency. Within Bitcoin, currently, 1000 people own 40 percent of the total market supply. Ethereum, the second largest cryptocurrency by market cap has 100 individuals owning 40 percent of the supply. There is even further drastic concentration of wealth in less prominent coins such as Gnosis, Qtum, and Storj. These three coins which are all within the top 100 coins by market cap have a few groups of individuals controlling more than 90 percent of total supply (Kharif, 2017). This creates an environment where cryptocurrency exchanges do not have the appropriate liquidity of a “whale” unloading his shares of cryptocurrencies. Furthermore, such excessive concentration within a small group of individuals creates more opportunities for price manipulation. These two factors of illiquidity may lead to greater price volatility within the asset class and potential of bubble-like price action.

II. Greater Fool Theory

There exists a social phenomenon known as the Greater Fool Theory. Participants within a market comprehend that the underlying asset is overvalued way beyond intrinsic valuations. The participants continue to actively bid up the price of the asset searching for a “greater fool” that will come along and pay a higher price. The foundation of this theory lies on the human bias of overestimating our abilities and having the false belief that there will always be an investor less knowledgeable to serve as the greater fool. This phenomenon seems to be in place within cryptocurrency markets as there is no required registration to partake in most Initial Coin Offerings and exchanges. An Initial Coin Offering is a fundraising mechanism that allows for a new project to sell their underlying crypto tokens in exchange for bitcoin. The idea is similar to an Initial Public Offering where the investors obtain shares of the company. Within an IPO there is an extreme regulatory oversight as well as a review of track record and credibility of the company. A regulatory body greatly investigates detailed information regarding the duration, access, utility of the offering. Most importantly IPOs are only allocated to institutional investors (Geiger, 2017). Within the ICO market, there is no regulatory framework and compliance. Furthermore, the offering is available to anyone willing to invest. The lack of restriction in who can participate leads to the potential of having a massive number of unaccredited investors who do not have the proper understanding and skillset in how financial markets operate.

The inclusion of participants with no little to no prior knowledge of financial markets can lead to cryptocurrencies becoming greatly overvalued as these individuals lack the expertise and skill set to intrinsically price assets within a rational bound. In *The ICO Gold Rush* (Zetzsche et al., 2017) 450 ICOs were investigated by informational accuracy and regulatory compliance. It was found that less than 10 percent of the token acquired by investors had any degree of functionality. Over 90 percent of the tokens acted solely as speculative trading instruments providing no intrinsic value to the investor. Even with the clear concern surrounding the legitimacy and practicality of some of the cryptocurrencies, the ICO volume exceeded $20 billion at the end of January (Zetzche et al., 2017). The potential lack of financial knowledge and due diligence among unaccredited investors has the potential to of creating asset bubble environment. The rise of ICO’s offering purely speculative instruments as examined in Zetzche’s work further portrays this scenario.

III. Bounded Rationality

This theory relies on the belief that the current marketplace where the asset is trading is asymmetrical in information. Thus the individuals purchasing the inflated asset have limited information on how to appropriately price the underlying asset. Due to a lack of resources and skillset leads the participants in misunderstanding pricing models and making suboptimal decisions as limited bounded rationality bounds individuals. Within efficient and rational markets, homogenous goods obey the Law of One Price (LOOP). Cryptocurrencies such as Bitcoin are homogenous in that each Bitcoin is completely identical. Although each unit of Bitcoin is identical, there still exists large price deviations within exchanges. In *Financial Regulations and Price Inconsistencies Across Bitcoin Markets*, Pieters & Vivanco (2017) found that the lack of required ID to open an account greatly contributed to the that significant differences in prices among bitcoin exchanges.

Outside of the Law of One Price dilemma, there has been significant inconsistencies within ICOs. A shocking 31 percent of do not provide any information about the backers of the project. 23 percent of the white papers fail to provide any description of how the project's financials currently stand. Out of the 450 ICOs examined by Zetzche et al. not a single ICO provided the inclusion of an external auditor to verify the claims and facts cited in the documents. The lack of financial information leaves participants with a very limited outlook on the entire project. This issue of bounded rationality results in the potential situations where investors are buying cryptocurrencies on the premise of false information – such a scenario can greatly magnify asset bubbles.

IV. Herding

Herding is a theory that is often the premise of empirical models that attempt to examine asset bubble formations. Due to human nature, there is a natural inclination for individuals to mimic the actions of a larger group. Within the bubble context, this behavior is typically irrational, and the individuals continue the behavior due to the social pressure of conformity. Furthermore, the common rationale that it is unlikely for such a large collection of individuals to be wrong further amplifies the underlying problem (Hanna, 2018).

There is a plethora of theories and phenomenon that attempt to pinpoint the fundamental causation of asset bubbles. The core to understanding asset bubbles, however, relies primarily on valuations. The intrinsic value of an asset relies on the summation of future cash flow which is then discounted to the present day. A problem arises when a new revolutionary technology emerges as it is difficult to assess the intrinsic value as there is no historical data. The new technology brings forth the potential to disrupt the current economic ecosystem due to its innovation. The problem that arises is that growth rate, adoption rate, and several other factors can't be accurately quantified to determine the future cash flows the asset will produce. The large discrepancy in understanding future earnings allows for an extreme valuation to be produced -- this disagreement among pricing typically leads to higher volatility which is represented by beta (Cheah & Fry, 2015). This was one of the main problems surrounding the internet bubble of 2000 as there isn't a fundamental value anchored to the technology and soon unrealistic prices become justified and accepted. Herding is an important component and underlying mechanism behind the LPPL model and will be further analyzed within our theoretical framework.

Several papers that have evaluated Bitcoin and its price action. Malhorta & Maloo (2014) utilized the unit root test in 2013 to conclude that due to the strong explosiveness in the Bitcoin exchange rates there is a reason to believe the asset is in a bubble. Similar results were found by Cheah & Fry (2015) where the bubble component of Bitcoin accounted for 48.7% of the observed price and concluded that the fundamental value of Bitcoin is zero.

In *Econometric Analysis of Bitcoin and its 2013 Bubbles*, Fiser examines the price action of Bitcoin from 2012-2015 using three ARIMA, GARCH, and LPPL models. The ARIMA model was unable to predict future development of Bitcoin price because the ARIMA process had significant conditional heteroscedasticity in the error term. To overcome this issue, Fiser had to adopt the GARCH model. The GARCH process is not stationary as well as the conditional variance did not converge to a constant unconditional variance in the long run. The GARCH process essentially lead to the estimated variances to grow linearly over the time series and when further investigating the data from the GARCH model there are questions whether the model properly captures the variance of the price action. Fiser lastly tested the price data of Bitcoin using the LPPL model and found that the model was most effective in testing Bitcoin due to the extreme volatility and price action. The LPPL model was able to predict a crash on April 2013 accurately, however, failed to forecast a crash on November, 2013 convincingly.

In *Popping the Bitcoin Bubble: An Application of Log-Periodic Power Law modeling to Digital Currency,* MacDonell was able to forecast a crash on December 4, 2013 successfully of Bitcoin using the LPPL model. The model prediction was two days off from the actual crash. Based on the current literature the LPPL model seems to be the predominant method of evaluating asset bubbles within cryptocurrencies.

There has been a considerable amount of literature published on the price action of Bitcoin and the existence of an asset bubble. The current outstanding research has under-emphasized investigating the relationship between asset bubbles and cryptocurrencies outside of Bitcoin. In 2017 13 cryptocurrencies outperformed Bitcoin in percentile gains (Wong, 2018). There has been very limited academic research investigating the asset bubble question among these coins. Rather than focusing on a few popular cryptocurrencies, this paper will aim to analyze the existence of an asset bubble within the aggregate cryptocurrency market. Therefore the total market capitalization of all cryptocurrencies including Bitcoin will be evaluated. The contribution of this research will hopefully provide a broader perspective on asset bubbles and the cryptocurrency asset class as a whole. Such an analysis is useful as it could potentially serve as a benchmark to compare individual cryptocurrencies to the entire asset class to further determine whether an individual cryptocurrency asset bubble is predominately systematic or idiosyncratic in relation to the cryptocurrency asset class.

If the LPPL model does not detect the presence of a bubble, then further investigation can be made into what tangible variables have contributed to the increased price of the cryptocurrencies. Such an outcome would signify that there is a fundamental value associated with cryptocurrencies.

