# The Economics of Bitcoins

## News, Supply vs Demand and Slumps

## Marc Gronwald

# The Economics of Bitcoins - News, Supply vs. Demand and Jumps

Marc Gronwald[*]

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## Abstract

This paper conducts the first detailed analysis of the dynamics of Bitcoin prices. The application of an autoregressive jump-intensity GARCH model allows one to study the role of both volatility clusters and extreme price movements. The results suggest that the influence of the latter is particularly pronounced - larger than in other markets - and remains largely unchanged over time. These results gain importance as the Bitcoin market only recently emerged and is characterised by a number of distinct market features which imply that there are no uncertainties on the Bitcoin supply-side. Thus, the observed price movements are attributable to demand side factors.

**Keywords:** Bitcoins, Jump models, Commodity Pricing

**JEL-Classification:** C12, C22, C58, G12

## 1 INTRODUCTION

The virtual currency of Bitcoin emerged in 2008, developed by a group of anonymous programmers with the purpose to make possible online payments without involvement of a financial institution or other third parties; see Nakamoto (2008). Bitcoin is the most popular virtual currency and received considerable attention from both the general public and academia, mainly due to the spectacular price behaviour, its general novelty value and certainly also extraordinary events and scandals related to Bitcoin. It does not come as a surprise that monetary theorists as well as central banks are particularly interested in this phenomenon. Lo and Wang (2014), for instance, discuss whether or not Bitcoin has the ability to perform the functions required of a fiat money. European Central Bank (2012) emphasises that virtual currencies generally can have the function of serving as medium of exchange within a specific community. Among the issues the very comprehensive paper by Boehme et al. (2015) discusses is whether or not Bitcoin can disrupt existing monetary systems.

Bitcoins can be obtained, first, by verifying transactions within the Bitcoin network - this process is commonly referred to as Bitcoin mining. Second, Bitcoins are also traded on various exchanges. The following figures illustrate that the Bitcoin market is economically highly relevant, and, thus, deserves the attention it currently receives. The market capitalisation currently is about 4 billion USD: the peak was close to 14 billion beginning of 2014.[1] Slightly more than 14 million Bitcoins are in circulation, around

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[1]Data source: https://blockchain.info.

250,000 unique Bitcoin addresses are used per day and there are more than 100,000 transactions per day. In addition to this, virtual currencies are a new phenomenon in general and are, at the same time, associated with the emergence of a new tradable entity and a new market place. Studying the price behaviour of such a newly developed tradable entity in the context of otherwise developed economies and financial markets is deemed particularly attractive.

The detailed analysis into the dynamics of Bitcoin prices this paper conducts is - to the best knowledge of the author - the first one to date.[2] The paper analyses Bitcoin price behaviour using an autoregressive jump-intensity GARCH model introduced by Chan and Maheu (2002). This method has been tested and proven by the empirical finance community and allows one to study the role of both volatility clusters and extreme price movements - two features often exhibited by financial market data. Volatility clusters usually emerge in more nervous market environments while extreme price movements - captured by the jump component of this model - are driven by extraordinary news. The model applied in this paper allows one to study how the role of extreme price movements develops over time and also to compare this role across markets.

The main results can be summarised as follows: Extreme price movements play a particularly strong role - stronger than in other markets - and remain largely unchanged over time. The applied jump models fit the data reasonable well; they outperform benchmark GARCH models and most of

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[2] To be precise, the paper analyses the Bitcoin USD exchange rate. For ease of reading, this exchange rate is referred to as Bitcoin price.

the jump parameters are significant. A short cross-market comparison shows that Bitcoin prices are more sensitive to news than crude oil prices. These results gain particular importance as the Bitcoin market only recently emerged and is characterised by a number of distinct market features: the total number of Bitcoins is fixed and both the number of Bitcoins in circulation as well as its growth rate is known with certainty. As this implies that there is no uncertainty on the supply-side of Bitcoin, it can be concluded that the observed price fluctuations are attributable to demand side factors.

