Quantifying the sustainability of Bitcoin and Blockchain

FRY, John Mickael and SERBERA, Jean-Philippe <http://orcid.org/0000-0001-6867-4405>

Published version

FRY, John Mickael and SERBERA, Jean-Philippe (2020). Quantifying the sustainability of Bitcoin and Blockchain. Journal of Enterprise Information Management.

Quantifying the sustainability of Bitcoin and Blockchain

October 2019

Abstract

Purpose. We develop new quantitative methods to estimate the level of speculation and long-term sustainability of Bitcoin and Blockchain.

Design/Methodology/Approach. We explore the practical application of speculative bubble models to cryptocurrencies. We then show how the approach can be extended to provide estimated brand values using data from Google Trends.

Findings. We confirm previous findings of speculative bubbles in cryptocurrency markets. Relatedly, Google searches for cryptocurrencies seem to be primarily driven by recent price rises. Overall results are sufficient to question the long-term sustainability of Bitcoin with the suggestion that Ethereum, Bitcoin Cash and Ripple may all enjoy technical advantages relative to Bitcoin. Our results also demonstrate that Blockchain has a distinct value and identity beyond cryptocurrencies – providing foundational support for the second generation of academic work on Blockchain. However, a relatively low estimated long-term growth rate suggests that the benefits of Blockchain may take a long time to be fully realised.

Originality/value. We contribute to an emerging academic literature on Blockchain and to a more established literature exploring the use of Google data within business analytics. Our original contribution is to quantify the business value of Blockchain and related technologies using Google Trends.

Keywords: Behavioural Modelling; Blockchain; Google Trends; Long-Term Investment; Speculative Bubbles

1 Introduction

Blockchain is a decentralised transaction ledger. Each party on a Blockchain has access to the entire database and its complete history. Communication, and verification, occurs directly between peers rather than through a central node or intermediary. The verification process is known as mining and is now only profitable using the latest application-specific integrated circuits (Fanning and Centers, 2016). In this way there is, at least in principal, no central point of weakness. This provides a consensus mechanism termed “absolute law” in Jun (2018) though the need for some fundamental level of trust is likely to remain in order to form a majority consensus view on networks (Hawlitschek et al., 2018). Every transaction, and its associated value, are visible to anyone with access to the system. Once transactions are entered in the Blockchain, and accounts updated, the records are “chained” to the previous block of transactions and cannot be altered. Thus, Blockchain results in a database record that is permanent, chronologically ordered and universally available to all users on the network. Blockchain’s digital nature means users can set up algorithms to automatically trigger transactions between nodes. This leads to the possibility of “smart contracts” whereby, for example, payments could be automatically made to a supplier as soon as a shipment has been delivered (Iansiti and Lakhani, 2017). This complements existing attempts to incorporate point of sale and real-time inventory information in supply chains (Date and Raoot, 2014). This potential for smart contracts has led to immense interest across a broad range of possible applications – see Section 2.

This possibility of foundational societal change has led to intense popular interest in Blockchain (see e.g. Tapscott and Tapscott, 2016; Laurence, 2017). To date Blockchain has been under-explored academically though recent reviews can be found in Hawlitschek et al. (2018) and Morabito (2017). Historically, the literature has been dominated by studies of Bitcoin and other cryptocurrencies (Corbet et al., 2018; Katsiampa, 2017; Phillip et al., 2018). However, from 2016 onwards a new stage of the literature has begun to focus upon Blockchain and smart contracts (Miau and Yang, 2018). We thus contribute to this new stage of the literature by extending a model originally fitted to Bitcoin in Cheah and Fry (2015) to apply to Blockchain more generally.

In this paper we develop new mathematical models to quantify the sustainability of Bitcoin and Blockchain. From a theoretical perspective we aim to provide ways of countering a pro-innovation bias that is known to dominate much of the academic literature (Abrahamson, 1991). For example, much academic work implicitly assumes that the diffusion of innovation will always benefit adopters (Abrahamson, 1991) or that technologies will be enthusiastically adopted by customers (Talke and Heidenreich, 2014). However, reality is more complex. Abrahamson (1991) speaks of managerial fads in relation to either the adoption of inefficient innovations or the rejection of efficient ones. Excess speculation can also accompany periods of genuine innovation (Zeira, 1999). The danger of excessive hype associated with Blockchain is highlighted in Hawlitschek et al. (2018). As such we aim to sound a timely note of caution. Our results are consistent with the view that progress made may be gradual (Iansiti and Lakhani, 2017). Inter alia privacy and security issues both need to be adequately addressed (Jun, 2018). Issues related to unequal economic development may also limit the global uptake of Blockchain technologies (Soja et al., 2015).

The contribution of this paper is as follows. We produce a quantitative behavioural model for Blockchain using the Google Trends Search Index to infer the fundamental brand value of Blockchain and of cryptocurrencies. This builds on a large literature on the use of Google data in applied forecasting work (Fantazzini, 2014; Kristoufek, 2013) and adds to the range of different methodologies applied to Blockchain (Miau and Yang, 2018). Our model extends related papers that have focussed exclusively on cryptocurrencies (Cheah and Fry, 2015; Fry and Cheah, 2016) and accounts for the fact that technology adoption is associated with both behavioural factors (Sun et al., 2016) and herding (Walden and Browne, 2009). The specific innovations with respect to Fry and Cheah (2016) include more refined estimates of the effect size, investigation of a trading-type environment via estimates of the long-term growth rate and the extension of the base model into non-financial contexts (see e.g. Hendricks and Vestergaard, 2018). Our results confirm previous findings of speculative bubbles in cryptocurrency markets and shows that the economic size of the effects can be substantial. Results also suggest that competitor cryptocurrencies such as Ethereum*, Ripple and Bitcoin Cash may have better long-

*We use the general term Ethereum to describe both the Blockchain technology and the cryptocurrency. Other authors use the term Ether to distinguish the cryptocurrency from the underlying Blockchain technology (see e.g. Laurence, 2017). Here, we take the view that this distinction complicates the discussion of multiple cryptocurrency markets.

term prospects than Bitcoin. Google searches for cryptocurrencies seem to be primarily driven by recent price rises. However, Google searches for Blockchain can be shown to fundamentally different in nature. Thus, our numerical results reinforce the importance of the distinction between cryptocurrencies and the subject of Blockchain more generally.

The layout of this paper is as follows. A review of early Blockchain applications is given in Section 2. Section 3 discusses the theoretical modelling of speculative bubbles. Section 4 discusses an application to the four major cryptocurrency markets. Section 5 discusses behavioural modelling of Google Trends to determine brand value. Section 6 discusses an empirical application to Blockchain and cryptocurrency markets. The research synthesis is in Section 7. Section 8 concludes and discusses the opportunities for further work.

