

# Quantifying the sustainability of Bitcoin and Blockchain

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## 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

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8 and Blockchain. From a theoretical perspective we aim to provide ways of countering a pro-  
9 innovation bias that is known to dominate much of the academic literature (Abrahamson, 1991).  
10 For example, much academic work implicitly assumes that the diffusion of innovation will always  
11 benefit adopters (Abrahamson, 1991) or that technologies will be enthusiastically adopted by  
12 customers (Talke and Heidenreich, 2014). However, reality is more complex. Abrahamson  
13 (1991) speaks of managerial fads in relation to either the adoption of inefficient innovations  
14 or the rejection of efficient ones. Excess speculation can also accompany periods of genuine  
15 innovation (Zeira, 1999). The danger of excessive hype associated with Blockchain is highlighted  
16 in Hawlitschek et al. (2018). As such we aim to sound a timely note of caution. Our results are  
17 consistent with the view that progress made may be gradual (Iansiti and Lakhani, 2017). Inter  
18 alia privacy and security issues both need to be adequately addressed (Jun, 2018). Issues related  
19 to unequal economic development may also limit the global uptake of Blockchain technologies  
20 (Soja et al., 2015).

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32 The contribution of this paper is as follows. We produce a quantitative behavioural model  
33 for Blockchain using the Google Trends Search Index to infer the fundamental brand value of  
34 Blockchain and of cryptocurrencies. This builds on a large literature on the use of Google  
35 data in applied forecasting work (Fantazzini, 2014; Kristoufek, 2013) and adds to the range  
36 of different methodologies applied to Blockchain (Miau and Yang, 2018). Our model extends  
37 related papers that have focussed exclusively on cryptocurrencies (Cheah and Fry, 2015; Fry  
38 and Cheah, 2016) and accounts for the fact that technology adoption is associated with both  
39 behavioural factors (Sun et al., 2016) and herding (Walden and Browne, 2009). The specific  
40 innovations with respect to Fry and Cheah (2016) include more refined estimates of the effect  
41 size, investigation of a trading-type environment via estimates of the long-term growth rate and  
42 the extension of the base model into non-financial contexts (see e.g. Hendricks and Vestergaard,  
43 2018). Our results confirm previous findings of speculative bubbles in cryptocurrency markets  
44 and shows that the economic size of the effects can be substantial. Results also suggest that  
45 competitor cryptocurrencies such as Ethereum\*, Ripple and Bitcoin Cash may have better long-  
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57 \*We use the general term Ethereum to describe both the Blockchain technology and the cryptocurrency. Other  
58 authors use the term Ether to distinguish the cryptocurrency from the underlying Blockchain technology (see e.g.  
59 Laurence, 2017). Here, we take the view that this distinction complicates the discussion of multiple cryptocurrency  
60 markets.

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8 term prospects than Bitcoin. Google searches for cryptocurrencies seem to be primarily driven  
9 by recent price rises. However, Google searches for Blockchain can be shown to fundamentally  
10 different in nature. Thus, our numerical results reinforce the importance of the distinction  
11 between cryptocurrencies and the subject of Blockchain more generally.  
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15 The layout of this paper is as follows. A review of early Blockchain applications is given in  
16 Section 2. Section 3 discusses the theoretical modelling of speculative bubbles. Section 4 dis-  
17 cusses an application to the four major cryptocurrency markets. Section 5 discusses behavioural  
18 modelling of Google Trends to determine brand value. Section 6 discusses an empirical applica-  
19 tion to Blockchain and cryptocurrency markets. The research synthesis is in Section 7. Section  
20 8 concludes and discusses the opportunities for further work.  
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## 28 **2 Review of early Blockchain applications**