The extant empirical literature this paper contributes to can be summarised as follows: Baek and Elbeck (2014) use the method of detrended ratios in order to study relative volatility as well as drivers of Bitcoin returns. They find that Bitcoin volatility is internally driven and conclude that the Bitcoin market is currently highly speculative. Cheah and Fry (2015) test for speculative bubbles in Bitcoin prices and find that they exhibit speculative bubbles. In addition, the authors state that the fundamental value of Bitcoin is zero. In a similar paper, Cheung et al. (2015) apply a recently proposed popular testing procedure in order to search for periodically collapsing bubbles. They find evidence of these type of bubbles in particular in the period between 2011 and 2013. Yelowitz and Wilson (2015) use Google search data in order to shed light on the characteristics of users interested in Bitcoin. Their analysis shows that "computer programming enthusiasts" and criminals seem to be particularly interested in Bitcoin, while interest does not seem to be driven by political and investment motives. Yermack (2013), finally, finds that Bitcoin prices are considerably more volatile than other currencies and that there is "virtually zero correlation" with the price

of gold.

The remainder of the paper is organised as follows: Section 2 provides a detailed descriptive analysis of the data, 3 outlines the empirical approach applied in this paper. Sections 4 and 5 present the main empirical results as well as a discussion of which; Section 6 offers some concluding remarks.

## 2  DATA

It has already been mentioned above that Bitcoins are traded on various exchanges. This paper uses two Bitcoin price series from two different exchanges: first, Mt.Gox, until its shutdown the most liquid Bitcoin exchange, and second, BTC-e. Brandvold et al. (2015) find that Mt.Gox and BTC-e are the leading markets with the highest information share. The periods of observation are 7/02/2011 - 2/24/2014 and 8/14/2011 and 8/27/2015, respectively; data frequency is daily, and log-returns of the prices are used.

Figure 1 presents the data used in this paper in levels as well as in returns. It should not need considerable emphasis that these eye-catching price dynamics deserve a closer investigation. The most famous episode is certainly the price hike witnessed end of 2013 and beginning of 2014. The Bitcoin price peaked at about 1,200 USD. Subsequent to this extraordinary period, Bitcoin prices seem to have stabilised - at least for Bitcoin standards - and volatility seems to be considerably lower than in earlier periods. However also prior to this price hike - and thus, before the general public started developing a particular interest in Bitcoin - remarkable price movements are present: in early stages of 2013, for instance, Bitcoin prices increased very
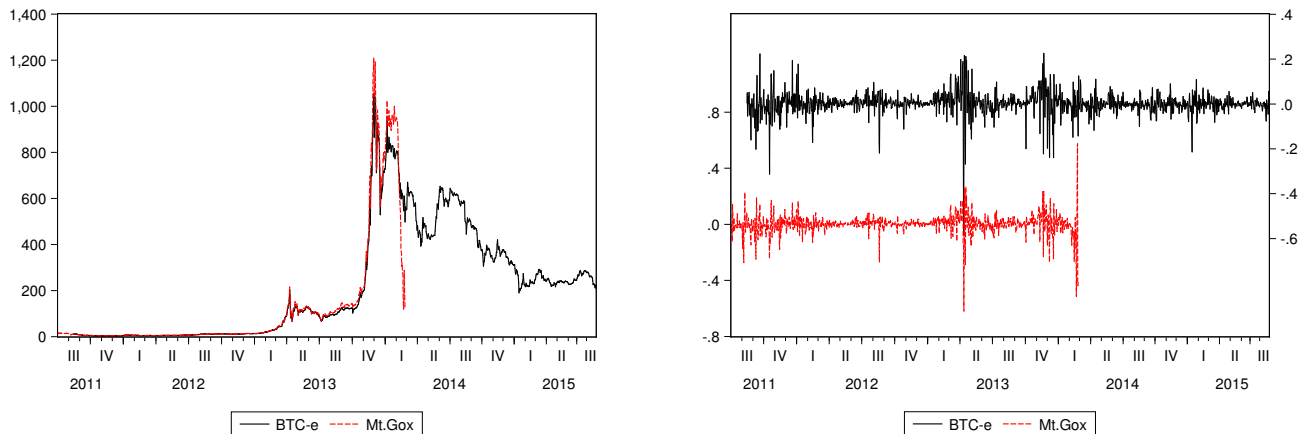
Figure 1: Bitcoin prices - levels and returns

fast, reaching 200 USD for the first time. Throughout the entire sample
period volatility clusters as well as extreme price movements seem to be
present.