2 Review of early Blockchain applications

Bitcoin is the first widespread usage of Blockchain technology. However, Blockchain has an identity and a reach potentially far beyond this. There appear to be two key conditions for Blockchain applications. These conditions are convenience and consensus/trust. As discussed in Fry and Cheah (2016) cryptocurrencies can be viewed, at least in part, as a natural extension of other forms of electronic payment. Similarly, other Blockchain applications complement existing supply-chain developments (Barata et al., 2018). In particular, Bitcoin's construction also highlights the importance of building consensus. Part of the motivation behind Bitcoin was the way in which many national currencies have been progressively devalued by national governments (Dowd, 2014). In particular, Bitcoin's mining processes, linked to the solution of complex mathematical cryptography problems which in turn form the verification of the Blockchain, are intended to replicate the seemingly objective ways in which national currencies were historically linked to precious metals such as gold or silver. In a similar vein these mining processes are also intended to reward individuals who contribute to the platform via their computational resources. However, these dual concepts of convenience and consensus can be applied to much more general forms of contractual agreement. Potential applications where consensus is required include e-id, land registers, social security records and securities trading (Jun, 2018). Blockchain applications have also been used to promote the development of photovoltaic technology (Hou et al., 2018) and to share patient records (Kim and Hong, 2017). Smart contracts clearly accentuate aspects of convenience outlined above (Iansiti and Lakhani, 2017). Ultimately, Blockchain may be used to mitigate information risks in supply chains (Sharma and Routroy, 2016). Another possibility is the use of Initial Coin Offerings, as opposed to Initial Public Offerings, to **raise** funds for industry (Tapscott and Tapscott, 2017; Adhami et al., 2018) and entrepreneurship, start-ups and innovation (Chen, 2018). Applications to insurance, music industry download royalties, decentralised storage and logistics, decentralised internet of things and anti-counterfeit measures are discussed in Nofer et al. (2017). In this way Blockchain applications can be seen as a natural extension of existing e-business (see e.g. Chatzoglou and Chatzoudes, 2016).

Blockchain is a fundamental technology that may ultimately take decades to be fully absorbed into our economic and social infrastructure (Iansiti and Lakhani, 2017). Nevertheless, the potential clearly exists for the wholesale replacement of bureaucratic systems in a dizzying array of different areas (Jun, 2018). Inter alia internet sharing platforms such as Uber and Airbnb may no longer be required (Huckle et al., 2016). Transparent and distributed records via Blockchain may enable the verification of financial transactions without the need for intermediaries such as banks (Yermack, 2017). Blockchain has also recently been adopted by Mastercard for non-Bitcoin payments. However, technological adoption does not always benefit adopters (Abrahamson, 1991). Current cryptographic technology remains vulnerable to hacking (Freund, 2017). Historically, payment systems have proved vulnerable in unanticipated ways (Anderson and Murdoch, 2014). There is also a need to develop new technologies to add privacy and security to the raw Blockchain technology (Jun, 2018). Moreover, some fundamental levels of trust are likely to always be required (Hawlitschek et al., 2018).

As the first meaningful application of Blockchain technology the cryptocurrency experience offers some useful insights. Though today's cryptocurrencies may not ultimately last long they may nonetheless play a prominent role in shaping future progress. Question marks over their long-term sustainability (Dowd, 2014) are further reinforced by the extremely volatile naure of cryptocurrency markets (Blau, 2017; Corbet et al., 2018; Fry, 2018). In Vranken (2017) there is even some debate as to whether the electricity consumption required for Bitcoin's mining processes is environmentally sustainable. In Eken and Baloğlu (2017) cryptocurrencies are compared to wildcat money during the free banking era. Drawing on this comparison, cryptocurrencies, and other Blockchain technologies, may thus ultimately be at the mercy of national government regulation – see e.g. the introduction of the new e-Franc in Switzerland.

3 Bitcoin and financial bubbles

In this section we discuss models for bullish and bearish trends in financial markets. The dynamics of the model are governed by counter-cyclical expectations – an observation that may also have relevance for macroeconomic models (De Paoli and Zabcyzk, 2012) and applied work on business cycle forecasting (Binner and Wattam, 2013). We provide new, more refined, ways of estimating the effect size and the long-term growth rate. The model is then further developed and extended to provide a theoretical model for Google Trends data in Section 5 below.

Let P_t denote the price of an asset at time t and let $X(t) = \log(P(t))$. Following Johansen et al. (2000) our starting point is the equation

$$P(t) = P_1(t)(1-\kappa)^{j(t)}, \tag{1}$$

where $P_1(t)$ satisfies

$$dP_1(t) = \left[\mu(t) + \sigma^2(t)/2\right] P_1(t)dt + \sigma(t)P_1(t)dW_t, \tag{2}$$

where W_t is a Wiener process and $j(t)$ is a jump process satisfying

$$j(t) = \begin{cases} 0 & \text{before the change in regime} \\ 1 & \text{after the change in regime.} \end{cases} \tag{3}$$

Prior to the change in regime $P(t) = P_1(t)$ and it follows that $X(t)$ satisfies

$$dX_t = \mu(t)dt + \sigma(t)dW_t - vdj(t), \tag{4}$$

where $v = -log(1-\kappa)$. $v > 0$ corresponds to a speculative bubble model during bullish market phases (Johansen et al., 2000; Cheah and Fry, 2015). $v < 0$ corresponds to a model for negative bubbles and shocks in cryptocurrency markets (Fry and Cheah, 2016).

Equation (4) shows how the change in regime impacts upon market prices. If the change in regime has not occurred by time t we have that

$$\begin{aligned} E[j(t+\Delta)-j(t)] &= \Delta h(t)+o(\Delta), & (5) \\ \mathrm{Var}[j(t+\Delta)-j(t)] &= \Delta h(t)+o(\Delta), & (6) \end{aligned}$$

where $h(t)$ is the hazard rate.

Assumption 1 (Intrinsic Rate of Return) *The intrinsic rate of return is assumed constant and equal to* μ*:*

$$E[X_{t+\Delta}-X_t|X_t]=\mu\Delta+o(\Delta). \tag{7}$$

First-order condition. From Assumption 1 equations (4-5) and (7) give

$$\mu(t)-vh(t)=\mu; \quad \mu(t)=\mu+vh(t). \tag{8}$$

Equation (8) shows that if $v>0$ the rate of return must increase in order to compensate a representative investor for the risk of a crash. Alternatively, if $v<0$ the model describes bearish behaviour in financial markets. However, our model also predicts an effect upon the volatility (see below).