Theoretical Framework

The problem within frameworks when observing asset bubbles is that no specific superior model applies to all asset bubbles. One prominent economist summarized the dilemma as "Econometric detection of asset price bubbles cannot be achieved with a satisfactory degree of certainty. For each paper that finds evidence of bubbles, there is another one that fits the data equally well without allowing for a bubble. We are still unable to distinguish bubbles from time-varying or regime-switching fundamentals, while many small sample econometrics problems of bubble tests remain unresolved" (Geraskin & Fantazzini, 2013, p. 2).

One of the standard econometric models that are typically used when analyzing potential bubble formation is the Autoregressive Conditional Heteroskedasticity model (ARCH). ARCH is a statistical model for a time series of data that aims to describe the variance within current error terms. The ARCH model computation is based on the function of previous time interval error terms. The model is ideal for data sets that appear to be heteroskedastic with periods of volatility followed by a minimal noise among the time series. The ARCH model, however, is based on conditional heteroskedasticity where the periods of high volatility and calm are easily discernable. When evaluating asset bubbles, the periods of volatility do not typically occur at set times – greatly limiting the functionality of ARCH within asset bubbles (Fiser, 2015).

To overcome the limitations of ARCH, a generalized ARCH (GARCH) model is typically utilized within financial time series as it assumes the randomness of the variance process will vary with the variance (Brooks, 2014). The limiting factor with GARCH models is that they are not technically stochastic as the volatility is pre-determined from the previously given values. This key distinction is what makes the LPPL model most suitable when examining asset bubbles is that the model uses a stochastic approach. A non-stationary stochastic random walk component overcomes the time-varying drift. Johansen & Sornette (2001) conclude that the GARCH model performs well in predicting variations among normal trading periods, however insufficiently establishes fluctuations within large crashes. The advantage of using the LPPL model when compared to other models is that the LPPL model aims to predict the continuation and termination of the bubble within the same estimation (Geraskin, 2013).

The *Law Periodic Power Law* approach was developed by Johansen et al. (2000) to detect asset bubbles. The model has had incredible success in the past and has been able to demonstrate that about two-thirds of crashes are endogenous. One of the creators of the model, Didier Sornette, has set up a Financial Crisis Observatory to identify financial asset bubbles within stocks, bonds, and commodities. The FCO has been successful in predicting the asset bubbles within the US real estate bubble in 2006, Oil bubble in 2008 and the Chinese stock market bubble ex ante (Sornette et al., 2015).

The log periodic power law model evaluates the price action of an asset following a periodic log oscillation and predicts the crash of the asset. The main idea behind the model is that it is impossible for an asset to exhibit exponential price growth continuously and therefore the increasing oscillation within the price action of the asset provides for an indicator of a subsequent crash. The first use case of the LPPL model was within earthquakes and predicting within a probability band when the rupture will occur. The model measures a precursor signal and assumes that there is a positive feedback loop where each following precursor signal puts further pressure on the entire system until the system finally reaches the critical point. In the context of earthquakes, the critical point would be rupture itself. The probability of the critical point occurring is dependent on the separating spaces, time distances and the magnitude of each precursor (Sornette & Sammis, 1995).

The LPPL model does, however, contain limitations. There are six parameters that need to be found for the model. Finding the seven parameters is difficult, and there is a chance that the optimization algorithm that is utilized to find the parameters are trapped in a local minimum without finding the actual global minimum. Without the proper calibration of all the parameters the predictive power of the model greatly decreases. The LPPL model also needs a long-range time series to model the dynamics of the price movements. Therefore its functionality is greatly diminished when evaluating short-term price movements (Gustavsson et al., 2016).

LPPL Model

The first assumption that the model makes is the asset is purely speculative and pays no dividend and ignores interest rates, risk aversion, information asymmetry and market-clearing conditions. Following this assumption, the martingale hypothesis can be inferred where

$$E_t[p(t')] = p(t) \qquad (1)$$

The martingale hypothesis is assumed since the model is a stochastic process and t' is greater than t. The $p(t)$denotes the price of the asset at time t. Since cryptocurrencies don't produce any dividends, the fundamental value of $p(t) = 0$. Using this equality, any $p(t)$ value greater than zero signifies a bubble, since this is the deviation from the fundamental value which was established at zero through the equality (Johansen, 2000).

The next process in understanding this framework is examining the agents participating. Within this framework, there are two types of agents. The first group consists of rational agents that have identical preferences and characteristics. The second group consists of irrational agents who exhibit strong herding behavior. All the traders within the system including the rational and irrational agents are connected in a global network, whereas his/her local network influences each participant. The local network of a trader consists of their friends, colleagues and other sources of information concerning the underlying traded asset. The decision of the market participants is based on the opinion of the trader's external local network or from idiosyncratic internal signals. When the internal idiosyncratic signal dominates, there will be randomness and instability within the market as the number of buyers and sellers balance each other out (Sornette et al., 2015). However, once herding becomes prevalent within the system and spreads through the network, the external factor outweighs the idiosyncratic component, and there is a crash within the system. The crash occurs because all the participants have collectively begun to sell. The crash hazard rate is a variable which models the price action and is denoted by $h(t)$. $H(t)$ is the probability per unit of time that the crash will take place. This is in relation likewise to the probability that more agents will assume the sell position than the buy position, which would dictate a fall in price. Within this framework there doesn't have to be just a strong collection force of herding for a crash to occur, rather the crash can begin from an imitative local micro-interaction which leads to a macroscopic effect (Geraskin & Fantazzini, 2013).

Based on the mean field theory, the imitative reaction between traders derives the hazard rate in equation 2.

$$\frac{Dh(t)}{dt} = Ch^{\delta}, \quad \text{with } \delta > 1 \qquad (2)$$

The C is a constant that is greater than 0, and $\delta > 1$ represents the average number of interactions between traders minus one (MacDonell, 2014). As the number of interactions among the participants increases, there is an increased probability of a critical rate occurring as the oscillations movement increases. Through integrating the equation two we are left with equation three where B is a positive constant.

$$h(t) = B(t_c - t)^{-a}, \; a = \frac{1}{\delta - 1} \qquad (3)$$

Equation 3 allows us to derive $t(c)$, which is the critical time of the asset bubble crash. The critical $t(c)$ is unknown however and only defined with probabilistic terms. The model applies a non-zero probability of a crash occurring, therefore a jump process which provides discrete movements is defined as zero before the crash and one after the crash. By ensuring that the martingale condition is still met where t' is greater than t, we can obtain the behavior of the price preceding the crash when the jump process still equals zero. This provides us with the following differential equation:

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$$log \frac{p(t)}{p(t_0)} = K \int_{t_0}^{t} h(t')dt' \quad (4)$$

Equation 4 dictates that as h(t) increases and there is a greater probability of a crash, there must be a faster price increase to constitute the equality within the martingale condition. Logically this is equivalent to a riskier investment demanding a higher rate of return (Johansen et al., 2000). There are two states that the agents within the model can operate either buy or sell.

$$s_i = \text{sign}\left(K \sum_{j \in N(i)} s_j + \sigma \varepsilon_i\right) \quad (5)$$

When S_i is equivalent to 1 the agent is in the state of buying and when S_i is -1 the agent is within the state of selling. K is a positive constant that represents the behavior of the collection of participants and the coupling strength between them providing the degree of imitation among market participants. $N(i)$ is the set of traders who influence the traders and S_j is the current state of the traders. The σ is the tendency of idiosyncratic behavior for all traders and finally ε_i is the random draw from a normal distribution (Geraskin, 2013).