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31 Bitcoin is the first widespread usage of Blockchain technology. However, Blockchain has an  
32 identity and a reach potentially far beyond this. There appear to be two key conditions for  
33 Blockchain applications. These conditions are convenience and consensus/trust. As discussed  
34 in Fry and Cheah (2016) cryptocurrencies can be viewed, at least in part, as a natural exten-  
35 sion of other forms of electronic payment. Similarly, other Blockchain applications complement  
36 existing supply-chain developments (Barata et al., 2018). In particular, Bitcoin's construction  
37 also highlights the importance of building consensus. Part of the motivation behind Bitcoin was  
38 the way in which many national currencies have been progressively devalued by national govern-  
39 ments (Dowd, 2014). In particular, Bitcoin's mining processes, linked to the solution of complex  
40 mathematical cryptography problems which in turn form the verification of the Blockchain, are  
41 intended to replicate the seemingly objective ways in which national currencies were historically  
42 linked to precious metals such as gold or silver. In a similar vein these mining processes are also  
43 intended to reward individuals who contribute to the platform via their computational resources.  
44 However, these dual concepts of convenience and consensus can be applied to much more general  
45 forms of contractual agreement. Potential applications where consensus is required include e-id,  
46 land registers, social security records and securities trading (Jun, 2018). Blockchain applications  
47 have also been used to promote the development of photovoltaic technology (Hou et al., 2018)  
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8 and to share patient records (Kim and Hong, 2017). Smart contracts clearly accentuate aspects  
9 of convenience outlined above (Iansiti and Lakhani, 2017). Ultimately, Blockchain may be used  
10 to mitigate information risks in supply chains (Sharma and Routroy, 2016). Another possibility  
11 is the use of Initial Coin Offerings, as opposed to Initial Public Offerings, to raise funds for  
12 industry (Tapscott and Tapscott, 2017; Adhami et al., 2018) and entrepreneurship, start-ups  
13 and innovation (Chen, 2018). Applications to insurance, music industry download royalties, de-  
14 centralised storage and logistics, decentralised internet of things and anti-counterfeit measures  
15 are discussed in Nofer et al. (2017). In this way Blockchain applications can be seen as a natural  
16 extension of existing e-business (see e.g. Chatzoglou and Chatzoudes, 2016).  
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24 Blockchain is a fundamental technology that may ultimately take decades to be fully ab-  
25 sorbed into our economic and social infrastructure (Iansiti and Lakhani, 2017). Nevertheless,  
26 the potential clearly exists for the wholesale replacement of bureaucratic systems in a dizzy-  
27 ing array of different areas (Jun, 2018). Inter alia internet sharing platforms such as Uber and  
28 Airbnb may no longer be required (Huckle et al., 2016). Transparent and distributed records via  
29 Blockchain may enable the verification of financial transactions without the need for intermedi-  
30 aries such as banks (Yermack, 2017). Blockchain has also recently been adopted by Mastercard  
31 for non-Bitcoin payments. However, technological adoption does not always benefit adopters  
32 (Abrahamson, 1991). Current cryptographic technology remains vulnerable to hacking (Freund,  
33 2017). Historically, payment systems have proved vulnerable in unanticipated ways (Anderson  
34 and Murdoch, 2014). There is also a need to develop new technologies to add privacy and secu-  
35 rity to the raw Blockchain technology (Jun, 2018). Moreover, some fundamental levels of trust  
36 are likely to always be required (Hawlitschek et al., 2018).  
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48 As the first meaningful application of Blockchain technology the cryptocurrency experience  
49 offers some useful insights. Though today's cryptocurrencies may not ultimately last long they  
50 may nonetheless play a prominent role in shaping future progress. Question marks over their  
51 long-term sustainability (Dowd, 2014) are further reinforced by the extremely volatile nature of  
52 cryptocurrency markets (Blau, 2017; Corbet et al., 2018; Fry, 2018). In Vranken (2017) there is  
53 even some debate as to whether the electricity consumption required for Bitcoin's mining pro-  
54 cesses is environmentally sustainable. In Eken and Baloğlu (2017) cryptocurrencies are compared  
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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 Zabczyk, 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

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

where  $P_1(t)$  satisfies

$$dP_1(t) = [\mu(t) + \sigma^2(t)/2] P_1(t)dt + \sigma(t)P_1(t)dW_t, \quad (2)$$

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

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

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

$$dX_t = \mu(t)dt + \sigma(t)dW_t - v dj(t), \quad (4)$$

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

$$E[j(t + \Delta) - j(t)] = \Delta h(t) + o(\Delta), \quad (5)$$

$$\text{Var}[j(t + \Delta) - j(t)] = \Delta h(t) + o(\Delta), \quad (6)$$

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

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

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

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

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

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  $\sigma^2$ :*

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

*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

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

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

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

*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

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

From equation (12) define

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

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

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

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:

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



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8 Use of the median within this context reflects its utility in applied statistics (see e.g. Tukey,  
9 1977), including invariance under monotonic transformations (Sornette and Malevergne, 2006).  
10 Equation (13) thus leads to a more robust estimate of the economic size of the effect compared  
11 to much of the literature.  
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15 In Cheah and Fry (2015) it is found that the size of the speculative bubble in Bitcoin prices is  
16 sufficiently large as to preclude long-term investment. In the sequel we show how this approach  
17 can be both made more rigorous and applied to practical investment problems. Given an initial  
18 price  $P_0$  the probability that the investment gains in the long-term for large  $t$ , and once any  
19 short-term bubble or negative bubble effects subside, can be calculated as  
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$$24 \quad Pr(P_t > P_0) = Pr(X_t - X_0 > 0) = \Phi\left(\frac{\mu t}{\sigma\sqrt{t}}\right), \quad (14)$$

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26 where  $\Phi(\cdot)$  denotes the standard normal CDF. Hence, it follows from (14) that  
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$$29 \quad \lim_{t \rightarrow \infty} Pr(P_t > P_0) = 1 \text{ iff } \mu > 0. \quad (15)$$

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31 Thus, equation (15) suggests that there is evidence for long-term growth precisely when we can  
32 reject the null hypothesis  
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$$35 \quad H_0 : \mu \leq 0; \quad H_1 : \mu > 0. \quad (16)$$

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37 Thus, equation (16) leads to a strengthened investment condition compared to that in Cheah  
38 and Fry (2015) and is related to classical approaches to long-term investment (Maslov and  
39 Zhang, 1998). Equation (16) also reflects renewed interest in momentum and sentiment effects  
40 throughout economics (see e.g. Asem and Tian, 2010; McLean and Zhao, 2014). There are also  
41 links to the scientific study of technical analysis (Park and Irwin, 2007) and to a more systematic  
42 treatment of the naive momentum trading strategies often used by practitioners (see e.g. Burns,  
43 2014).  
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47 To summarise, our model can be used to discover speculative bubbles in cryptocurrency  
48 markets as follows. As discussed in Section 4 the model can be calibrated to empirical prices  
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8 using the method of maximum likelihood. Equation (12) means that we can test for the presence  
9 or absence of a bubble by testing the null hypothesis  $v = 0$  against the alternative hypothesis  
10  $v > 0$ . Equation (13) gives a way of determining the economic size of the bubble given estimates  
11 of  $\alpha$ ,  $\beta$  and  $v$ . Finally, equation (16) gives a way of quantifying whether or not it would be  
12 worthwhile to buy and hold the cryptocurrency in the long-term.  
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#### 19 **4 Quantifying speculative bubbles in cryptocurrency prices**