Assumption 2 (Intrinsic Level of Risk) *The intrinsic level of risk is assumed constant and equal to* σ^2*:*

$$Var[X_{t+\Delta}-X_t|X_t]=\sigma^2\Delta+o(\Delta). \tag{9}$$

Second-order condition. Our model predicts that the change in regime has an additional effect on the price risk. From Assumption 2 equations (4), (6) and (9) give

$$\sigma^2(t)+v^2h(t)=\sigma^2; \quad \sigma^2(t)=\sigma^2-v^2h(t). \tag{10}$$

The model thus states that it is the interplay between risk and return that fundamentally governs the behaviour of financial markets. The effect may be different in bullish and bearish markets. This is accompanied by a decrease in the volatility function $\sigma^2(t)$ – a result which though counter-intuitive actually represents a collective market over-confidence (Cheah and Fry, 2015). Specification of the hazard rate thus completes the model. Here, we follow Cheah and Fry (2015) in using

$$h(t) = \frac{\beta t^{\beta-1}}{\alpha^\beta + t^\beta}. \tag{11}$$

Economic size of the effect. Beyond the narrower issue of of statistical significance an estimate of the economic size of the effect can be constructed as follows. If $v \neq 0$ we have that

$$\begin{aligned} X_t &\sim N(X_0 + \mu t + vH(t), \sigma^2 t - v^2 H(t)), \\ H(t) &= \int_0^t h(u)du = \ln\left(1 + \frac{t^\beta}{\alpha^\beta}\right). \end{aligned} \tag{12}$$

From equation (12) define

$$\widetilde{P}(t) = \text{Median } P(t) = P_0 e^{\left(\mu + \frac{\sigma^2}{2}\right)t}\left(1 + \frac{t^\beta}{\alpha^\beta}\right)^v$$

Following standard financial terminology (Campbell et al., 1997) define the fundamental value as

$$P_F(t) = [\widetilde{P}(t)|v = 0] = P_0 e^{\mu t}$$

If $v \neq 0$ a robustified estimate of the economic size of the effect can be obtained as the "average distance" between fundamental and observed prices:

$$\begin{aligned} \text{Effect size} &= 1 - \frac{1}{T}\int_0^T \frac{P_F(t)}{\widetilde{P}(t)} dt \\ &= 1 - \frac{1}{T}\int_0^T \left(1 + \frac{t^\beta}{\alpha^\beta}\right)^{-|v|} dt. \end{aligned} \tag{13}$$

Use of the median within this context reflects its utility in applied statistics (see e.g. Tukey, 1977), including invariance under monotonic transformations (Sornette and Malevergne, 2006). Equation (13) thus leads to a more robust estimate of the economic size of the effect compared to much of the literature.

In Cheah and Fry (2015) it is found that the size of the speculative bubble in Bitcoin prices is sufficiently large as to preclude long-term investment. In the sequel we show how this approach can be both made more rigorous and applied to practical investment problems. Given an initial price P_0 the probability that the investment gains in the long-term for large t, and once any short-term bubble or negative bubble effects subside, can be calculated as

$$Pr(P_t > P_0) = Pr(X_t - X_0 > 0) = \Phi\left(\frac{\mu t}{\sigma\sqrt{t}}\right), \tag{14}$$

where $\Phi(\cdot)$ denotes the standard normal CDF. Hence, it follows from (14) that

$$\lim_{t\to\infty} Pr(P_t > P_0) = 1 \text{ iff } \mu > 0. \tag{15}$$

Thus, equation (15) suggests that there is evidence for long-term growth precisely when we can reject the null hypothesis

$$H_0 : \mu \leq 0;\ \ H_1 : \mu > 0. \tag{16}$$

Thus, equation (16) leads to a strengthened investment condition compared to that in Cheah and Fry (2015) and is related to classical approaches to long-term investment (Maslov and Zhang, 1998). Equation (16) also reflects renewed interest in momentum and sentiment effects throughout economics (see e.g. Asem and Tian, 2010; McLean and Zhao, 2014). There are also links to the scientific study of technical analysis (Park and Irwin, 2007) and to a more systematic treatment of the naive momentum trading strategies often used by practitioners (see e.g. Burns, 2014).

To summarise, our model can be used to discover speculative bubbles in cryptocurrency markets as follows. As discussed in Section 4 the model can be calibrated to empirical prices using the method of maximum likelihood. Equation (12) means that we can test for the presence or absence of a bubble by testing the null hypothesis $v = 0$ against the alternative hypothesis $v > 0$. Equation (13) gives a way of determining the economic size of the bubble given estimates of α, β and v. Finally, equation (16) gives a way of quantifying whether or not it would be worthwhile to buy and hold the cryptocurrency in the long-term.

4 Quantifying speculative bubbles in cryptocurrency prices

In this section we fit our model to empirical prices from the four major cryptocurrencies as determined by their current market capitalisation. Motivated by the recent boom and bust in cryptocurrencies we examine Bitcoin and Ripple prices from January 1st 2015-January 1st 2018 and compare against newer altcoins that have only come into being more recently. In particular, we look at Ethereum prices from August 7th 2015-January 1st 2018 and Bitcoin Cash prices from July 23rd 2017 to January 1st 2018. A plot of the data is shown in Figure 1.

The model in Section 3 can be calibrated to the data using the method of maximum likelihood. Results shown in Table 1 give significant evidence of speculative bubbles in all markets with the exception of Bitcoin Cash. This reinforces previous findings of speculative bubbles in cryptocurrency markets (Blau, 2017; Cheah and Fry, 2015; Corbet et al., 2018). Moreover, the effect size can be substantial (Cheah and Fry, 2015). Inter alia our model suggests Ethereum prices are over-valued by around 26%. Application of the long-term investment criterion shown in equation (16) would suggest buying Ripple and Ethereum but not Bitcoin or Bitcoin Cash. For Ripple and Ethereum the estimated long-term growth rate shown in equation (16) is both positive and statistically significant. That our mathematical model returns this interpretation may reflect long-term technical advantages that Ripple and Ethereum have relative to Bitcoin (Swan, 2015). In contrast, for Bitcoin and Bitcoin Cash the estimated long-term growth rate shown in equation (16) is not significantly different from zero. That our mathematical model returns this interpretation may reflect question marks over the long-term primacy of Bitcoin and the Bitcoin technology relative to other cryptocurrencies (Dowd, 2014).