Figures 2 and 3 vividly illustrate that Bitcoin price returns are far from
normally distributed. Displayed are kernel density estimates as well as
quantile-quantile plots for the full sample, an early subsample and a late
subsample, with 31/12/2012 serving as cut-off point. The empirical distri-
butions are highly leptocurtic - more clustered around the mean and with
heavier tails. This leptocurtosis is particularly pronounced in the early sub-
sample and in the BTC-e market. The quantile-qualtile plots confirm this
finding. These plots further illustrate that extreme price movements seem
to be more common in the Mt.Gox exchange and in particular in the late
subsample.

Figure 2: Kernel density estimates. BTC-e left column, Mt.Gox right column; full samples (upper panel), early subsample (middle panel) and late subsample (lower panel).
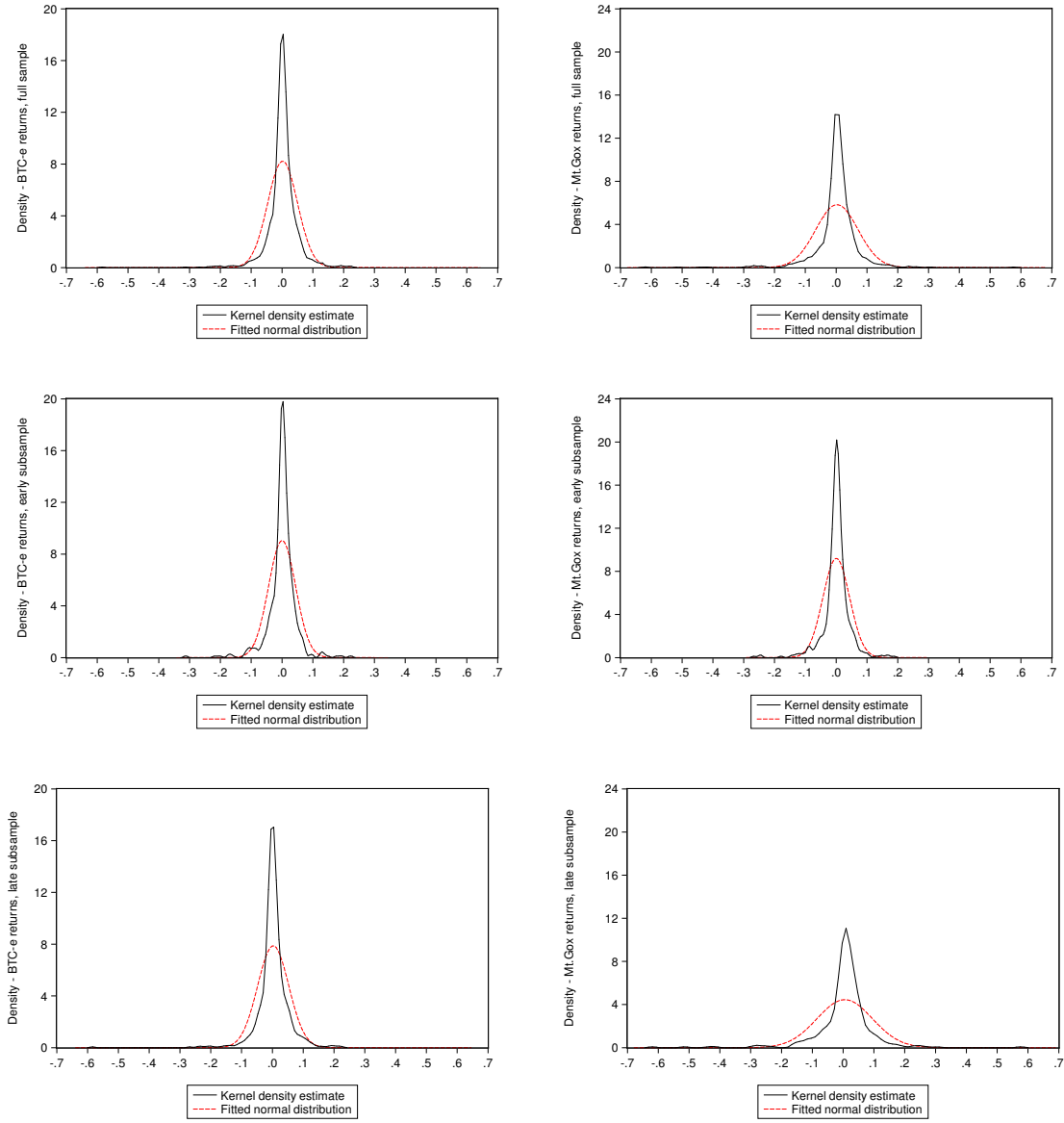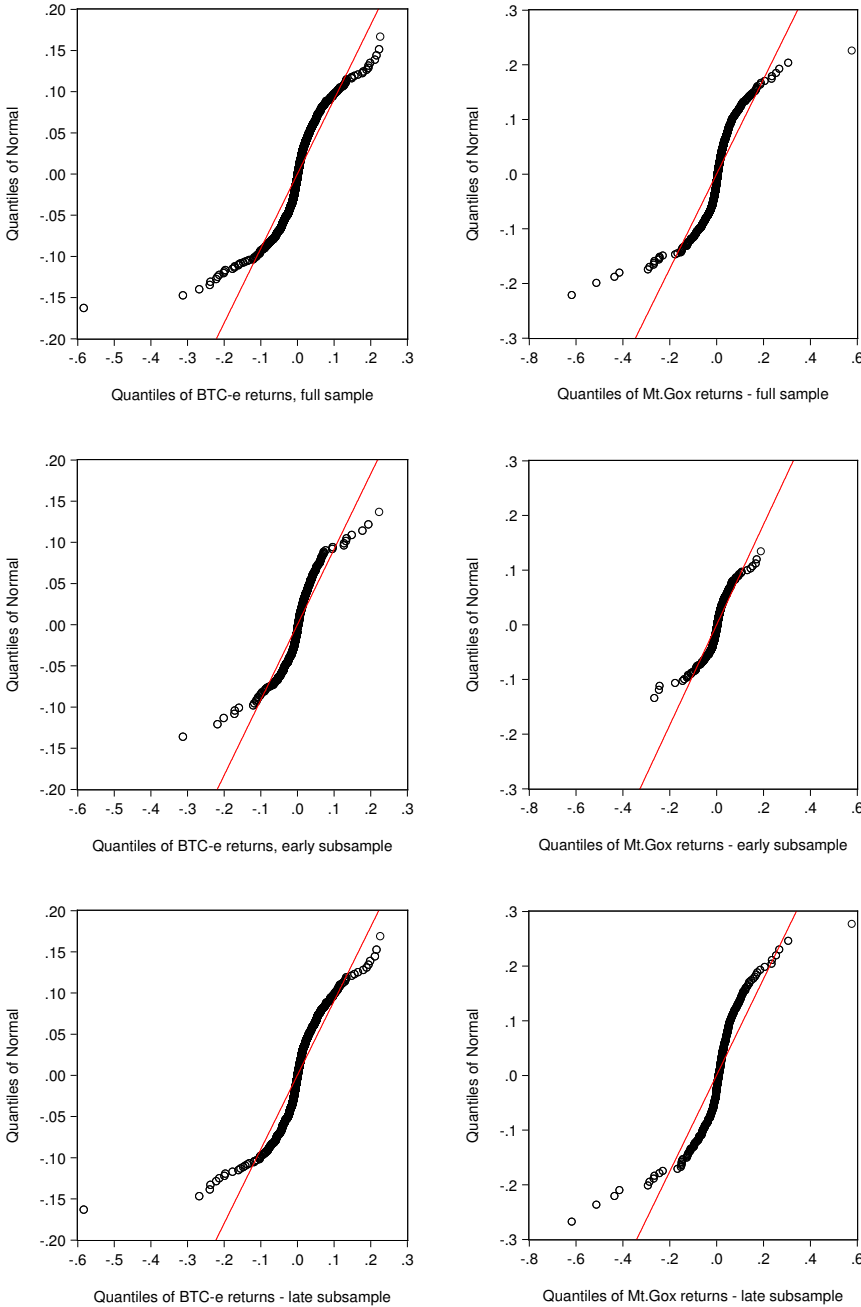
Figure 3: Quantile-quantile plots. BTC-e left column, Mt.Gox right column; full samples (upper panel), early subsample (middle panel) and late subsample (lower panel).