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21 In this section we fit our model to empirical prices from the four major cryptocurrencies as  
22 determined by their current market capitalisation. Motivated by the recent boom and bust in  
23 cryptocurrencies we examine Bitcoin and Ripple prices from January 1st 2015-January 1st 2018  
24 and compare against newer altcoins that have only come into being more recently. In particular,  
25 we look at Ethereum prices from August 7th 2015-January 1st 2018 and Bitcoin Cash prices  
26 from July 23rd 2017 to January 1st 2018. A plot of the data is shown in Figure 1.  
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33 The model in Section 3 can be calibrated to the data using the method of maximum likeli-  
34 hood. Results shown in Table 1 give significant evidence of speculative bubbles in all markets  
35 with the exception of Bitcoin Cash. This reinforces previous findings of speculative bubbles in  
36 cryptocurrency markets (Blau, 2017; Cheah and Fry, 2015; Corbet et al., 2018). Moreover, the  
37 effect size can be substantial (Cheah and Fry, 2015). Inter alia our model suggests Ethereum  
38 prices are over-valued by around 26%. Application of the long-term investment criterion shown  
39 in equation (16) would suggest buying Ripple and Ethereum but not Bitcoin or Bitcoin Cash.  
40 For Ripple and Ethereum the estimated long-term growth rate shown in equation (16) is both  
41 positive and statistically significant. That our mathematical model returns this interpretation  
42 may reflect long-term technical advantages that Ripple and Ethereum have relative to Bitcoin  
43 (Swan, 2015). In contrast, for Bitcoin and Bitcoin Cash the estimated long-term growth rate  
44 shown in equation (16) is not significantly different from zero. That our mathematical model  
45 returns this interpretation may reflect question marks over the long-term primacy of Bitcoin  
46 and the Bitcoin technology relative to other cryptocurrencies (Dowd, 2014).  
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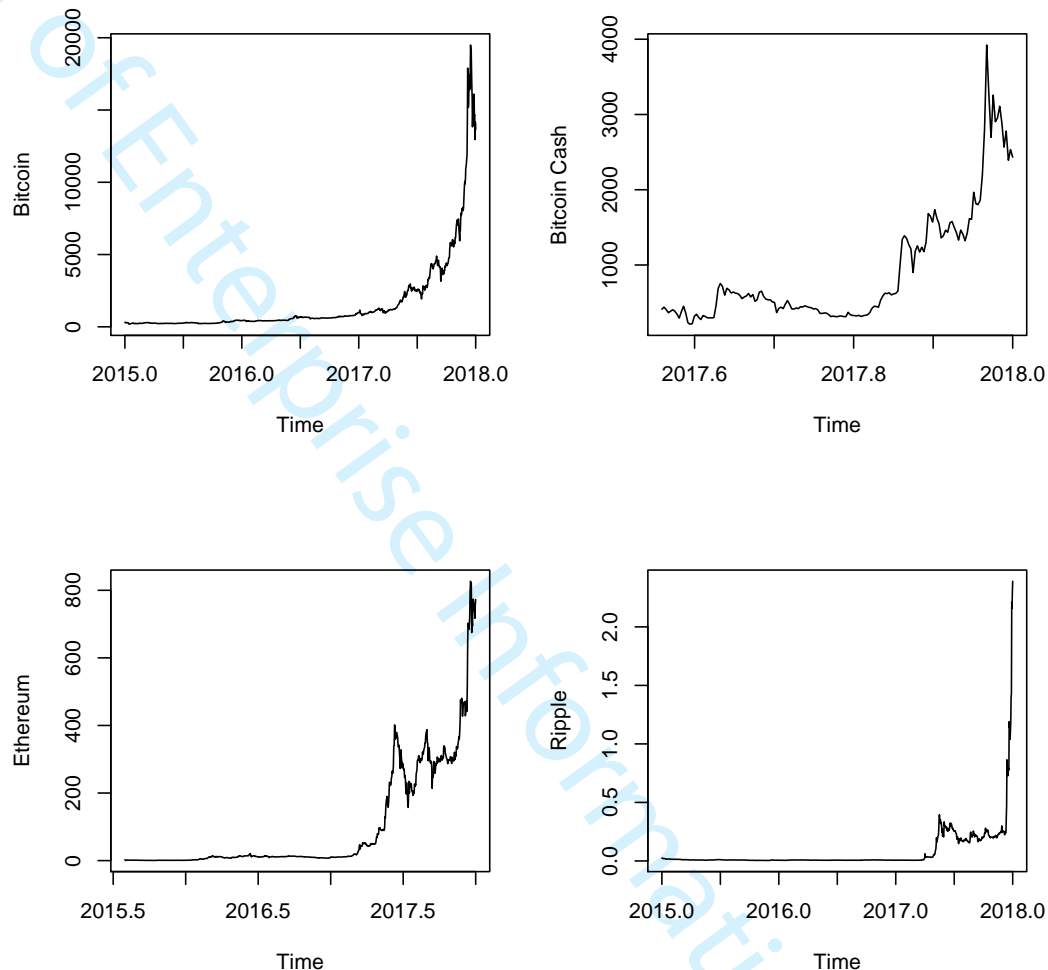


Figure 1: Plot of cryptocurrency prices over time: Bitcoin (top left), Bitcoin Cash (top right), Ethereum (bottom left) and Ripple (bottom right).