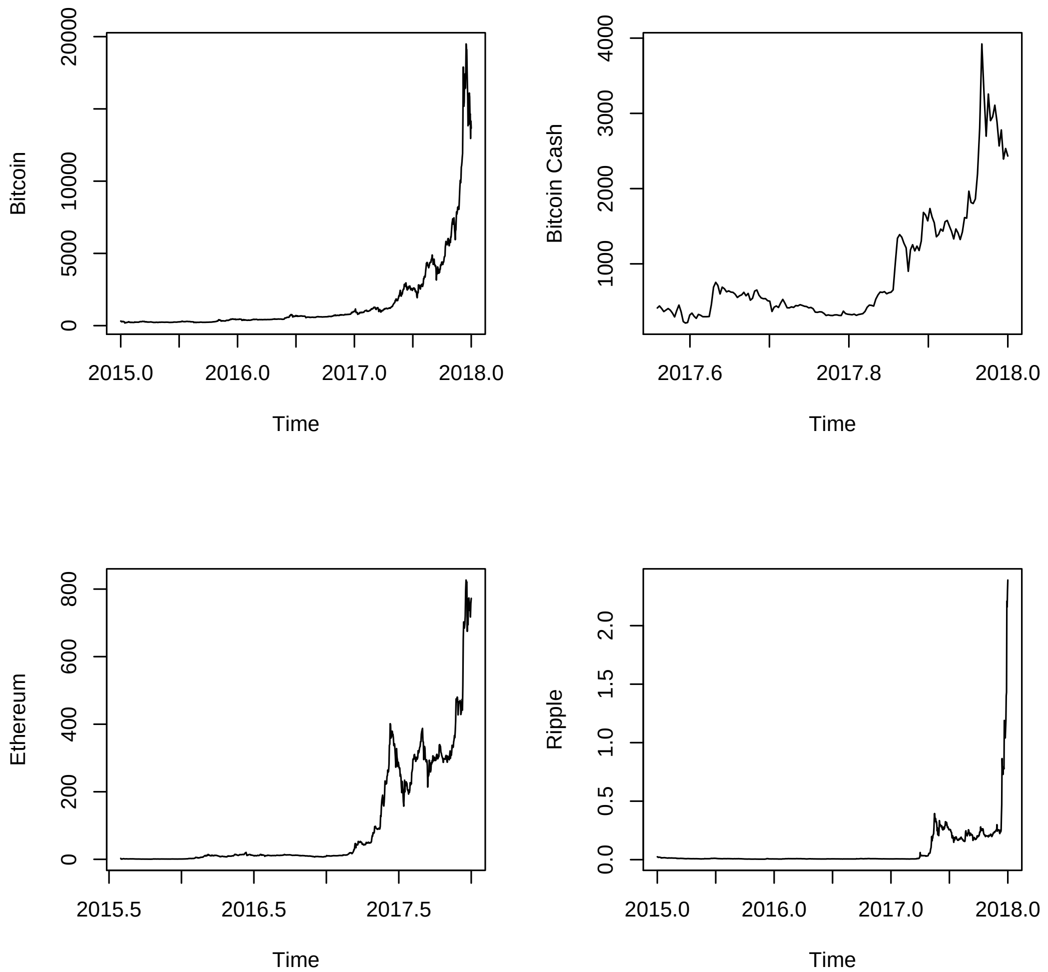

Figure 1: Plot of cryptocurrency prices over time: Bitcoin (top left), Bitcoin Cash (top right), Ethereum (bottom left) and Ripple (bottom right).

5 Behavioural modelling for Bitcoin and Blockchain using Google Trends

The Google Trends Search Index is an index on a 0-100 integer scale expressing the relative frequency with which a given term has been searched for over time. A value of 100 denotes the peak popularity of the term i.e. the maximum number of searches within any given week or year. In contrast, a value of 0 indicates that there have been less than 1% of the maximum number of searches. The structure of the data thus presents specific challenges. For instance

Maximum likelihood ratio test for a speculative bubble $H_0: v = 0$, $H_1: v \neq 0$		
Cryptocurrency	χ^2**-value**	p**-value**
Bitcoin	40.472	0.000
Ethereum	2636.863	0.000
Ripple	101.818	0.000
Bitcoin Cash	4.393	0.111
Test for long-term growth $H_0: \mu \leq 0$		
Cryptocurrency	t**-value**	p**-value**
Bitcoin	0.352	0.725
Ethereum	3.018	0.003
Ripple	2.153	0.031
Bitcoin Cash	1.116	0.266
Estimated coefficient of over-pricing		
Bitcoin	0.006	
Ethereum	0.265	
Ripple	0.000	
Bitcoin Cash	0.000	

Table 1: Results of hypothesis tests and estimated coefficient of over-pricing based on historical prices.

Risteski and Davcev (2014) use Google Trends search data to generate a proxy financial time series index. In contrast, in this paper we undertake theoretical modelling of the raw Google Trends Search Index without the need to employ any further data processing.

We consider a Poisson model for the Google Trends search index G_t at time t:

$$G_t \sim \text{Po}(\lambda_t) \tag{17}$$

$$\ln \lambda_t = f(P_t). \tag{18}$$

The G_t are assumed to be mutually independent and also independent of P_t which denotes the unobserved price of an underlying asset. This defines a Hidden Markov model (Bishop, 2006) and a mixed-Poisson Distribution (Karlis and Xekalaki, 2005) and builds on previous Poisson modelling of internet-search data (Tierney and Pan, 2012). Here, P_t is assumed to represent the unobserved value or price of the brand. This approach also reflects the importance of finance and marketing applications for business analytics (Ranyard et al., 2015). This approach is also motivated by the principled treatment of non-linearities and the use of internet search data as possible predictors as suggested by Balcilar et al. (2017). The intuition behind our model is that as the price of the unobserved asset increases the expected number of searches increases, reflecting enhanced interest. Inter alia this would be consistent with empirical data presented in Kristoufek (2013). This means that the function $f(\cdot)$ in (18) must satisfy

$$f(0) = -\infty; \ \lim_{x \to \infty} f(x) = \infty. \tag{19}$$

A natural choice in equation (19) is $f(x) = \ln\ x$ mirroring the construction of classical statistical (Bingham and Fry, 2010; Chapter 8) and statistical mechanics models (Yeomans, 1992).

Deterministic price series models. If the unobserved price process is constant $P_t = P_0$ then the model reduces to an iid Poisson model. If the unobserved price process is increasing or decreasing over time a natural model to use is $P_t = P_0 e^{\mu t}$. In this case the model reduces to a classical Poisson regression model (Bingham and Fry, 2010; Chapter 8) with a logarithmic link function and time as the explanatory variable. More generally, a natural alternative to use might be $P_t = P_0 e^{\int_0^t \mu(u)du}$ (see below).

Stochastic price series models. A stochastic model for prices can be obtained by letting $X_t = \log\ P_t$ and setting

$$dX_t = \mu(t) + \sigma(t)dW_t \tag{20}$$

The case $\mu(t) = \mu$, $\sigma(t) = \sigma$ corresponds to the classical Black-Scholes model (Black and Scholes, 1973). Other choices of $\mu(t)$ and $\sigma(t)$ enable counter-cyclical expectations to be incorporated into the model. See Section 2. In terms of model estimation deterministic models can be fitted using standard techniques for generalised linear models but are probably too simplistic to apply to real datasets. In contrast, stochastic models can be fitted via an approximate filtering algorithm based on a Gaussian approximation using

$$E[G_t] = E[P_t]. \tag{21}$$

$$\begin{aligned} \mathrm{Var}(G_t) &= E[\mathrm{Var}(G_t|P_t)] + \mathrm{Var}[E(G_t|P_t)] \\ &= E[P_t] + \mathrm{Var}[P_t]. \end{aligned} \tag{22}$$

6 Long-term forecasting of Blockchain and cryptocurrencies using Google Trends

In this section we fit our model to the worldwide Google Trends Search Index for the terms Blockchain, Bitcoin and Ripple from January 4th 2015-December 31st 2017. This time period is chosen to coincide with the recent boom and bust in cryptocurrency prices. Since they are more recently formed we also use the worldwide Google Trends Search Index for Ethereum (from January 3rd 2016-December 31st 2017) and for Bitcoin Cash (March 5th 2017-December 31st 2017). Plots of this data are shown below in Figures 2-3 and show qualitatively similar patterns throughout the period in question. Summary statistics are shown below in Table 2.