The importance of this equation stems in that the critical time t_c is can be defined when K(t_c) reaches K_c. The behavior can be equated as K_c - $K(t_{c)}$ = constant × $(t_c - t)$. This allows us to solve for the critical point of K_c. The general solution is listed below in terms of hazard rate h(t):

$$h(t) = B(t_c - t)^{-\alpha} + C(t_c - t)^{-\alpha} cos\left[\omega log(t_c - t) + \psi\right] \quad (6)$$

The hazard rate can be generalized to equation six where $\frac{\omega}{2\pi}$ determines log frequency of the oscillation term and ψ represents the phase constant that is moving the oscillation. the log frequency increases significantly when t approaches the critical time. The increase in the hazard rate is a sequence of accelerating oscillations. The hazard rate will reach its maximum near the critical date and provides the log-periodic oscillations. The price action of the underlying asset right before the critical point is summarized below in equation 7.

$$p(t) \approx A + B(t_c - t)^{\beta} + C(t_c - t)^{\beta} \, cos\left[\omega \, log(t_c - t) + \phi\right] \quad (7)$$

p(t)	Price at time t
$\boldsymbol{t_c}$	critical point
$\boldsymbol{\beta}$	the exponential price growth, constraints of {0,1}
$\boldsymbol{\omega}$	the oscillation amplitude with the constraints of {2, 20}
$\boldsymbol{\phi}$	fixed phase constant parameter with of constraint $\boldsymbol{0 < \phi < 2\pi}$
A	price at the critical time p($\boldsymbol{t_c}$)
B	constant embodying the scale of a power law with the constraint < 0
C	constant that captures the magnitude of the oscillation around price growth with the constraint that the absolute value of C must be < 1

This is the Log Periodic Power Law, and it provides the price action growth of an asset when the hazard rate is reached, thus the lead up to a crash. The difficulty of the LPPL model is that there are four linear paraments (A, B, C, $\boldsymbol{t_c}$) and 3 non-linear paraments in $\boldsymbol{\phi}$, $\boldsymbol{\beta}$ and $\boldsymbol{\omega}$. The three non-linear paraments provide for the oscillations of the function and are found through using a through using a search algorithm. This is the main difficulty of the LPPL model is being able to calibrate the non-linear components in relation to past critical points where crashes have occurred.

Due to the difficulty of estimating an LPPL model, Johansen and Sornette (2001) devised an approximation method. Within this method $\boldsymbol{\phi}$, $\boldsymbol{\beta}$ and $\boldsymbol{\omega}$ are chosen as nonlinear parameters, rewriting the LPPL model as:

$$y_i = A + Bf_i + Cg_i, \text{ where } y_i = p(t)$$

Through this approach, we can obtain our linear variables through the ordinary least square method of running multivariable linear regressions. This will allow us to find A, B, and C as they are linear variables. Furthermore, a search algorithm is utilized to find the values of the nonlinear parameters which minimize the sum of squared residuals (Macdonell, 2014).

Data

The main contribution of this paper is that the LPPL model is applied to the entire cryptocurrency market. The main difficulty with this objective is that cryptocurrencies are a very infantile asset class that do not have a standardized index that is properly weighted and representative of the market. Within the equities there are several indices such as the S&P 500 and the NASDAQ that provide for a standardized basket of assets that provide for a proper benchmark and track the cumulative change. Typically these indexes are related to a certain market sector, size and a variety of other possible factors. Indexes provide for a strong baseline in evaluating performance and price action. The lack of an index resulted in having to create from scratch a cryptocurrency market index.

The first stage of obtaining my data was constructing an index that would serve a strong baseline throughout the financial time series. Since there is tremendous volatility within the cryptocurrency markets, I opted not to choose the 100 largest cryptocurrencies as my proxy. The 100 largest cryptocurrencies would greatly fluctuate through the time series with different cryptocurrencies surpassing each other in market capitalization and creating inconsistencies within the time series. Furthermore, this option would be further problematic in formatting the data. To fully capture the price action and obtain a strong baseline, I choose instead to calculate the aggregate market capitulation of all the cryptocurrencies being traded. This method allows for further consistency within the data set but also serves as one of the contributions of this paper as current LPPL research regarding cryptocurrencies has mainly fixated on a single cryptocurrency such as Bitcoin. It is important to note that there is a significant correlation between Bitcoin and Altcoins.

The price data of the cryptocurrency market index was obtained by using a scraper that drew its information from coinmarketcap.com. Coinmarketcap.com was chosen as the source of data due to the credibility of the website and the fact that the website tracks every active exchange and all of the cryptocurrencies being traded. The scraper was built on python and used the sys, re, urllib2, argparse and datetime modules. The scraper takes the average of the open and close price of each currency listed on coinmarketcap.com. The average price is then multiplied by the circulating suppy to obtain the market capitulation. It extracts the data from html format into a csv file format. There was a total of 1,719 observations extracted from March 4, 2013, to January 11, 2018. Within this data, there are 1,398 different cryptocurrenices representing a total of 659,374 price points throughout the time period. For every given date within the time series, there was a summation of the total market capitulization of all 1,398 cryptocurrnecies for the corresponding date. Figure 3 below represents the summary statistics of the data set. Figure 4 provides the price action of the total cryptocurrency time series.

Mean	36,421,442,448
Standard Error	2,293,173,225
Median	7,973,159,853
Standard Deviation	95,076,853,517
Sample Variance	9,039,608,074,647,180,000,000
Kurtosis	28
Skewness	5
Range	827,835,784,466
Minimum	833,662,134
Maximum	828,669,446,600
Sum	62,608,459,568,761
Count	1,719
Confidence Level (95.0%)	4,497,705,615

Figure 3

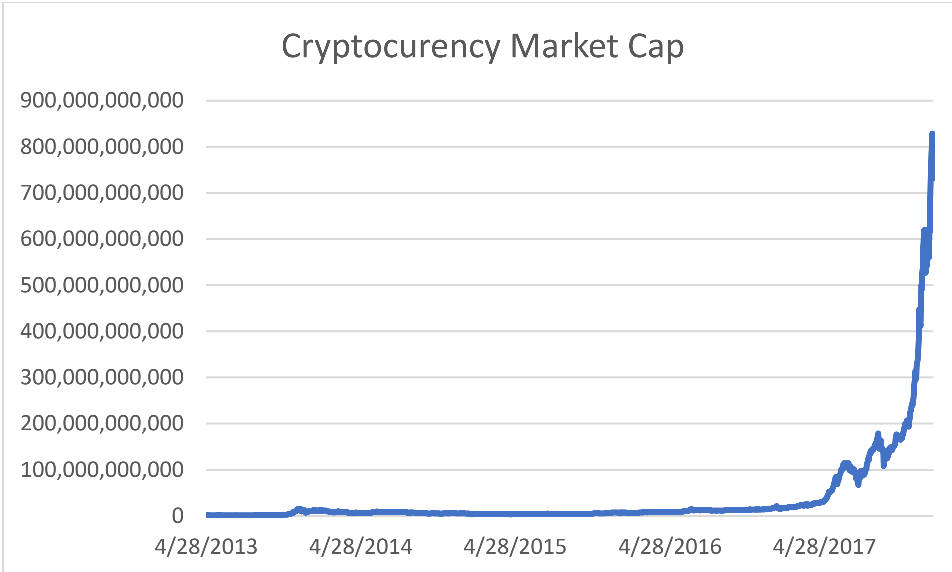


Figure 4

Empirical Specifications and Results

After compiling the data and creating an index that tracks the aggregate cryptocurrency market the next stage was determining the parameters of the log periodic power law model to create a simulation that most accurately portrays the price action. The most difficult component of the LPPL model is finding the nonlinear parameters. The objective in selecting the parameters is to obtain the lowest possible root mean squared error between the data and the LPPL model. The model was written within the computer software R. To find the nonlinear parameters of $\boldsymbol{\phi}$, $\boldsymbol{\beta}$ and $\boldsymbol{\omega}$ a function within R was used called expand.grid which allowed to create a data frame from all the combinations of the supplied vectors. The vectors within this function are the parameter range that corresponds to the theoretical framework developed by Johansen & Sornette (2001). A search algorithm was utilized in finding the three nonlinear parameters with the lowest residual. The search algorithm first ran a global range on all three nonlinear parameters and with each combination of nonlinear parameters proceeded to run a multilinear regression that provided a residual. Eventually, the model becomes fine-tuned as the parameters corresponding to the lowest residual are chosen.

Nonlinear Parameters	Min range	Max range	Interval
$\boldsymbol{\omega}$	2	20	.02
$\boldsymbol{\phi}$	0	6.28	.25
$\boldsymbol{\beta}$	0	1	.01

For the above ranges using the specified intervals, the search algorithm tested a total of 23,331 combinations of $\boldsymbol{\phi}$, $\boldsymbol{\beta}$**,** and $\boldsymbol{\omega}$**.** The search algorithm worked in the following manner; the first combination tested was 2 for $\boldsymbol{\omega}$, 0 for $\boldsymbol{\phi}$ and 0 for $\boldsymbol{\beta}$. Proceeding forward from the first combination the algorithm would then run the program again but changing one of the nonlinear variables by a single unit of the interval. Thus, for the second search the following numbers were inputted into the parameters, 2.02 for $\boldsymbol{\omega}$, 0 for $\boldsymbol{\phi}$ and 0 for $\boldsymbol{\beta}$. Each proceeding search would change one single parameters while keeping the two parameters constant so that the third search would result in 2.02 for $\boldsymbol{\omega}$, 0.25 for $\boldsymbol{\phi}$ and 0 for $\boldsymbol{\beta}$**.** Every search within this process created a multilinear regression to find the linear parameters. The search that provided the lowest residuals were chosen for the linear parameters A, B, and C.

