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Asset Management Upstart: Virtual Currencies

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ABSTRACT

Cryptocurrencies are commonly perceived as a disruptive technology that raises both hopes and fears in the minds of different categories of stakeholders within the economy. In fact, Cryptocurrencies offer several potential benefits as innovative and efficient payment system but at the same time, they are the source of potential risks that could harm investors, consumers, businesses, financial systems and even the national security. The mixed views on cryptocurrencies and their future continue to be the driving force behind the excessive volatility of their market values. This has in turns attracted a growing interest from researchers in demystifying the complex world of cryptocurrencies which remains ambiguous and puzzling for the majority of market participants. Aiming to extend earlier research efforts, the present paper examines the conditional cross effects and volatility spillover between the most prominent cryptocurrency (i.e., Bitcoin) and a set of financial indicators.

KEYWORDS

Bitcoin; Risk; Return; Diversification; Virtual currency.

1. Introduction

The sudden surge of volatility in the exchange rate of Bitcoin by the end of 2013 triggered another strand of studies examining the speculative feature of Bitcoin (Kristoufek, 2015; Yermack, 2015; Baek and Elbeck, 2015, Dyhrberg, 2016b). For example, Kristoufek (2015) shows that Bitcoin price cannot be explained by economic theories, it is instead driven by speculation. In the same vein, Yermarck (2015) concludes that Bitcoin resembles more like a speculative investment than like a true currency. Yermarck's remarks were corroborated by influential economists such as Robert Shiller, Nouriel Roubini and Stephen Roach who labelled Bitcoin as a typical example of a bubble waiting to burst (Monaghan, 2018). In an earlier statement, Alan Greenspan, the former Federal Reserve chairman stated that "You have to really stretch your imagination to infer what the intrinsic value of bitcoin is. I haven't been able to do it. Maybe somebody else can." (Kearns, 2013)

In this paper, we extend the emerging literature on cryptocurrencies by analyzing the dynamic between Bitcoin and a selection of financial assets and see whether Bitcoin offers diversification and risk management benefits to investors. To do so we use a larger sample and recent time series data. In fact, recent evidence suggests that a fledgling relationship between Bitcoin and gold has emerged only by the end of 2017 (Landsman, 2018). Moreover, we propose a new empirical design based on various specifications to examine the conditional volatility dynamic of Bitcoin and other financial assets, and measure the conditional cross effects and volatility spillover between them. All the proposed models are rooted from VARMA (1,1)-DCC-GARCH by adding some potential characteristics likely to best describe the interaction between Bitcoin and financial assets. The nature of interaction between Bitcoin and financial variables and their transmission mechanisms are taken into account when analyzing the diversification and hedging effectiveness across the financial assets.

2. Empirical Design

Since the seminal paper of Engle (1982), ARCH models become the most popular specifications in modelling time series volatility. A related stream of literature has emerged to take into account some stylized facts of financial time-series, such as asymmetric and long memory effects (e.g., Engle and Ng, 1993; Nelson, 1991; Sentana, 1995; Glosten et al, 1993). Building on Engle (1982), multivariate GARCH models have been developed offering a superior capability in modeling volatility dependence between time series. Examples of multivariate GARCH models includes, among others, CCCGARCH model (Bollerslev, 1990), BEKK-GARCH (Engle and Kroner, 1995), DCC-GARCH (Engle, 2002).

GARCH models have become popular tools in modelling volatility of time series data (Agnolucci, 2009; among others).

In our study, we implement various specifications of GARCH model to investigate the volatility spillover effect between Bitcoin and exchange rates, stock market, and commodity series, in pairs. In particular, we employ the following four base specifications to model the volatility dependence: VARMA (1,1)-DCC-GARCH, VARMA (1,1)-DCC-EGARCH, VARMA (1,1)-DCC-GARCH, VARMA (1,1)-cDCC-FIAPARCH, and the VARMA (1,1)-DCC-GJR-GARCH models.