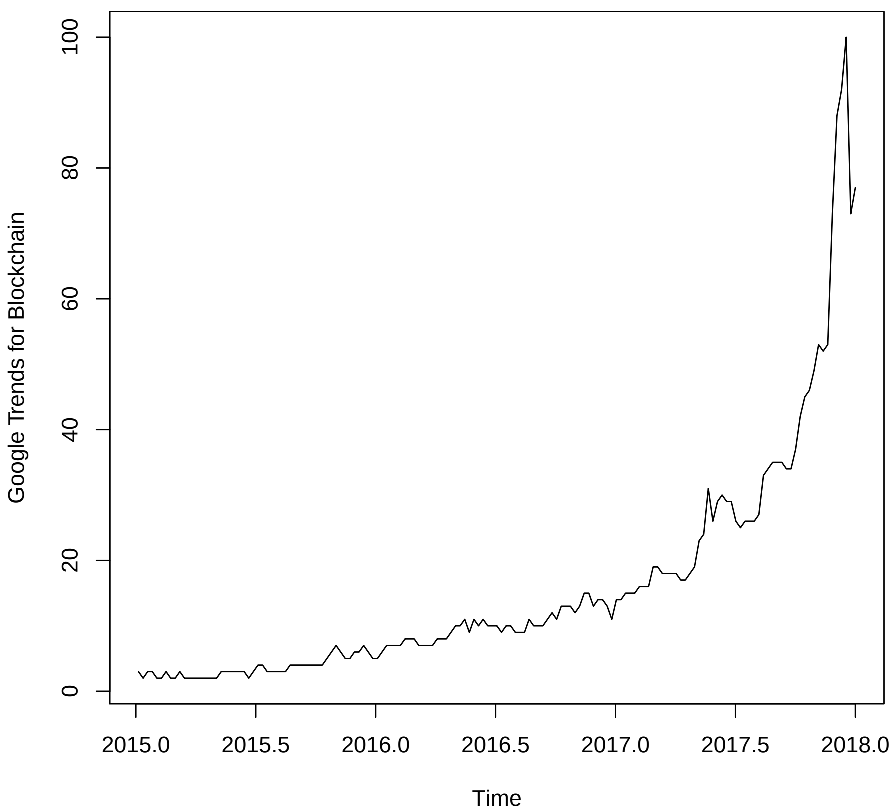

Figure 2: Plot of the weekly Google Trends Search Index (Worldwide) for Blockchain: January 4th 2015-December 31st 2017.

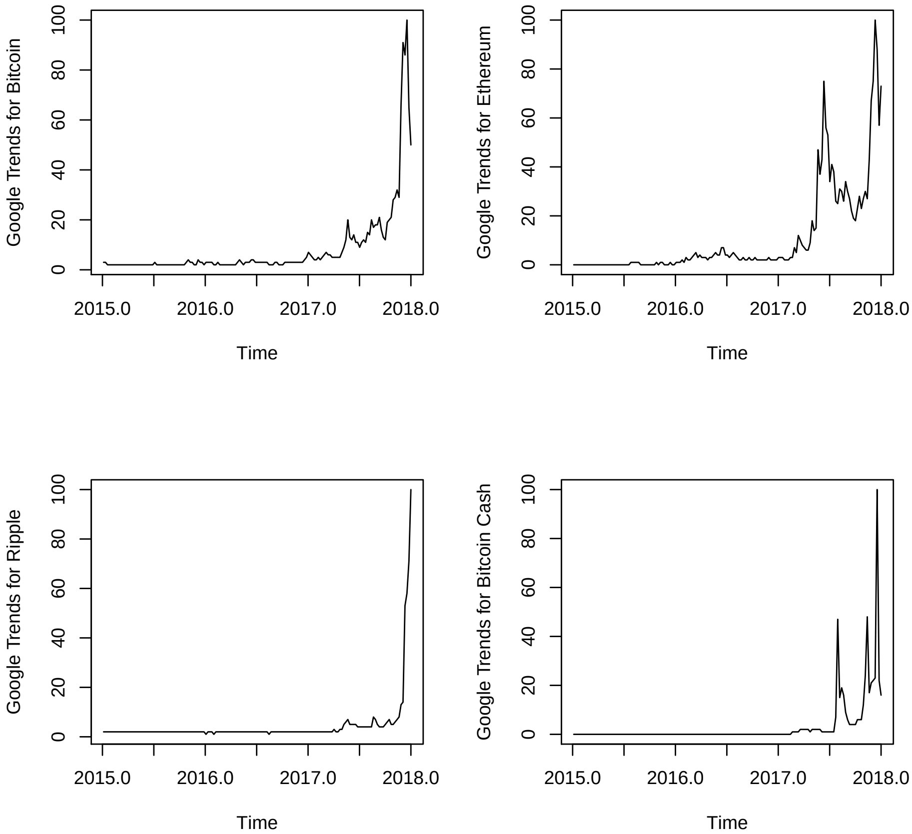

Figure 3: Plot of the weekly Google Trends Search Index (Worldwide) for Bitcoin coin (top left panel), Ethereum (top right panel), Ripple (bottom left panel), Bitcoin Cash (bottom right panel) for January 4th 2015-December 31st 2017.

	Blockchain	Bitcoin	Ethereum	Ripple	Bitcoin Cash
Mean	15.91083	8.292994	15.82857	4.484076	11.09091
Median	10	3	4	2	4
Maximum	100	100	100	100	100
Minimum	2	2	1	1	1
St. Dev	18.04175	15.29549	21.29484	11.25156	17.74079
Skewness	2.407826	4.066823	1.868402	6.40735	3.207341
Kurtosis	6.443128	17.89535	3.112291	43.32764	12.20732

Table 2: Summary statistics for data from the Google Trends Search Index.

The models in Section 5 are fitted to the data using a maximum likelihood approach based on a Gaussian approximation. Results shown in Table 3 depict marked differences between

Blockchain and cryptocurrencies. Evidence is found of bubbles in the brand value of all major cryptocurrencies. Moreover, the estimated economic size of the effect is substantial – of the order of 80-90%. The implication is that, rather than responding to fundamental information, Google Searches for cryptocurrencies may be primarily prompted by recent price rises. Similar findings are reported in Kristoufek (2013). This would also seem consistent with academic work that classifies cryptocurrencies as more of a speculative asset than a genuine currency (Baeck and Elbeck, 2015; Dyhrberg, 2016). Moreover, results in Lazer et al. (2014) show that failure to appropriately adjust raw Google search figures can lead to biased estimates in empirical forecasting work. Our results do suggest that Bitcoin Cash and Ethereum may have some long-term value – but the effects are only marginally statistically significant at best. In contrast no evidence is found of a bubble in Blockchain's brand value. However, the long-term growth rate shown in equation (16) is not statistically significant. Results appear consistent with the interpretation that Blockchain clearly has wider significance beyond cryptocurrency markets but that the gains brought about by Blockchain technology may ultimately take decades before they are fully realised (Iansiti and Lakhani, 2017).