A. Identifying Critical Points

The utility of the LPPL model stems from the fact that the model when properly calibrated has the ability to forecast crashes. One of the common downfalls in fitting the LPPL model is choosing the wrong crash date (critical point). To avoid this potential problem, Bree & Joseph (2013) incorporated the following guidelines when identifying a critical point. The first criteria is that there is a drop in price of at least 25 percent, down to .75 of the peak price. Within the critical point, there has to be 60 days before the peak where there is no value higher than the actual peak. These criteria allow for only the most pronounced crashes to be tested.

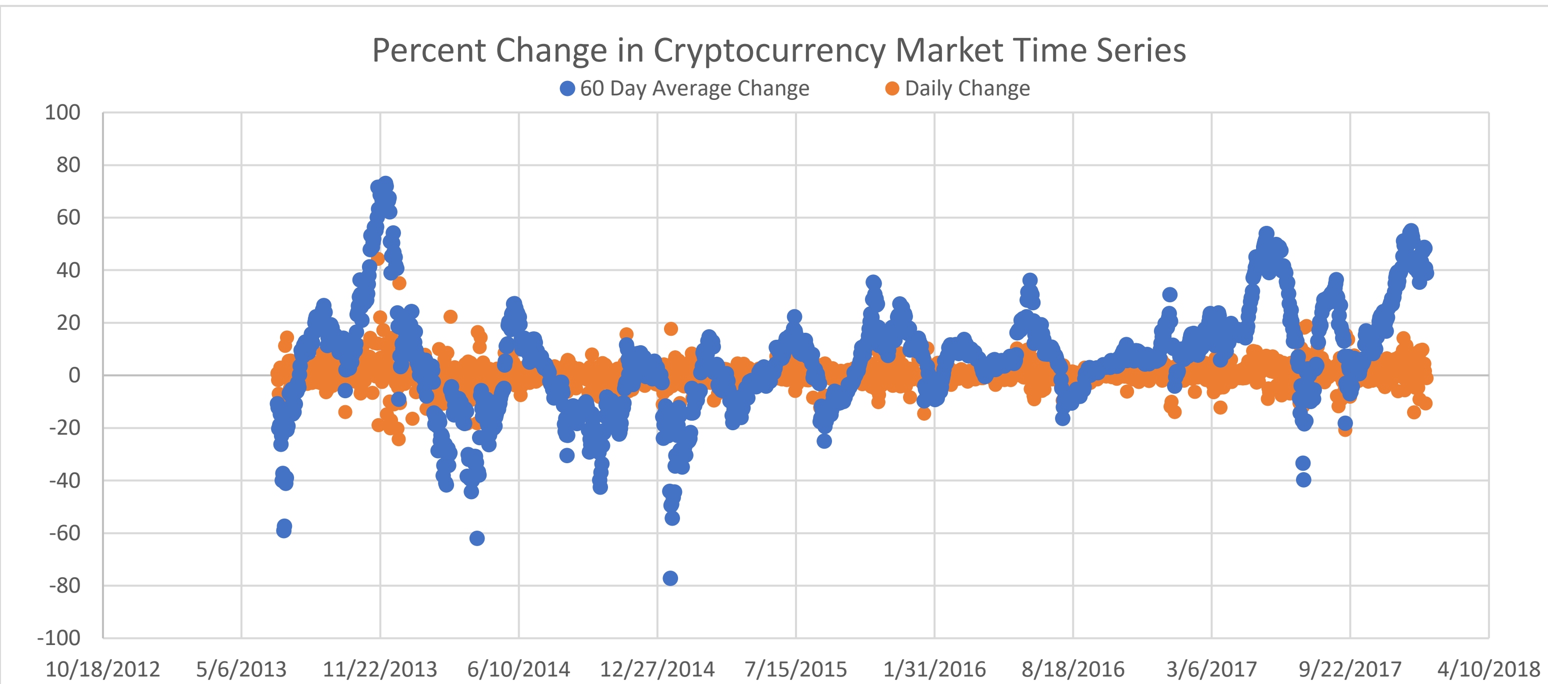


Figure 5

Figure 5 provides a visual representation of the volatility of the cryptocurrency market index with regards to 60-day average and daily changes in percentiles. The critical points that were chosen followed the two guidelines outlined above. Once the critical points were identified the LPPL model is fitted from the beginning of the time series to the day before the critical point.

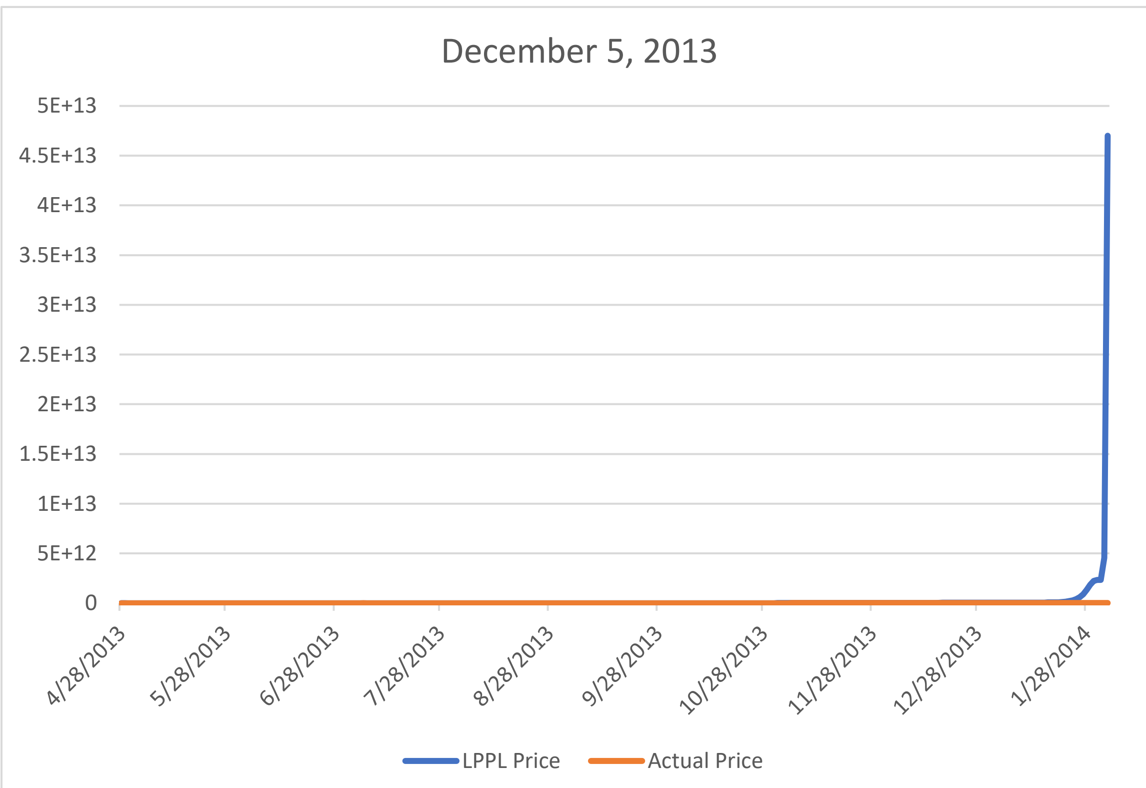
Using the parameters found from the fitting process the LPPL model generates 60 day forward estimates to see if the model was able to predict the critical point accurately. The LPPL model forecasts the price action following the critical point. Below are the critical points that were chosen. The summary statistics of each critical point along with the parameters are referenced in the appendix under critical points statistics.