## 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

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

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

$$\ln \lambda_t = f(P_t). \quad (18)$$

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

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

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

$$dX_t = \mu(t) + \sigma(t) dW_t \quad (20)$$

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

$$E[G_t] = E[P_t]. \quad (21)$$

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

## 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.

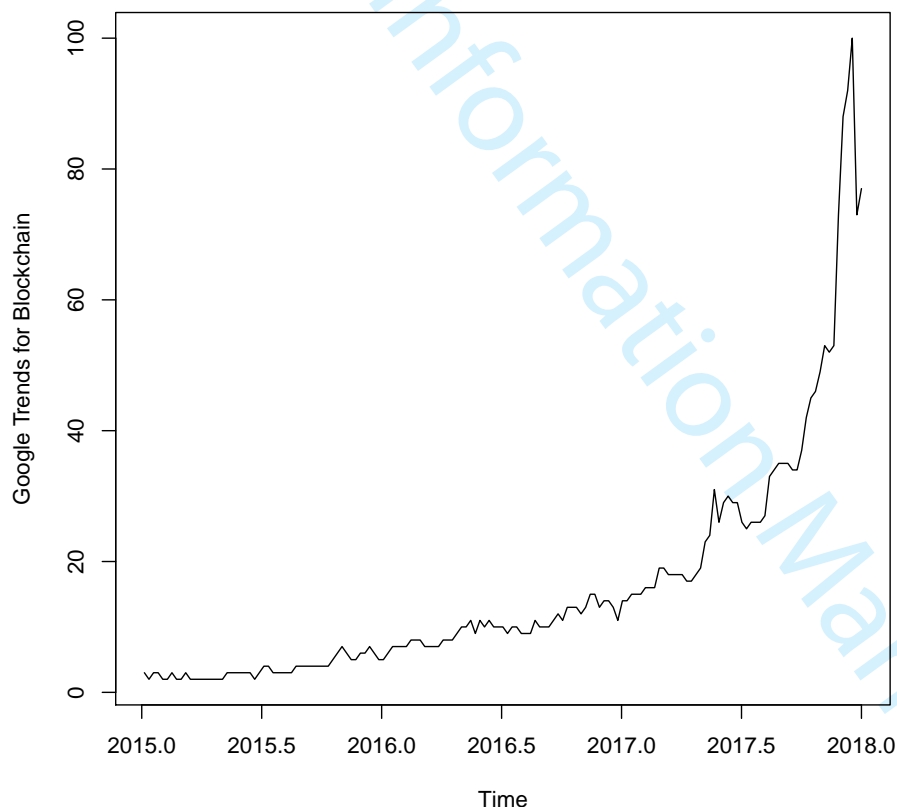


Figure 2: Plot of the weekly Google Trends Search Index (Worldwide) for Blockchain: January 4th 2015-December 31st 2017.

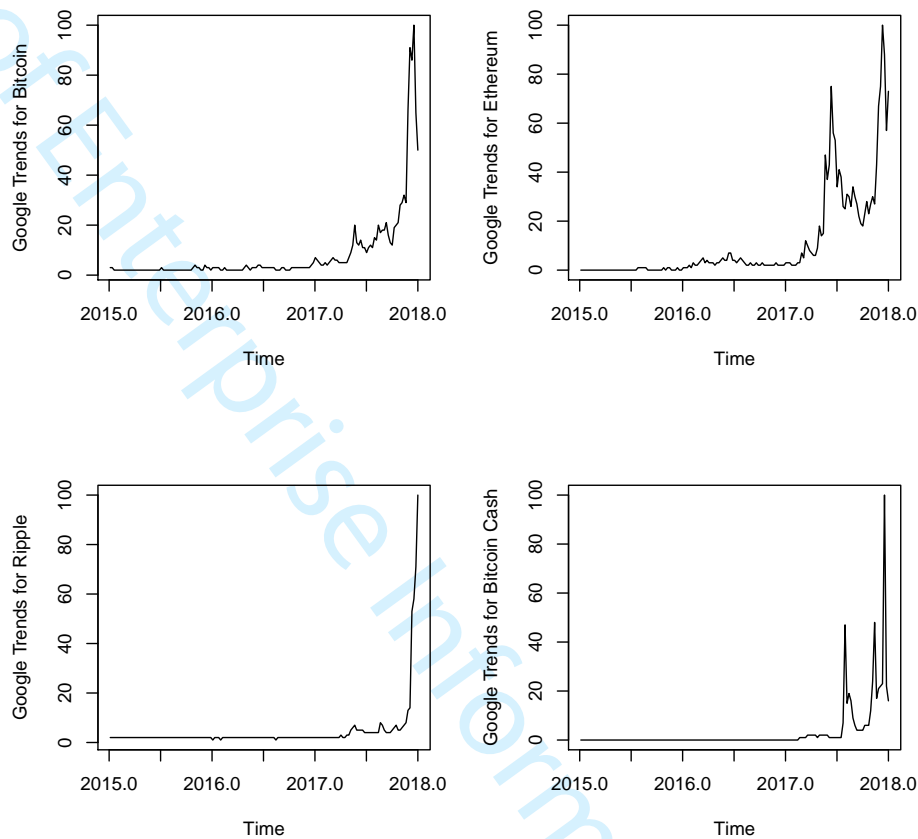


Figure 3: Plot of the weekly Google Trends Search Index (Worldwide) for Bitcoin coin (top left panel), Ethereum (top right panel), Ripple (bottom left panel), Bitcoin Cash (bottom right panel) for January 4th 2015-December 31st 2017.