7 Research synthesis

We add to a growing economics and finance literature that discusses the issue of bubbles and excessive speculation in Bitcoin and cryptocurrencies (Corbet et al., 2018; Gandal et al., 2018). In refining previous work (Cheah and Fry, 2015) we show how debates addressing long-term sustainability and long-term investment prospects may be better framed. Our financial model may then be further extended and applied to wider debates about Blockchain and new technologies. We thus contribute to an emerging academic literature on Blockchain (Iansiti and Lakhani, 2017) and add to the methodological diversity of studies in the area (Miau and Yang, 2018). Our paper also adds to previous attempts to use Google Trends data in a wide variety of different economic and social problems (Fantazzini, 2014).

Data from Google Trends has previously been used to motivate studies of bubbles and speculative behaviour – see e.g. the simple qualitative plots in Geraskin and Fantazzini (2013) and Cheah and Fry (2015). Here, in contrast, we follow a more overtly mathematical modelling

Maximum likelihood ratio test for a speculative bubble $H_0 : v = 0$, $H_1 : v \neq 0$		
Search Term	**χ^2-value**	**p-value**
Blockchain	0.0434	0.979
Bitcoin	10.877	0.004
Ethereum	6.026	0.049
Ripple	30.396	0.000
Bitcoin Cash	8.372	0.015
Test for long-term growth $H_0 : \mu \leq 0$		
Search Term	**t-value**	**p-value**
Blockchain	0.317	0.751
Bitcoin	-0.582	1.000
Ethereum	1.251	0.105
Ripple	-2.272	1.000
Bitcoin Cash	1.367	0.086
Estimated coefficient of over-pricing		
Blockchain	0.000	
Bitcoin	0.790	
Ethereum	0.855	
Ripple	0.903	
Bitcoin Cash	0.931	

Table 3: Results of hypothesis tests and estimated coefficient of over-pricing based on historical data from Google Trends.

approach. This provides a principled treatment of onilne search data and the attendant non-linearities in prediction problems (Balcilar et al., 2017). Our over-arching aim is to provide new ways of quantifying bubbles and excessive speculation in non-financial data (see e.g. Hendricks and Vestergaard, 2018). We present empirical evidence of differences between the general Blockchain brand and searches for cryptocurrencies. This emphasises that Blockchain has an identity and an interest beyond first-generation cryptocurrency applications (Hawlitschek et al., 2018).

8 Conclusions and further work

In this paper we develop a model to quantify the business value of Blockchain and related technologies. We build on a rich body of work on cryptocurrencies (Corbet et al., 2018; Katsiampa, 2017; Phillip et al., 2018) and a new stage of the literature that prioritises Blockchain (Miau and Yang, 2018). We extend previous work in Cheah and Fry (2015) in two ways. Firstly, we develop a more robust investment criterion to try to discern genuine opportunities from purely illusory ones. Secondly, we extend this model to impute the fundamental brand value of cryptocurrencies and the Blockchain using data available from Google Trends. We thus contribute to live research themes in business analytics (Ranyard et al., 2015), empirical forecasting work using Google Trends (Fantazzini, 2014) and the mathematical modelling of Blockchain and cryptocurrencies (Alabi, 2017).

We confirm previous findings of speculative bubbles in cryptocurrency markets (Blau, 2017; Cheah and Fry, 2015; Corbet et al., 2018). Moreover, the effect size can be substantial. Here, it is estimated that Ethereum prices are around 26.5% over-valued during the period in question. The above notwithstanding, our model suggests that Ethereum and Ripple may ultimately represent a better long-term investment than Bitcoin. This may reflect technological advantages of Ethereum and Riple relative to Bitcoin (Swan, 2015) alongside concerns that Bitcoin may ultimately be superseded by another digital currency (Dowd, 2014). A second stage of the analysis suggests that Bitcoin Cash may also hold some advantages relative to Bitcoin.

Allied to the above we extend the first-stage model to enable us to use the Google Trends Search Index to infer long-term brand value. This builds on a wealth of applied forecasting work using Google Trends (see e.g. Fantazzini, 2014 and the references therein) including previous applications to Bitcoin (Kristouffek, 2013). This also compliments previous approaches to analysing Blockchain such as the bibliometric analyses performed in Miau and Yang (2018). Our model exhibits marked differences between cryptocurrencies and the wider subject of Blockchain as a whole. Google searches on cryptocurrencies seem to be driven chiefly by recent price rises. This contrasts sharply with the Google searches for Blockchain, which seem to be more closely aligned to fundamental applications. The opportunities for Blockchain thus clearly extend beyond cryptocurrencies (Iansiti and Lakhani, 2017). However, low estimated long-term growth rates tally with concerns raised that it may be a long time before the opportunities associated with Blockchain are fully realised (Iansiti and Lakhani, 2017). As an illustration of some of the problems that still need to be overcome, different levels of economic development remain a barrier to widespread Blockchain implementation (Soja et al., 2015). Current cryptographic technology also remains vulnerable to hacking (Freund, 2017).

Technological adoption is closely associated with behavioural factors (Sun et al., 2016) and herding (Walden and Browne, 2009). There are clear links with finance and speculative bubbles when such processes are associated with technological innovation and/or an influx of new investors (Gisler and Sornette, 2009; Zeira, 1999). One of the key intended features associated with Blockchain is increased democratisation of the global economy. Non-traditional investors may access cryptocurrencies outside of the regular financial system (Yelowitz and Wilson, 2015). Further, Blockchain's transparent and distributed records allow for the verification of financial transactions without the need for intermediaries such as banks (Yermack, 2017). Future work will explore additional theoretical work at the interface of finance and technological innovation. Technically inefficient innovations exist that may not necessarily benefit adopters (Abrahamson, 1991). Informational cascades in networks, though often associated with the adoption of new technology, can also occur in various different social science settings, including finance (Bikchandani et al., 1992). Blockchain developments also hold additional interest from an economic perspective. One possibility is that arrangements such as partial equity ownerships can help facilitate additional investment in Blockchain (see e.g. a related model for partial ownerships in Serbera, 2017). Moreover, there is some potential for Initial Coin Offerings, as opposed to Initial Public Offerings, to generate profits (Tapscott and Tapscott, 2017; Adhami et al., 2018). Further topics for future research, helpfully suggested by two anonymous referees, include extensions of the model to sentiment analysis (e.g. extracted from Twitter) and a systematic literature review of the academic literature on Bitcoin and Blockchain.