Critical Points
December 5, 2013
June 17, 2016
January 5, 2017
January 7, 2018

December 5, 2013, was chosen as a critical point as it was the peak price of the time series up to this date. At this data point, the cryptocurrency market cap reached a peak of $15,874,831,048 and proceeded to crash to a low of $6,903,446,929 on December 19, 2013, signifying a drop in the price of 56%. Although there are typically several factors that contribute to a crash one of the reasons for the drastic depreciation in price was due to China's largest cryptocurrency exchange no longer accepting deposits in renminbi (Hern, 2013).

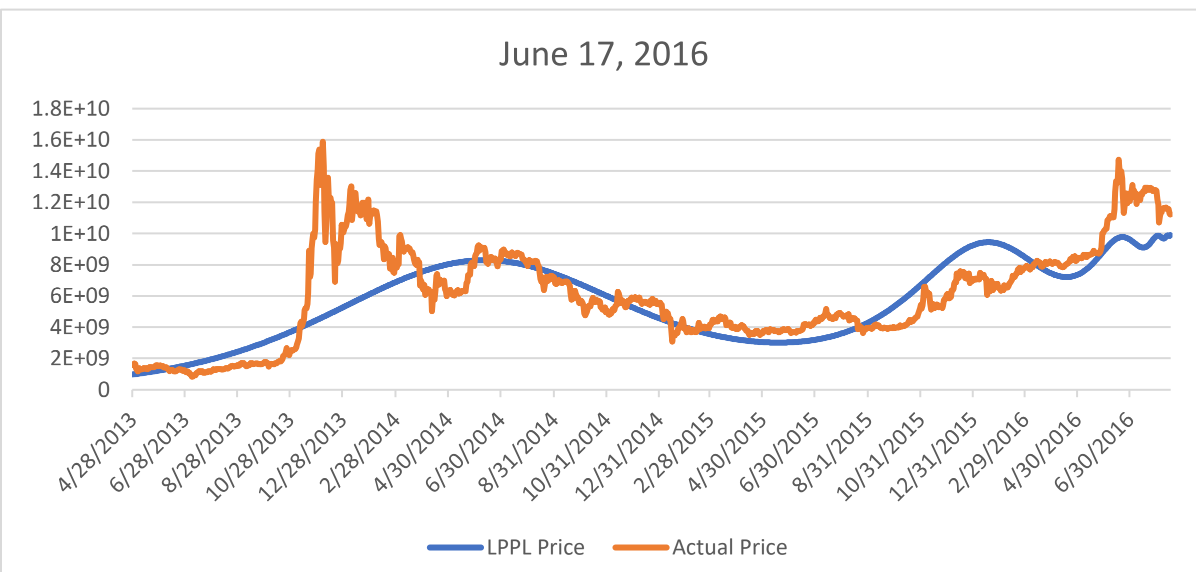
The LPPL model fails to detect this critical point and subsequent crash. The model greatly overshoots the critical point and continues an upward trajectory and continuation of the bubble. Surprisingly the R squared value between the LPPL fit and data set before the 60-day forecast is .93. Although the model seems to be properly calibrated given the high R squared value, the model drastically failed in identifying the crash. This result embodies the considerable difficulties in fitting all of the parameters. One possible explanation for the inaccurate forecast is that there aren't enough data points provided for proper calibration as there are only 200 data points for the time series on December 5, 2013. This is one of the limitations of the model as the predictive power greatly decreases with a smaller data set.

A	B	C	β	ϕ	ω
120.8351	-89.91533	0.5958553	0.02	3.25	2.8



On June 17, 2016, the cryptocurrency market cap hit a critical point at $14,722,699,945 and within the next six days proceeded to crash to a low of $11,027,234,949. The catalyst of the crash was the hacking of DAO (distributed autonomous organization) which held $150 million worth of Ethereum that was raised from the crowdsourcing of ICOs. Due to a technical issue surrounding code a hacker was able to steal $55 million successfully. The event caused a sell-off within cryptocurrencies as the security of the blockchain was questioned (Siegel, 2016). The incident caused a decrease in the price of 25 percent. The LPPL model was accurately able to forecast the crash and predicted the peak critical point four days later on June 21, 2016. The model reached a peak value of $9,777,086,284 at the critical point. This a difference of 33 percent between the actual critical point. It is important to note that although the model wasn't accurate in regards to amplitude, it proceeded to forecast the same price action trend line.

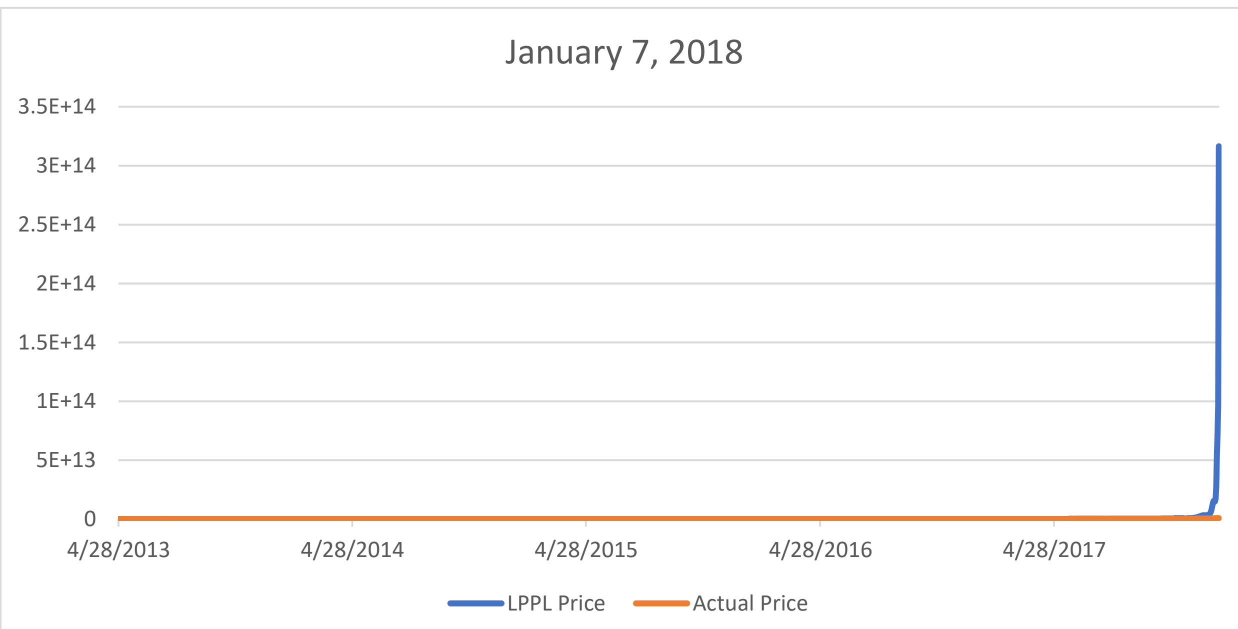
A	B	C	β	ϕ	ω
23.01592	-0.001476193	0.001254859	1	4.75	3.5



The critical peak point of $21,305,249,756 was reached on January 5, 2017. Within the following seven days on January 12, 2017, the cryptocurrency market cap index recorded a bottom price of $14,688,029. The sell-off that resulted in a price decrease of 31 percent is speculated to be linked with China's central bank releasing a statement to investors to exercise extreme caution among participating in cryptocurrencies. This potential catalyst of the crash is further backed up by the fact that the Chinese renminbi had the biggest two day gain ever recorded. It is speculated that the appreciation in renminbi was due to the conversion of Bitcoin back into the Chinese currency (Williams-Grut, 2017). The LPPL model forecasts the same critical crash date as the actual time series. While the actual peak price point was at $21,305,249,976, the model predicted a price of $16,134,318,393 signifying a difference of 24 percent. The divergence in forecasting amplitude may have been a result of the calibration as these parameters had an R squared of .73.

A	B	C	β	ϕ	ω
23.57095	-0.001900589	0.001075538	1	4.75	1.4

The final critical point of the time series was on January 7, 2018 where a peak price of $815,100,000,032 was reached. On January 14, 2018, a low was recorded at $433,553,000,000 consisting of a decrease in cryptocurrency market cap of 47 percent. The massive fluctuation in price was not attributed to a single factor. The LPPL model failed to detect this critical point and greatly overpredicted the peak without forecasting a crash. The parameters produced an R squared value of .86. Thus the fit between the actual data was satisfactory. The same problem was experienced at the first critical point on December 5, 2014. One of the key similarities between the two parameter sets is that both the β is extremely low at .02. β may be the nonlinear parameter that is the limiting factor and needs further calibration. Given that the R square value was relatively high in both scenarios this is not an easy fix as when dealing with six parameters it is difficult to pinpoint causation.