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## 3 Empirical model

The so-called autoregressive jump-intensity GARCH model has been proposed by Chan and Maheu (2002). This model consists of a jump component, which is able to capture extreme price movements, as well as a GARCH component, which captures volatility clusters. Chan and Maheu's (2002) model has been tested and proven by the empirical finance community; areas of application of this and similar models include crude oil prices (Gronwald, 2012), exchange rates (Chan, 2003) as well as copper prices (Chan and Young, 2006). Jumps in commodity prices are generally considered reflecting reactions of prices to surprising news; see e.g. Jorion (1988). The model consists of the following mean equation:

$$y_t = \mu + \sum_{i=1}^{l} \phi_i y_{t-i} + \sqrt{h_t} z_t + \sum_{k=1}^{n_t} X_{t,k} \tag{1}$$

with $z_t \sim NID(0,1)$. It is assumed that $h_t$ follows a GARCH($p$,$q$) process:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{2}$$

The last term denotes the jump component. It is assumed that the (conditional) jump size $X_{t,k}$ is normally distributed with mean $\theta_t$ and variance $\delta_t^2$; $n_t$ describes the number of jumps that arrive between $t-1$ and $t$ and follows a Poisson distribution with $\lambda_t > 0$:

$$P(n_t = j | \Phi_{t-i}) = \frac{\lambda_t^j}{j!} e^{-\lambda_t} \tag{3}$$

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$\lambda_t$ is called jump-intensity. The model is estimated in two variants: a constant jump-intensity model with $\lambda_t = \lambda$, $\theta_t = \theta$, and $\delta_t^2 = \delta^2$ and a time-varying jump-intensity model. For the latter, $\lambda_t$ is assumed to follow the auto-regressive process

$$\lambda_t = \lambda_0 + \sum_{i=1}^{r} \rho_i \lambda_{t-i} + \sum_{i=1}^{s} \gamma_i \xi_{t-i}. \tag{4}$$

The jump-intensity residual $\xi_t$ is calculated as

$$\xi_{t-i} \equiv E[n_{t-i}|\Phi_{t-i}] - \lambda_{t-i} = \sum_{j=0}^{\infty} j P(n_{t-i}|\Phi_{t-i}) - \lambda_{t-i}. \tag{5}$$

Using the observation $x_t$ and Bayes rule, the probability of the occurrence of $j$ jumps at time $t$ can be written as

$$P(n_t = j|\Phi_t) = \frac{f(x_t|n_t = j, \Phi_{t-1})P(n_t = j|\Phi_{t-1})}{P(x_t|\Phi_{t-1})} \tag{6}$$

The application of the time-varying jump intensity model allows one to study how the influence of extreme price movements changes over time. According to Nimalendran (1994), finally, the total variance $\Sigma^2$ of a process can be decomposed in a jump-induced part and a diffusion-induced part:

$$\Sigma^2 = h_t + \lambda_t(\theta^2 + \delta^2). \tag{7}$$

This decomposition procedure allows one to compare statistical behaviour across different markets. Finally, calculating this measure using the time-varying jump intensity makes possible to study how the share of jump-

induced variance changes over time. The following sections present and discuss the results.

## 4  RESULTS

Table 1 presents the estimated parameters of the constant as well as the autoregressive jump-intensity model; Table 2 compares the goodness-of-fit of the conditional jump models to that of a standard GARCH(1,1) model estimated as benchmark. Figure 4, finally, presents the estimated time-varying $\lambda$ coefficient as well as time-varying shares of variance induced by jumps.