The implications for practice are three-fold. Firstly, from an operational perspective, we provide ways of quantifying long-term brand values using Google Trends. Secondly, Google data show marked differences between Blockchain and cryptocurrencies. This suggests that practitioners cannot fully understand Blockchain simply by looking at past experiences with cryptocurrencies. Thirdly, our bubble models suggest practitioners should temper their expectations and plan accordingly. Historically, the introduction of new technologies has been associated with excessive speculation (Reinhart and Rogoff, 2009; Zeira, 1997). We cautiously note that there remain several contemporary and future challenges that Blockchain has yet to overcome. Current barriers include a relatively slow rate of progress (Iansiti and Lakhani, 2017) and vulnerabilities to hacking (Freund, 2017). Future problems include a historically high failure rate for innovations and the potential for innovation resistance amongst customers (Talke and Heidenreich, 2014).

Acknowledgements

The authors would like to acknowledge helpful and supportive comments from two anonymous referees. The usual disclaimer applies.

References

[1] Abrahamson, E. (1991). "Managerial fads and fashions; the diffusion and rejection of innovations." *Academy of Management Review*, Vol. 16, pp. 586-612.

[2] Adhami, S., Giudici, G. and Martinazzi, S. (2018) "Why do businesses go crypto? An empirical analysis of initial coin offerings." *Journal of Economics and Business*, Vol. 100, pp. 64-75.

[3] Anderson, R. and Murdoch, S. J. (2014). "EMV: Why payment systems fail." *Communications of the ACM*, Vol. 57, pp. 24-28.

[4] Alabi, K. (2017). "Digital blockchain networks appear to be following Metcalfe's law." *Electronic Commerce Research and Applications*, Vol. 24, pp. 23-29.

[5] Asem, E. and Tian, G. Y. (2010). "Market dynamics and momentum profits." *Journal of Financial and Quantitative Analysis*, Vol. 45, pp. 1549-1562.

[6] Baeck, C. and Elbeck, M. (2015). "Bitcoins as an investment or speculative vehicle? A first look." *Applied Economics Letters*, Vol. 22, pp. 30-34.

[7] Balcilar, M., Bouri, E., Gupta, R. and Roubaud, D. (2017) "Can volume predict Bitcoin returns and volatility? A quantiles-based approach." *Economic Modelling*, Vol. 64, pp. 74-81.

[8] Barata, J., Cunha, P. R. and Stal, J. (2018). "Mobile supply chain management in the Industry 4.0 era: An annotated bibliography and guide for future research." *Journal of Enterprise Information Management*, Vol. 31, pp. 173-192.

[9] Bickchandani, S., Hirshleifer, D. and Welch, I. (1992). "A theory of fads, fashion, custom and cultural change as informational cascades." *Journal of Political Economy*, Vol. 100, pp. 992-1026.

[10] Bingham, N. H. and Fry, J. M. (2010). *Regression: Linear models in statistics.* Springer, London Dordtrecht Heidelberg New York.

[11] Binner, J. M. and Wattam, S. (2013). "A composite leading indicator of inflation for the UK: A Kalman Filter approach." *Global Business and Economic Review*, Vol. 5, pp. 242-264.

[12] Bishop, C. M. (2006) *Pattern recognition and machine learning.* Springer.

[13] Black, F. and Scholes, M. (1973). "The pricing of options and corporate liabilities." *Journal of Political Economy*, Vol. 72, pp. 637-659.

[14] Blau, B. M. (2017). "Price dynamics and speculative trading in Bitcoin." *Research in International Business and Finance*, Vol. 41, pp. 493-499.

[15] Burns, R. (2014). *The naked trader: How anyone can make money trading shares*, 4th ed. Harriman House, Petersfield, Hampshire.

[16] Campbell, J. Y., Lo, A. and MacKinlay, J. A. C. (1997). *The econometrics of financial time series.* Princeton University Press, Princeton.

[17] Chatzoglou, P. and Chatzoudes, D. (2016). "Factors affecting e-business adoption in SMEs: an empirical research." *Journal of Enterprise Information Management*, Vol. 29, pp. 327-358.

[18] Cheah, E-T. and Fry, J. (2015). "Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitoin." *Economics Letters*, Vol. 130, pp. 32-36.

[19] Chen, Y. (2018). "Blockchain tokens and the potential democratization of entrepreneurship and innovation." *Business Horizons*, Vol. 61, pp. 567-575.

[20] Corbet, S., Lucey, B. and Yarovya, L. (2018). "Datestamping the Bitcoin and Ethereum bubbles." *Finance Research Letters*, Vol. 26, pp. 81-88.

[21] Date, G. H. and Raoot, A. D. (2014). "Review on IT adoption: insights from recent technologies." *Journal of Enterprise Information Management*, Vol. 27, pp. 488-502.

[22] De Paoli, B. and Zabczyk, P. (2012). "Why do risk premia vary over time? A theoretical investigation under habit formation." *Macroeconomic Dynamics*, Vol. 16, pp. 252-266.

[23] Dowd, K. (2014). *New private monies. A bit-part player?* Institute of Economic Affairs, London.

[24] Dyhrberg, A. H. (2016). "Bitcoin, gold and the dollar – a GARCH volatility analysis." *Finance Research Letters*, Vol. 16, pp. 85-92.

[25] Eken, M. H. and Baloğlu, E. (2017). "Crypto currencies and their destinies in the future." *Journal of Finance and Banking Studies*, Vol. 6, pp. 1-11.

[26] Fanning, K. and Centers, D. P. (2016). "Blockchain and its coming impact on financial services." *Corporate Finance and Accounting*, Vol. July/August 2016, pp. 53-57.

[27] Fantazzini, D. (2014). "Nowcasting and forecasting the monthly food stamps data in the US using online search data." *PLoS ONE*, Vol. 9, e11894.

[28] Freund, A. (2017). "Economic incentives and Blockchain security." *Journal of Securities Operations and Custody*, Vol. 10, pp. 67-76.

[29] Fry, J. (2018) "Booms, busts and heavy-tails: the story of Bitcoin and cryptocurrency markets?" *Economics Letters*. Vol. 171, pp. 225-229.

[30] Fry, J. and Cheah, E-T. (2016). "Negative bubbles and shocks in cryptocurrency markets." *International Review of Financial Analysis*, Vol. 47, pp. 343-352.

[31] Gandal, N., Harrick, J. T., Moore, T. and Oberman, T. (2018). "Price manipulation in the Bitcoin ecosystem." *Journal of Monetary Economics*, Vol. 95, pp. 86-96.

[32] Geraskin, P. and Fantazzini, D. (2013). "Everything you always wanted to know about log-periodic power laws for bubble modelling but were afraid to ask." *European Journal of Finance*, Vol. 19, pp. 366-391.

[33] Gisler, M. and Sornette, D. (2009). "Exuberant innovations: the Apollo Program." *Society*, Vol. 46, pp. 55-68.

[34] Hawlitschek, F., Noteheisen, B. and Teubner, T. (2018). "The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy." *Electronic Commerce Research and Applications*, Vol. 29, pp. 50-63.