A	B	C	β	ϕ	ω
107.7739	-74.30387	0.2880415	0.02	6.25	5

B. Crash Hazard Rate Analysis

To further investigate the chosen critical points and the corresponding LPPL fit that was calibrated the crash hazard rate was analyzed. The hazard rate provides the probability per unit of time that the crash will take place. Once the LPPL parameters are obtained it is with relative ease that the hazard rate can be computed. As examined in the theoretical framework, equation 9 provides the LPPL model fitting.

$$p(t) \approx A + B(t_c - t)^{\beta} + C(t_c - t)^{\beta} \cos\left[\omega \log(t_c - t) + \phi\right] \quad (9)$$

Equation 10 provides the context of the hazard rate. Based on the work of Sornette et al. (2011) equation 9 can be substituted into equation 10 to provide the following constraint listed in equation 11.

$$Log \frac{p(t)}{p(t_0)} = K \int_{t_0}^{t} h(t')dt' \quad (10)$$

$$b \equiv Bm - |C|\sqrt{m^2 + \omega^2} \geq 0 \quad (11)$$

The constraint must be greater than or equal to zero as the probability of a crash must be within these ranges. Constraint b provides for the crash hazard rate and the variables within the constraint equation are obtained from the process of finding the LPPL parameters. The variable b is then scaled from 0 to 1 to indicate the probability of a crash occurring.

The LPPL model parameters were computed every 60-day period of the data set, in each 60-day interval the search process described above was conducted. Given that the time series of the cryptocurrency market index spans from March 4, 2013, to January 11, 2018, there was a total of 27 sets of parameters created for the 60-day time window of the model. Thus, for each

60-day interval, there was a separately fitted LPPL model within the 60-day time frame. The parameters were then plugged into equation 11 to obtain the corresponding hazard rate of each 60-day time interval. The same process was utilized when computing a 2-day average hazard rate for each of the critical points.

The following table below includes the hazard rates computed for both the global 60-day period and the critical points.

Time	Global Hazard Rate 60 day	December 2013 Hazard Rates	June 2016 Hazard Rate	January 2017 Hazard Rate	January 2018 Hazard Rate
1	0.994582329	0.994542929	0.999219815	0.999681077	0.979985884
2	0.994398643	0.53686037	0.999251078	0.999754221	0.970418496
3	0.994713807	0.983531871	0.999283156	0.999780594	0.97396675
4	0.995000905	0.987691751	0.999316314	0.999807985	0.973851592
5	0.994764941	0.990309332	0.999224572	0.99974256	0.974204488
6	0.994952357	0.991360846	0.999255852	0.999767357	0.971203828
7	0.99513759	0.990671101	0.999288405	0.999792452	0.967683435
8	0.995071004	0.99061799	0.999321889	0.999818416	0.967500828
9	0.974443171	0.99058226	0.99918535	0.999845692	0.959036922
10	0.816068424	0.990877079	0.999215005	0.999873572	0.954257652
11	0.770468608	0.996658138	0.999245451	0.999772538	0.942793692
12	0.719225824	0.996203047	0.99927699	0.999796169	0.942430871
13	0.645257181	0.998786617	0.999361119	0.999820887	0.935859576
14	0.651003773	0.999249171	0.999389722	0.999846282	0.920151546
15	0.712127576	0.999421362	0.999419412	0.999872295	0.911113078
16	0.695785423	0.99908117	0.999450029	0.999899605	0.900040094
17	0.553252052	0.999329675	0.999329675	0.999836701	0.888735139
18	0.263640218	0.999241344	0.999356562	0.999860982	0.874368079
19	0.221240098	0.99952687	0.999384652	0.999886333	0.862960056
20	0.200472737	0.999767357	0.999413855	0.999912487	0.8455757
21	0.128179341	0.999920878	0.999443809	0.999939698	0.829101254
22	0	1	0.999364056	0.99990685	0.809904391
23	0.498632846	0.829485088	0.999390113	0.999931796	0.806122647
24	0.517557486	0.869905532	0.999417179	0.999957276	0.807101151
25	0.420621034	0.942683595	0.999444665	0.999867516	0.80580796
26	0.452810499	0.970352552	0.999324025	0.999887062	0.80774358
27	0.458572294	0.748338381	0.99934733	0.999907366	0.788315098
28		0.408000873	0.999372124	0.999927791	0.807528306
29		0.4294441	0.999396844	0.999949463	0.788526619

30		0.577768376	0.999318058	0.999893781	0.749203108
31		0.633782441	0.999338207	0.999910402	0.749176457
Min	0	0.408000873	0.99918535	0.999681077	0.749176457
Max	0.99513759	1	0.999450029	0.999957276	0.979985884
Mean	0.653999265	0.898193293	0.99933372	0.999853136	0.885957041
Std	0.311131993	0.182216273	7.43327E-05	6.86633E-05	0.077413384
Stde	0.05987738	0.032727009	1.33505E-05	1.23323E-05	0.013903854

The global hazard rate was confined to a 60-day time frame due to computational power constraints as each 60-day parameters results in 23,331 multilinear regressions. To find the hazard rate of the entire time series required 629,937 multilinear regressions. Running a 2-day time frame on the global time series would equate to 20,251,308 multilinear regressions—which is far beyond the scope of my computer's capacity.

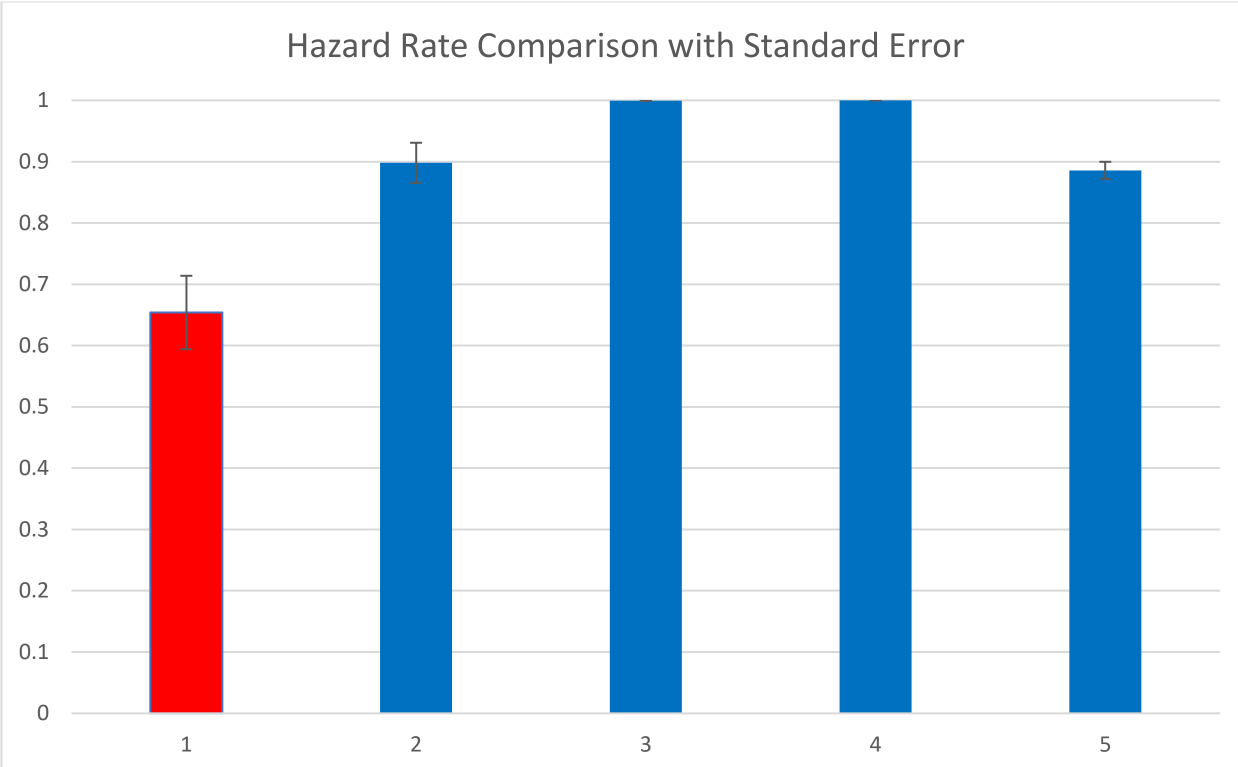
Since the critical points were known within the time series, this allowed the search algorithm to be further granular within the parameters by limiting the time frame to 2 days. The entire search process outlined in empirical specifications was completed using a 2-day window 60 days before the critical point. The 2-day time frame allowed for greater accuracy as the parameters were further calibrated. The obtained parameters for all four critical points are referenced in the appendix under hazard rate parameters section.