Table 1: Constant and time-varying jump-intensity models

| Parameter | Mt.Gox | | | BTC-e | | |
|---|---|---|---|---|---|---|
| | GARCH | Constant JI | ARJI | GARCH | Constant JI | ARJI |
| $\mu$ | 2.9E-03 | 2.8E-03 | 3.3E-03 | 4.4E-04 | 9.42E-04 | 9.5E-04 |
| | (0.0011) | (0.0001) | (0.0001) | (0.5753) | (0.0392) | (0.0429) |
| $\phi_1$ | 0.2663 | 0.2172 | 0.2000 | 0.2499 | 0.2195 | 0.2014 |
| | (0.001) | (0.0001) | (0.0001) | (0.0001) | (0.001) | (0.001) |
| $\phi_2$ | - | - | - | -0.1059 | -0.0853 | -0.0888 |
| | | | | (0.0001) | (0.0009) | (0.0004) |
| $\omega$ | 3.0E-05 | 1.6E-05 | 1.9E-04 | 1.2E-04 | 8.3E-06 | 8.5E-06 |
| | (0.0001) | (0.022) | (0.0054) | (0.0001) | (0.0148) | (0.0076) |
| $\alpha$ | 0.3481 | 0.2129 | 0.0897 | 0.3910 | 0.2316 | 0.1241 |
| | (0.0001) | (0.0001) | (0.0002) | (0.0001) | (0.0001) | (0.0001) |
| $\beta$ | 0.7456 | 0.6949 | 0.802 | 0.6206 | 0.6634 | 0.7476 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| $\delta$ | - | 0.0855 | 0.0723 | | 0.0519 | 0.0485 |
| | | (0.0001) | (0.0001) | - | (0.0001) | (0.0001) |
| $\theta$ | - | -0.113 | -0.004 | - | -0.0063 | -0.0021 |
| | | (0.1944) | (0..3311) | | (0.1248) | (0.4615) |
| $\lambda$ | - | 0.1562 | 0.111 | - | 0.2034 | 0.1461 |
| | | (0.0001) | (0.0001) | | (0.0001) | (0.0001) |
| $\rho$ | - | - | 0.7452 | - | - | 0.6061 |
| | | | (0.0001) | | | (0.0001) |
| $\gamma$ | - | - | 1.1180 | - | - | 0.6287 |
| | | | (0.0001) | | | (0.0024) |
| Jump-induced variance (%) | - | 53.62 | 60.73 | - | 52.96 | 61.36 |

Note: p-values in parentheses. Number of endogenous lags as well as inclusion of constant is based on standard information criteria as well as significance of parameters.

The estimation results show that all but one jump-parameter are statistically different from zero, and, moreover, a considerable share of the variance is found to be induced by jumps. The jump GARCH models clearly outper-

Table 2: Model performance

| Model selection criteria | | | | | | |
|---|---|---|---|---|---|---|
| | MtGox | | | BTC-e | | |
| Criterion | GARCH | Constant | ARJI | GARCH | Constant | ARJI |
| LogL | 1874.64 | 1964.44 | 1978.42 | 2817.006 | 2991.383 | 2995.913 |
| AIC | -3.359639 | -3.515621 | -3.537143 | -3.858622 | -4.102316 | -4.102973 |
| BIC | -3.337110 | -3.479575 | -3.492086 | -3.836861 | -4.069621 | -4.063035 |
| HQ | -3.351121 | -3.501992 | -3.520107 | -3.850503 | -4.090117 | -4.088072 |
| Likelihood ratio test | | | | | | |
| | MtGox | | | BTC-e | | |
| Models | Test statistic | | | Test statistic | | |
| CJI vs. GARCH | 179.61*** | | | 348.76*** | | |
| ARJI vs. GARCH | | 207.56*** | | | 357.81*** | |
| ARJI vs. CJI | | 27.95*** | | | 9.06** | |

Note: GARCH denotes a standard GARCH(1,1) model, CJI the time-constant jump intensity model and ARJI the autoregressive jump intensity model.

form the benchmark GARCH(1,1); the time-varying jump-intensity model is found to have the best goodness-of-fit.

Figure 4 reveals that higher jump-intensities are more frequent in 2011 and in 2012 than in later years. The largest peaks however occur during the fourth quarter of 2011, the third quarter of 2012, the second quarter 2013, and the first quarter of 2015. In the beginning of 2014, Mt.Gox prices are marked by particularly large jumps related to the market turbulences prior to its shutdown. BTC-e prices after 2014 seem to be slightly less sensitive to news and jump intensity peaks occur slightly more regular. The variance decomposition, furthermore, shows that the share of variance induced by jumps fluctuates around 60 %. Pronounced decreases only occur four times: to the same times large peaks of the jump-intensity occur. The share of jump-induced variance drops to about $15-30\%$. Although these findings at first glance seem to contradict each other, there is a simple explanation: in the aftermath of the extreme movements the volatility is generally higher,