[35] Hendricks, V. F. and Vestergaard, M. (2018). *Reality lost. Markets of attention, misinformation and manipulation.* Springer, New York.

[36] Hou, J., Wang, H. and Liu, P. (2018). "Applying the blockchain technology to promote the development of distrbuted photovoltaic in China." *International Journal of Energy Research*, Vol. 42, pp. 2050-2069.

[37] Huckle, S., Bhattacharya, R., White, M. and Beloff, N. (2016). "Internet of things, Blockchain and shared economy applications." *Procedia Computer Science*, Vol. 98, pp. 461-466.

[38] Iansiti, M. and Lakhani, K. R. (2017). "The truth about Blockchain." *Harvard Business Review*, Vol. 95, pp. 118-127.

[39] Johansen, A., Ledoit, O. and Sornette, D. (2000). "Crashes as critical points." *International Journal of Theoretical and Applied Finance*, Vol. 3, pp. 219-255.

[40] Jun, M. (2018) "Blockchain government – a next from of infrastructure for the twenty-first century." *Journal of Open Innovation; Technology, Market and Complexity*, Vol. 4, pp. 7.

[41] Karlis, D. and Xekalaki, E. (2005). "Mixed Poisson distributions." *International Statistical Review*, Vol. 73, pp. 35-58.

[42] Katsiampa, P. (2017). "Volatility estimation for Bitcoin: A comparison of GARCH models." *Economics Letters*, Vol. 158, pp. 3-6.

[43] Kim, K. and Hong, S. (2017). "A trusted sharing model for patient records based on permissioned Blockchain." *Journal of Internet Computing and Services*, Vol. 18, pp. 75-84.

[44] Kristoufek, L. (2013). "Bitcoin meets Google Trends and Wikipedia; Quantifying the relationship between phenomena of the internet era." *Scientific Reports*, Vol. 3, 3415.

[45] Laurence, T. (2017). *Blockchain for dummies.* Wiley, Hoboken, New Jersey.

[46] Lazer, D., Kennedy, R., King, G. and Vespignani, A. (2014). "The parable of Google flu: traps in Big Data analysis." *Science*, Vol. 343, pp. 1203-1205.

[47] Maslov, S. and Zhang, Y-C. (1998). "Optimal investment strategy for risky assets." *International Journal of Theoretical and Applied Finance*, Vol. 1, pp. 377-387.

[48] McLean, R. D. and Zhao, M. (2014). "The business cycle, investor sentiment and costly external finance." *Journal of Finance*, Vol. 69, pp. 1377-1409.

[49] Miau, S. and Yang, J. M. (2018). "Bibliometrics-based evaluation of the Blockchain research trend: 2008-March 2017." *Technology Analysis and Strategic Management*, Vol. 30, pp. 1029-1045.

[50] Morabito, V. (2017). *Business innovation through Blockchain: the B^3 perspective.* Springer.

[51] Nofer, M., Gomber, P., Hinz, O. and Schiereck, D. (2017). "Blockchain." *Business Information Systems Engineering*, Vol. 59, pp. 183-187.

[52] Park, C-H. and Irwin, S. H. (2007). "What do we know about the profitability of technical analysis?" *Journal of Economic Surveys*, Vol. 21, pp. 786-826.

[53] Phillip, A., Chan, J. and Peiris, S. (2018). "A new look at cryptocurrencies." *Economics Letters*, Vol. 163, pp. 6-9.

[54] Ranyard, J. C., Fildes, R. and Hu, T-I. (2015). "Reassessing the scope of OR practice: the influence of problem structuring methods and the analytics movement." *European Journal of Operational Research*, Vol. 245, pp. 1-13.

[55] Reinhart, C. M., and Rogoff, K. (2009) *This time it's different. Eight centuries of financial folly.* Princeton University Press, Princeton.

[56] Risteski, D. and Davcev, D. (2014) "Can we use daily internet search query data to improve predicting power of EGARCH models for financial time series volatility?", in *International Conference on Computer Science and Information Systems (ICCSIS 2014)*, pp. 34-38.

[57] Serbera, J-P. (2017). "A new strategy against hostile takeovers: a model of defense in participations." *Managerial and Decision Economics*, Vol. 38, pp. 832-844.

[58] Sharma, S. and Routroy, S. (2016). "Modeling information risk in supply chains using Bayesian networks." *Journal of Enterprise Information Systems*, Vol. 29, pp. 238-254

[59] Soja, P., Themistocleous, M., da Cunha, P. R. and da Silva, M. M. (2015). "Determinants of enterprise system adoption across the system lifecycle: exploring the role of economic development." *Information Systems Management*, Vol. 32, pp. 341-363.

[60] Sornette, D. and Malevergne, Y. (2006). *Extreme financial risks: From dependence to risk management.* Springer, Berlin Heidelberg New York.

[61] Sun, H., Fang, Y. and Zou, H. (2016). "Choosing a fit technology; understanding mindfulness in technology adoption and continuance." *Journal of the Association for Information Systems*, Vol. 17, pp. 377-412.

[62] Swan, M. (2015). *Blockchain: blueprint for a new economy.* O'Reilly Media.

[63] Talke, K. and Heidenreich, S. (2014). "How to overcome pro-change bias: incorporating passive and active innovation resistance in innovation decision models." *Journal of Product Innovation Management*, Vol. 31, pp. 894-907.

[64] Tapscott, D. and Tapscott, A. (2016). *Blockchain revolution: how the technology behind bitcoin is changing business and the world.* Penguin.

[65] Tapscott, D. and Tapscott, A. (2017). "How Blockchain is changing finance." *Harvard Business Review*, Vol. March 2017, pp. 2-6.

[66] Tierney, H. L. R. and Pan, B. (2012). "A Poisson regression examination of the relationship between website traffic and search engine queries." *Netnomics: Economic Research and Electronic Networking*, Vol. 13, pp. 155-189.

[67] Tukey, J. W. (1977). *Exploratory data analysis.* Addison-Welsey, Reading, Massachussets.

[68] Vranken, H. (2017). "Sustainability of bitcoin and blockchains." *Current Opinion in Environmental Sustainability*, Vol. 28, pp. 1-9.

[69] Walden, E. A. and Browne, G. J. (2009). "Sequential adoption theory; A theory for understanding herding behaviour in early adoption of novel technologies." *Journal of the Association for Information Systems*, Vol. 10, pp. 31-62.

[70] Yelowitz, A. and Wilson, M. (2015) "Characteristics of Bitcoin users: an analysis of Google search data." *Applied Economics Letters*, Vol. 22, pp. 1030-1036.

[71] Yeomans, J. M. (1992). *Statistical mechanics of phase transitions.* Oxford University Press, Oxford.

[72] Yermack, D. (2017). "Corporate governance and blockchains." *Review of Finance*, Vol. 21, pp. 7-31

[73] Zeira, J. (1999). "Informational overshooting, booms and crashes." *Journal of Monetary Economics*, Vol. 43, pp. 237-257.