	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

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8 Blockchain and cryptocurrencies. Evidence is found of bubbles in the brand value of all major  
9 cryptocurrencies. Moreover, the estimated economic size of the effect is substantial – of the  
10 order of 80-90%. The implication is that, rather than responding to fundamental information,  
11 Google Searches for cryptocurrencies may be primarily prompted by recent price rises. Similar  
12 findings are reported in Kristoufek (2013). This would also seem consistent with academic work  
13 that classifies cryptocurrencies as more of a speculative asset than a genuine currency (Baeck  
14 and Elbeck, 2015; Dyhrberg, 2016). Moreover, results in Lazer et al. (2014) show that failure  
15 to appropriately adjust raw Google search figures can lead to biased estimates in empirical  
16 forecasting work. Our results do suggest that Bitcoin Cash and Ethereum may have some long-  
17 term value – but the effects are only marginally statistically significant at best. In contrast  
18 no evidence is found of a bubble in Blockchain’s brand value. However, the long-term growth  
19 rate shown in equation (16) is not statistically significant. Results appear consistent with the  
20 interpretation that Blockchain clearly has wider significance beyond cryptocurrency markets but  
21 that the gains brought about by Blockchain technology may ultimately take decades before they  
22 are fully realised (Iansiti and Lakhani, 2017).  
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## 37 **7 Research synthesis**

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40 We add to a growing economics and finance literature that discusses the issue of bubbles and  
41 excessive speculation in Bitcoin and cryptocurrencies (Corbet et al., 2018; Gandal et al., 2018).  
42 In refining previous work (Cheah and Fry, 2015) we show how debates addressing long-term  
43 sustainability and long-term investment prospects may be better framed. Our financial model  
44 may then be further extended and applied to wider debates about Blockchain and new tech-  
45 nologies. We thus contribute to an emerging academic literature on Blockchain (Iansiti and  
46 Lakhani, 2017) and add to the methodological diversity of studies in the area (Miau and Yang,  
47 2018). Our paper also adds to previous attempts to use Google Trends data in a wide variety  
48 of different economic and social problems (Fantazzini, 2014).  
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56 Data from Google Trends has previously been used to motivate studies of bubbles and spec-  
57 ulative behaviour – see e.g. the simple qualitative plots in Geraskin and Fantazzini (2013) and  
58 Cheah and Fry (2015). Here, in contrast, we follow a more overtly mathematical modelling  
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<b>Maximum likelihood ratio test for a speculative bubble <math>H_0 : v = 0, H_1 : v \neq 0</math></b>		
<b>Search Term</b>	<b><math>\chi^2</math>-value</b>	<b><math>p</math>-value</b>
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
<b>Test for long-term growth <math>H_0 : \mu \leq 0</math></b>		
<b>Search Term</b>	<b><math>t</math>-value</b>	<b><math>p</math>-value</b>
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
<b>Estimated coefficient of over-pricing</b>		
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 online search data and the attendant nonlinearities 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,