Figure 6 below shows the average crash hazard rate of the global LPPL model that used the 60-day time interval along with the critical points that used a 2-day time interval. The global average hazard rate for the time series is .65, while the critical points where the LPPL model identified a crash are significantly higher, this further proves the robustness of the model.

The model was able unable to forecast the critical point for December 5, 2013 and January 7, 2018. The 2-day average hazard rates for these time frames are .89 and .88

respectively. These hazard rates are significantly lower than the hazard rates computed for June 17, 2016 and January 5, 2017. On June 17, 2016 and January 5, 2017 the LPPL model was able to predict the critical point accurately, and as a result the hazard rates are both within the .99 range. The high hazard rates correspond to the fact that the model was detecting a critical point and thus forecasted that a crash was imminent. For the two critical dates where the model failed to identify the crash the hazard rate is lower at approximately .89 as the model forecasted less of a probability that a crash will occur. Given that the model for these critical points continued to trend upwards the lower hazard rates makes logical sense.

To test the statistical significance between the global hazard rate and the critical point hazard rates an analysis of variances was done to test the differences between the means. The summary of the ANOVA test are referenced in the appendix on p.49. The p-value is 2.38^-14 well below the accepted standard of .05. Since the ANOVA test returned an overly statistically significant p-value the Tukey's test was ran to see the differences between the global hazard rate. The results of the Tukey's test are referenced in appendix. Tukey's test returned that the values between the global and all the critical point hazard rates were significantly different.



60-day Average Hazard rate	December 5, 2013 2-day Average Hazard Rate	June 17, 2016 2-day Average Hazard Rate	January 5, 2017 2-day Average Hazard Rate	January 7, 2018, 2-day Average Hazard Rate

Figure 6

Conclusion

The blockchain framework is a revolutionary technology that has the potential to one day greatly disrupt current industries as it aims to bring forth increased convenience, efficiency and security protocols. Cryptocurrencies are the forefront of this innovation and attempt to unlock the full potential of the blockchain. Although the technology behind cryptocurrencies is incredibly enticing, my main hypothesis was that there is a degree of euphoria that is characteristic of an asset bubble. Due to the explosive growth rates of cryptocurrencies, this paper aimed to empirically show that as a whole the cryptocurrency asset class was within an asset bubble. One of the main challenges in reaching such a conclusion was the lack of an index that properly characterized the price action of the entire cryptocurrency market. An index was created that tracked the cumulative change in market capitalization of all cryptocurrencies being traded in a four year period. Within the time series, four critical points were chosen based on the specific guideline to determine if the following crashes were the result of an asset bubble.

After calibrating the LPPL model to the data set, I was successfully able to forecast two of the four critical points where a crash occurred. Since the model finds periods of growth that are faster than exponential, it is appropriate to conclude that the accurate forward forecast of the model signifies an asset bubble within the time series. The model failed to identify two of the crashes. The failure of the forecast is most likely due to the difficulty with calibrating six parameters as the model greatly overestimated the time series and did not produce a critical point. Further investigation in utilizing different search methods for finding nonlinear parameters can be explored to determine if those critical points indicate a bubble. The hazard rate analysis further supported the basis of the LPPL findings for the 4 critical points.

Future work using different methodologies on asset bubbles within the cryptocurrency market cap index would provide a more comprehensive overview of bubbles within this new asset class. This paper discussed price manipulation and a lack of regulation as key factors that are potentially contributing to further amplification of asset bubbles within the cryptocurrency sector. Since the model predicted two of the critical points, there clearly exists some degree of an asset bubble and the contributing factors should be evaluated. Further investigation into the discussed factors would potentially allow for policy makers to create appropiate regulatory frameworks that provides a degree of stabilization within this new asset class.

Appendix

Critical Points Statistics

December 5, 2013

A	B	C	β	ϕ	ω
120.8351	-89.91533	0.5958553	0.02	3.25	2.8

Residual standard error: 0.1562 on 219 degrees of freedom

Multiple R-squared: 0.9394, Adjusted R-squared: 0.9389

F-statistic: 1699 on 2 and 219 DF, p-value: < 2.2e-16

June 17, 2016

A	B	C	β	ϕ	ω
23.01592	-0.001476193	0.001254859	1	4.75	3.5

Residual standard error: 0.3244 on 1144 degrees of freedom

Multiple R-squared: 0.7382, Adjusted R-squared: 0.7377

F-statistic: 1613 on 2 and 1144 DF, p-value: < 2.2e-16

Janaury 5, 2017

A	B	C	β	ϕ	ω
23.57095	-0.001900589	0.001075538	1	4.75	1.4

Residual standard error: 0.3192 on 1346 degrees of freedom

Multiple R-squared: 0.7814, Adjusted R-squared: 0.7811

F-statistic: 2406 on 2 and 1346 DF, p-value: < 2.2e-16

January 7, 2018

A	B	C	β	ϕ	ω
107.7739	-74.30387	0.2880415	0.02	6.25	5

Residual standard error: 0.4872 on 1713 degrees of freedom

Multiple R-squared: 0.8691, Adjusted R-squared: 0.869

F-statistic: 5689 on 2 and 1713 DF, p-value: < 2.2e-16

Hazard Rate Parameters

Global 60 day

A	B	C	m	omega	phi
21.27254	-0.00367	0.002418	1	4	1.2
24.70735	-1.11117	-0.13265	0.26	2	1
23.31973	-0.01073	-0.00505	1	3	2.1
22.93739	-0.00284	-0.00599	1	3	3.7
22.71857	-0.00118	-0.00481	1	3.5	1.2
22.92661	-0.00219	0.003303	1	4.5	4.7
22.96062	-0.00208	-0.00277	1	5.75	3.5
22.85734	-0.00154	0.002456	1	6.75	1
22.77525	-0.00122	0.002124	1	8	3.4
22.64139	-0.00081	-0.0019	1	9	1.2
22.52385	-0.00271	0.003769	1	2	5.4
22.59285	-0.00312	0.003828	1	2	5.7
22.46893	-0.00136	-0.00229	1	3	2.7
22.47816	-0.00102	0.001815	1	3.75	4.7
22.58165	-0.00105	-0.00156	1	4.25	5.2
22.81636	-0.00175	0.001789	1	3.5	3.8
22.90875	-0.00164	-0.00153	1	4	4.3
23.11966	-0.00191	0.001496	1	4	1.5
23.17702	-0.00168	0.001247	1	4.75	0.6
23.38669	-0.00203	0.001315	1	4	2
23.51807	-0.00203	0.0012	1	4.25	4
23.68221	-0.00207	-0.00111	1	4.5	2.9
25.15792	-0.33442	-0.02551	0.32	4	0.5
25.80825	-0.19831	-0.03623	0.44	2	4.6
25.98347	-0.0626	-0.01735	0.62	2	5
26.13691	-0.0282	0.009061	0.74	2.25	3.7
28.03642	-0.3754	0.05137	0.4	3	2.8