Figure 4: Jump intensities and jump-induced variance
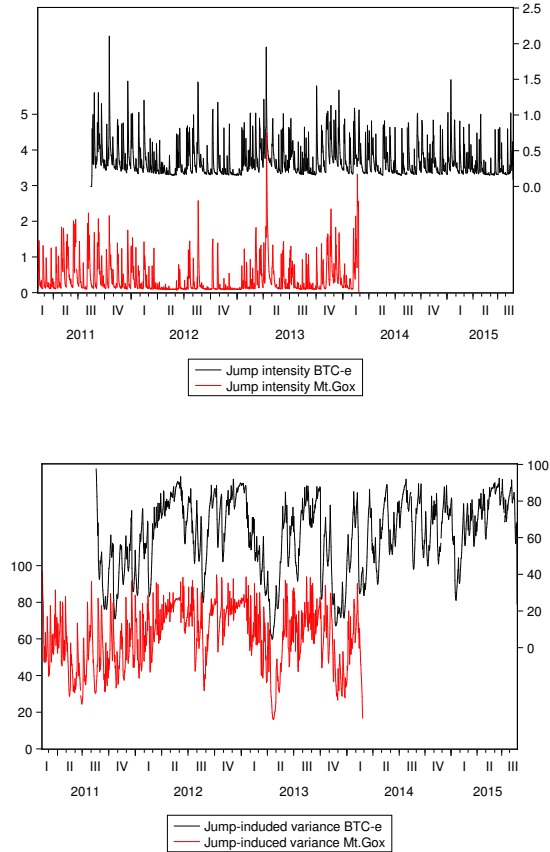


with a larger share of volatility captured by the GARCH component. Gronwald (2012) finds a similar pattern for the crude oil market.

Carrying forward this comparison between the results obtained in this paper and Gronwald's (2012) crude oil market study shows that there are remarkable differences between these markets. Gronwald (2012) finds the share of oil price variance induced by jumps to fluctuate around 40 %. This measure is considerably lower than for the Bitcoin prices. Moreover, in the

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aftermath of extreme price movements associated with the OPEC collapse 1986, the Gulf War 1991, and the oil price record high of 2008, this share drops drastically to just $5 - 10\%$ - also much lower than the values found for the Bitcoin market. Shares of the jump-induced variance of about $60\%$ as in the Bitcoin market are observed in the crude oil market in very early stages only - prior to 1986. In that period the crude oil market is considered very immature and, thus, particularly sensitive to news.

## 5  DISCUSSION

It has already been highlighted that the Bitcoin market is characterised by a number of unique features. This section further elaborates on this and also proposes innovative economic interpretations. First, the total number of Bitcoins is fixed - there are only 21 million units. Second, "all of the quantities and growth rates of Bitcoins are known with certainty by the public" (Yermack, 2013) and every single trade of Bitcoins is recorded in a publicly available database (Dwyer, 2015). Third, it is ensured that the growth rate of Bitcoins remains constant over time: if Bitcoin mining becomes more attractive, e.g. through higher Bitcoin prices, the complexity of the cryptographic puzzles adjusts accordingly. These rules have been designed in advance by the developers of Bitcoin. They will remain unchanged over time and have been established without the intervention of any regulator (see Boehme et al, 2015). For some authors these features are be problematic from an economic perspective: Yermack (2013), for instance, states the following: "In the case of a 'wild success' of Bitcoins and the replacement

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of sovereign fiat currency it would not be possible to increase the supply of Bitcoins in concert with economic growth." In the same vein, Lo and Wang (2014) conclude that "some features of bitcoin, as designed and executed to date, have hampered its ability to perform the functions required of a fiat money."