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8 we develop a more robust investment criterion to try to discern genuine opportunities from  
9 purely illusory ones. Secondly, we extend this model to impute the fundamental brand value  
10 of cryptocurrencies and the Blockchain using data available from Google Trends. We thus con-  
11 tribute to live research themes in business analytics (Ranyard et al., 2015), empirical forecasting  
12 work using Google Trends (Fantazzini, 2014) and the mathematical modelling of Blockchain and  
13 cryptocurrencies (Alabi, 2017).  
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19 We confirm previous findings of speculative bubbles in cryptocurrency markets (Blau, 2017;  
20 Cheah and Fry, 2015; Corbet et al., 2018). Moreover, the effect size can be substantial. Here, it  
21 is estimated that Ethereum prices are around 26.5% over-valued during the period in question.  
22 The above notwithstanding, our model suggests that Ethereum and Ripple may ultimately  
23 represent a better long-term investment than Bitcoin. This may reflect technological advantages  
24 of Ethereum and Riple relative to Bitcoin (Swan, 2015) alongside concerns that Bitcoin may  
25 ultimately be superseded by another digital currency (Dowd, 2014). A second stage of the  
26 analysis suggests that Bitcoin Cash may also hold some advantages relative to Bitcoin.  
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33 Allied to the above we extend the first-stage model to enable us to use the Google Trends  
34 Search Index to infer long-term brand value. This builds on a wealth of applied forecasting  
35 work using Google Trends (see e.g. Fantazzini, 2014 and the references therein) including pre-  
36 vious applications to Bitcoin (Kristouffek, 2013). This also compliments previous approaches to  
37 analysing Blockchain such as the bibliometric analyses performed in Miao and Yang (2018). Our  
38 model exhibits marked differences between cryptocurrencies and the wider subject of Blockchain  
39 as a whole. Google searches on cryptocurrencies seem to be driven chiefly by recent price rises.  
40 This contrasts sharply with the Google searches for Blockchain, which seem to be more closely  
41 aligned to fundamental applications. The opportunities for Blockchain thus clearly extend be-  
42 yond cryptocurrencies (Iansiti and Lakhani, 2017). However, low estimated long-term growth  
43 rates tally with concerns raised that it may be a long time before the opportunities associated  
44 with Blockchain are fully realised (Iansiti and Lakhani, 2017). As an illustration of some of  
45 the problems that still need to be overcome, different levels of economic development remain  
46 a barrier to widespread Blockchain implementation (Soja et al., 2015). Current cryptographic  
47 technology also remains vulnerable to hacking (Freund, 2017).  
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8 Technological adoption is closely associated with behavioural factors (Sun et al., 2016) and  
9 herding (Walden and Browne, 2009). There are clear links with finance and speculative bub-  
10 bles when such processes are associated with technological innovation and/or an influx of new  
11 investors (Gisler and Sornette, 2009; Zeira, 1999). One of the key intended features associated  
12 with Blockchain is increased democratisation of the global economy. Non-traditional investors  
13 may access cryptocurrencies outside of the regular financial system (Yelowitz and Wilson, 2015).  
14 Further, Blockchain's transparent and distributed records allow for the verification of financial  
15 transactions without the need for intermediaries such as banks (Yermack, 2017). Future work  
16 will explore additional theoretical work at the interface of finance and technological innovation.  
17 Technically inefficient innovations exist that may not necessarily benefit adopters (Abraham-  
18 son, 1991). Informational cascades in networks, though often associated with the adoption  
19 of new technology, can also occur in various different social science settings, including finance  
20 (Bikchandani et al., 1992). Blockchain developments also hold additional interest from an eco-  
21 nomic perspective. One possibility is that arrangements such as partial equity ownerships can  
22 help facilitate additional investment in Blockchain (see e.g. a related model for partial owner-  
23 ships in Serbera, 2017). Moreover, there is some potential for Initial Coin Offerings, as opposed  
24 to Initial Public Offerings, to generate profits (Tapscott and Tapscott, 2017; Adhami et al.,  
25 2018). Further topics for future research, helpfully suggested by two anonymous referees, in-  
26 clude extensions of the model to include sentiment analysis (e.g. extracted from Twitter), in  
27 turn combing this with Google Trends data, and a systematic literature review of the academic  
28 literature on Bitcoin and Blockchain.

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46 The implications for practice are three-fold. Firstly, from an operational perspective, we  
47 provide ways of quantifying long-term brand values using Google Trends. Secondly, Google  
48 data show marked differences between Blockchain and cryptocurrencies. This suggests that  
49 practitioners cannot fully understand Blockchain simply by looking at past experiences with  
50 cryptocurrencies. Thirdly, our bubble models suggest practitioners should temper their ex-  
51 pectations and plan accordingly. Historically, the introduction of new technologies has been  
52 associated with excessive speculation (Reinhart and Rogoff, 2009; Zeira, 1997). We cautiously  
53 note that there remain several contemporary and future challenges that Blockchain has yet to

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8 overcome. Current barriers include a relatively slow rate of progress (Iansiti and Lakhani, 2017)  
9 and vulnerabilities to hacking (Freund, 2017). Future problems include a historically high failure  
10 rate for innovations and the potential for innovation resistance amongst customers (Talke and  
11 Heidenreich, 2014).  
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22 claimer applies.  
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