December 5, 2013

A	B	C	m	omega	phi
21.27407	-0.00355	0.002302	1	4.25	2.5
21.27588	-0.0035	-0.00224	1	4.5	0.6
21.27874	-0.00343	-0.00217	1	4.5	0.7
21.28224	-0.00336	-0.00211	1	4.5	0.8
21.28733	-0.00335	0.002066	1	4.75	5.2
21.29485	-0.00333	0.002024	1	4.75	5.3
21.30198	-0.00331	0.001984	1	4.75	5.4
21.31798	-0.00341	-0.00198	1	4.75	2.3
21.37896	-0.01268	-0.00616	0.74	4.5	1.3
21.68087	-0.15596	-0.03684	0.32	4.75	2.6
21.83246	-0.24827	-0.04766	0.26	4.5	1.5
22.08378	-0.45664	-0.06871	0.18	3.75	4.4
22.44585	-0.73989	0.081025	0.14	4	2.5
22.37897	-0.64249	-0.07483	0.16	4.25	0.6
22.13877	-0.40012	-0.05783	0.22	4.5	1.8
22.21187	-0.42583	0.057681	0.22	4.75	6.2
22.88923	-0.97019	0.080203	0.14	5	1.2
33.48797	-11.3461	-0.13071	0.02	5	4.5
34.9081	-12.6418	0.129126	0.02	5.25	2.5
35.94185	-13.5775	-0.13025	0.02	5.25	5.7
36.9993	-14.532	0.13645	0.02	5.5	4
38.73037	-16.1153	-0.13397	0.02	6.5	5.5
41.55813	-18.6988	-0.11389	0.02	2	1.2
28.92585	-5.97979	0.110223	0.06	2	4
33.73513	-10.5529	-0.13606	0.04	2	0.9
27.03258	-3.78063	-0.13885	0.1	2	0.9
25.9332	-2.56848	0.144496	0.14	2	4.1
26.3401	-2.77765	-0.1598	0.14	2	1
25.71053	-2.03664	-0.15798	0.18	2	1
24.47054	-0.86452	0.122908	0.3	2	4.2
24.26808	-0.61471	0.108357	0.36	2	4.3

June 17, 2016

A	B	C	m	omega	phi
22.85621	-0.00168	0.001654	1	3.75	5.6
22.85387	-0.00167	0.001648	1	3.75	5.6
22.85168	-0.00165	0.001642	1	3.75	5.6
22.84948	-0.00164	0.001635	1	3.75	5.6
22.87578	-0.0017	-0.00165	1	3.75	2.5
22.87362	-0.00169	-0.00164	1	3.75	2.5
22.87137	-0.00168	-0.00163	1	3.75	2.5
22.86918	-0.00166	-0.00163	1	3.75	2.5
22.90692	-0.00176	0.001644	1	3.75	5.7
22.90477	-0.00175	0.001638	1	3.75	5.7
22.90274	-0.00173	0.001632	1	3.75	5.7
22.90069	-0.00172	0.001626	1	3.75	5.7
22.87967	-0.00159	0.001537	1	4	1.1
22.87777	-0.00158	0.001532	1	4	1.1
22.87585	-0.00157	0.001526	1	4	1.1
22.87398	-0.00156	0.00152	1	4	1.1
22.90875	-0.00164	-0.00153	1	4	4.3
22.90692	-0.00163	-0.00153	1	4	4.3
22.90504	-0.00162	-0.00152	1	4	4.3
22.90313	-0.00161	-0.00152	1	4	4.3
22.90138	-0.00159	-0.00151	1	4	4.3
22.92657	-0.00165	0.001522	1	4	1.2
22.92574	-0.00164	0.001517	1	4	1.2
22.92496	-0.00163	0.001512	1	4	1.2
22.92452	-0.00162	0.001506	1	4	1.2
22.96095	-0.00171	-0.00152	1	4	4.4
22.96067	-0.0017	-0.00152	1	4	4.4
22.9603	-0.00169	-0.00151	1	4	4.4
22.96055	-0.00168	-0.00151	1	4	4.4
22.98768	-0.00174	0.001514	1	4	1.3
22.98899	-0.00173	0.00151	1	4	1.3

January 5, 2017

A	B	C	m	omega	phi
23.22812	-0.00155	-0.00107	1	5.5	2.9
23.3633	-0.00201	-0.00132	1	4	5.1
23.36286	-0.002	-0.00132	1	4	5.1
23.36235	-0.00199	-0.00131	1	4	5.1
23.38715	-0.00204	0.00132	1	4	2
23.38669	-0.00203	0.001315	1	4	2
23.38641	-0.00202	0.00131	1	4	2
23.38611	-0.00201	0.001304	1	4	2
23.38561	-0.002	0.001299	1	4	2
23.38517	-0.00199	0.001293	1	4	2
23.42013	-0.00206	-0.00131	1	4	5.2
23.41976	-0.00205	-0.0013	1	4	5.2
23.41929	-0.00204	-0.0013	1	4	5.2
23.41888	-0.00203	-0.00129	1	4	5.2
23.41855	-0.00203	-0.00129	1	4	5.2
23.41805	-0.00202	-0.00128	1	4	5.2
23.44267	-0.00206	0.001287	1	4	2.1
23.44239	-0.00205	0.001282	1	4	2.1
23.44203	-0.00204	0.001277	1	4	2.1
23.44168	-0.00203	0.001271	1	4	2.1
23.44124	-0.00203	0.001266	1	4	2.1
23.42277	-0.00194	-0.00122	1	4.25	0.7
23.42256	-0.00194	-0.00122	1	4.25	0.7
23.42247	-0.00193	-0.00121	1	4.25	0.7
23.45538	-0.00199	0.001224	1	4.25	3.9
23.45605	-0.00198	0.00122	1	4.25	3.9
23.45679	-0.00198	0.001216	1	4.25	3.9
23.45782	-0.00197	0.001212	1	4.25	3.9
23.45872	-0.00196	0.001207	1	4.25	3.9
23.48275	-0.002	-0.00121	1	4.25	0.8
23.48467	-0.002	-0.00121	1	4.25	0.8

January 7, 2018

A	B	C	m	omega	phi
26.05123	-0.02058	0.00692	0.78	2	2.2
26.12822	-0.02815	0.009044	0.74	2.25	3.7
26.10917	-0.02458	0.008153	0.76	2.25	3.7
26.12621	-0.02467	0.008183	0.76	2.25	3.7
26.13745	-0.02453	-0.00805	0.76	2.25	0.6
26.17647	-0.02789	0.008732	0.74	2.25	3.8
26.21932	-0.03186	-0.00955	0.72	2.25	0.7
26.23966	-0.03201	-0.0096	0.72	2.25	0.7
26.32017	-0.04198	0.011575	0.68	2.25	3.9
26.3688	-0.04809	-0.01266	0.66	2.25	0.8
26.46613	-0.06351	0.015271	0.62	2.25	4
26.4904	-0.06385	0.015365	0.62	2.25	4
26.55004	-0.07345	-0.01682	0.6	2.25	0.9
26.67316	-0.09781	0.020313	0.56	2.25	4.1
26.74876	-0.11307	-0.02227	0.54	2.25	1
26.83908	-0.11858	0.024119	0.54	2.5	5.6
26.94093	-0.15312	0.027147	0.5	2.25	4.2
27.06845	-0.17998	0.030329	0.48	2.25	4.2
27.14245	-0.1859	-0.03161	0.48	2.5	2.6
27.2843	-0.21872	-0.03529	0.46	2.5	2.6
27.40937	-0.25507	0.038458	0.44	2.5	5.8
27.55553	-0.29909	-0.04221	0.42	2.5	2.7
27.61515	-0.30341	0.043263	0.42	2.5	5.8
27.62658	-0.30295	-0.04288	0.42	2.5	2.7
27.66035	-0.30476	-0.04319	0.42	2.5	2.7
27.59877	-0.26781	0.042135	0.44	2.75	1
27.74942	-0.31305	0.04556	0.42	2.75	1.1
27.65268	-0.26941	-0.04197	0.44	2.75	4.2
27.79743	-0.31442	-0.04526	0.42	2.75	4.3
27.95089	-0.37145	0.051553	0.4	3	2.7
27.98704	-0.37299	-0.05136	0.4	3	5.9

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
Column 1	27	17.65798	0.653999	0.096803
Column 2	31	27.84399	0.898193	0.033203
Column 3	31	30.97935	0.999334	5.53E-09
Column 4	31	30.99545	0.999853	4.71E-09
Column 5	31	27.46467	0.885957	0.005993

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	2.249044128	4	0.562261	22.23008	2.38E-14	2.433633
Within Groups	3.692749427	146	0.025293			
Total	5.941793555	150				

n	151	Dem df	147	QU Value	3.68
Factor Levels	4	num df	4	S Pooled	0.025293
	Comparison	Absolute Difference	Critical Range	Result	
	Global to 1	0.28825	0.112633	Significantly different	
	Global to 2	0.63782	0.112633	Significantly different	
	Global to 3	0.15071	0.112633	Significantly different	
	Global to 4	0.302527	0.112633	Significantly different	

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