This paper now aims at establishing a different perspective on this issue. It is just these unique market features that make this market a fascinating object of study. The total number of Bitcoins, the number of Bitcoins in circulation and the growth rate are known with certainty. In other words, there is no uncertainty on the supply-side of Bitcoins. Considering the following analogy between Bitcoin and the market for crude oil illustrates this: observers of the crude oil market usually follow with bated breath when OPEC announcements regarding their future oil production rates are made. Whether or not OPEC countries will adjust production generally has considerable effects. In other words, current availability of crude oil is uncertain. The same applies to crude oil reserves as well as crude oil resources: new explorations, the development of new technologies, and the price of crude oil itself will have an effect on the overall amount of crude oil that is available. It does not need further explanation that also these factors will affect the price of crude oil. Similar things apply to other commodity markets. The supply of Bitcoin, however, is not uncertain. The implication of this observation is that the observed price fluctuations and, thus, also the identified price jumps, can only be caused by demand-side factors.

## 6 CONCLUSIONS

Virtual currencies are a phenomenon that has emerged only recently and Bitcoin is the certainly most famous one - in terms of both economic relevance and also interest it received from the general public and academia alike. Center stage so far in the academic analysis takes the question whether Bitcoin is a currency or an asset and under which motivation economic agents get involved in Bitcoins. The preliminary conclusion is that Bitcoins are to be considered an asset or speculative investment rather than a currency. Yermack (2013), most prominently, argues that the fixed number of Bitcoins is a severe economic problem as the supply of money would not be able to be adjusted in concert with economic growth. A small but steadily increasing number of papers also studied Bitcoin prices empirically, mainly with the focus on Bitcoin volatility (see Baek and Elbeck, 2014) and bubble behaviour (see Cheung et al., 2015 and Cheah and Fry, 2015). These papers find that speculative activity is a major driver of Bitcoin prices. Yelowitz and Wilson's (2015) analysis of Google searches for Bitcoin shows that "computer programming enthusiasts and illegal activity drive interest in Bitcoin". Dowd and Hutchinson (2015), finally, come to a very drastic conclusion: "Bitcoin will bite the dust".

Regardless of whether or not this is going to happen, the Bitcoin market is a fascinating object of study. Bitcoin, in specific, and virtual currencies in general only recently emerged and are associated with the emergence of a new tradable entity and a new market place. The price dynamics observed in this new market can certainly be described as spectacular and it

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is noteworthy that Bitcoin itself has been developed without involvement of any regulatory authority or support from the academic front. Thus, it is a unique situation as the following discussion of spectacular price movements and newly developed markets illustrates. Among the earliest representatives is certainly the Dutch tulip mania 1634-1637. Regardless of whether the observed price movements are a bubble or are justified by economic fundamentals (see Garber, 1990), the noteworthy feature is that in the 17th century a modern market economy has not developed yet and, likewise, economic knowledge of market participants has not been very developed either. A similar assessment holds for the Mississippi as well as the South Sea Bubbles. Spectacular price movements are certainly also present in the market for crude oil. This market however is well established and most of the market participants are professionals, often with economic background. An example for another recently developed market is the European Union Emission Trading Scheme, a market for trading pollution permits. This market has been designed by politicians and lawyers and is based on economic reasoning. Nevertheless price movements are spectacular, but however can be largely explained by the design of the market (Hintermann, 2010; Gronwald and Hintermann, 2015). In contrast, Bitcoin is a newly emerged tradable entity, the overall economic environment is advanced, Bitcoin has been designed without involvement of regulatory authorities, market participants can be assumed to have at least certain understanding of markets, and Bitcoin has some unique features.

The eye-catching price movements observed in this market certainly justify a thorough analysis. Some existing research in this area dealt with is-

sues such as price volatility and price fundamentals. This paper contributes to this literature by conducting the first extensive analysis into the price dynamics of Bitcoin. It applies an autoregressive jump intensity GARCH model, a model which has been tested and proven by the empirical finance community. The key features of this model are that it is able to capture volatility clusters as well as extreme price movements. The importance of the latter, in addition, can be studied over time and across markets.

This paper finds that Bitcoin price dynamics are generally similar to other markets. Evidence of both volatility clusters and extreme price movements is found. The importance of these price movements remains largely unchanged over time. There are, however, some remarkable differences. The contribution of these large movements is considerably larger than in other financial markets. Thus, Bitcoin prices are more sensitive to news than prices in other markets. Among the explanations for this is certainly the immaturity of the market. The unique market features discussed in this paper, however, also imply that there is no uncertainty on the supply-side and, thus, all extreme price movements can only be driven by demand side factors.

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