We have also used several extensions of the above models by including additional characteristics that might exist in the spillover effect between financial series. The most appropriate model will be identified and used to analysis Bitcoin's portfolio diversification and hedging effectiveness.

$$h_{ii,t} = w_i + \alpha_i \varepsilon_{ii}^2{}_{,t-1} + \beta_i h_{ii,t-1} \qquad (1)$$

Q_t is a (n×n) variance-covariance matrix of standardized residuals which is defined as follows

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 u_{t-1} u'_{t-1} + \theta_2 Q_{t-1} \quad (2)$$

Where $\bar{Q} = E(u_t u_t')$ to a (n×n) symmetric positively-defined matrix of the unconditional variance-covariance of standardized residuals. θ_1 and θ_2 are the unknown parameters to be estimated. The sum of θ_1 and θ_2 should be less than one in order to insure positivity of the matrix Q_t. The DCC process relies on the decomposition of the conditional covariances as the product of conditional standard deviations and conditional correlations between two markets i and j such that.

Second, Ferson et al (1993) extend the same testing approach to Hansen's (1982) Generalized Method of Moments (GMM) estimation, which allows them to assume away homoscedasticity and normality. Both test statistics have asymptotic χ^2 distributions with two degrees of freedom. Kan and Zhou (2012) compare the sizes and powers of the two tests under several return distributions. In particular, when the returns under study have a joint multivariate elliptical distribution with excess kurtosis, which is a common characteristic of financial returns, the regular Wald test tends to over-reject the null, and the problem persists when the sample size increases. In this respect, the GMM-based test proposed by Ferson et al (1993) performs better, but lifting away the normality assumption entails a significant loss in statistical power. Kan and Zhou (2012) show that the amplitude of the power loss depends on the characteristics of the test asset; it is especially high when the test asset affects the global minimum-variance portfolio.

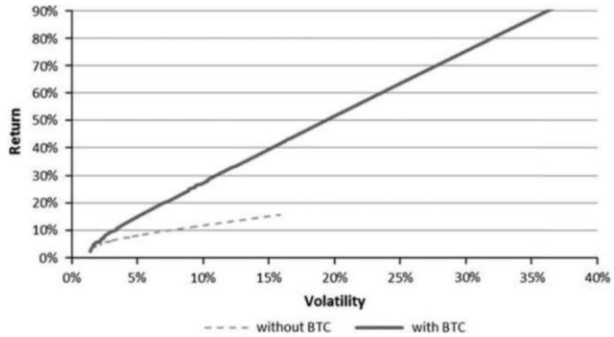

Figure 1. Mean-variance efficient frontiers without and with BTC

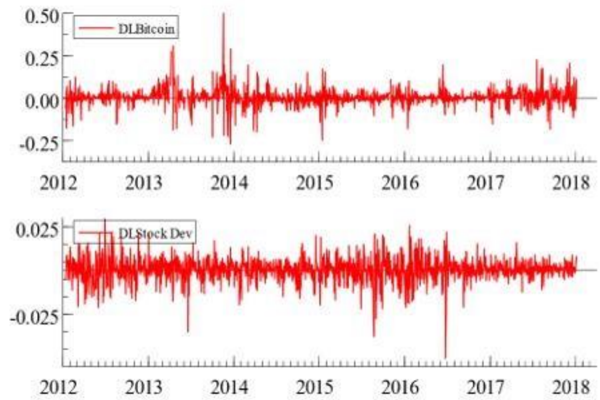

Figure 2. Returns of Selected Assets

In this subsection, we investigate the dynamic of volatility transmissions between Bitcoin and financial assets. The estimation results of the benchmark model, DCC-GARCH (1,1), and the competing models are reported in Table 1. All models confirm the significant returns and volatility spillovers. However, the results indicate that VARMA (1,1)-DCCGJRGARCH is the best-fit model for modelling the joint dynamics of different financial variables and Bitcoin, as evidenced by its log likelihood ratio (Aikake and Schwarz values). Indeed, the results of VARMA (1,1)-DCC-GJRGARCH estimation show that the autoregressive parameters are significant for all financial assets under consideration. In addition, the oneperiod lagged financial variables returns are found to significantly affect the current returns of Bitcoin at the 1% level. Moreover, the conditional volatilit Bitcoin of bitcoin returns is significantly affected by unpredicted changes in the returns on different financial variables. Thus, a shock to financial assets, regardless of their signs, implies an increase in the volatility of bitcoin returns.

3. Data and Results

Since 2009, 40 BTC exchanges have been created, 20 of which are still active today (Moore and Christin, 2013). BTC liquidity has improved dramatically since the currency was created (see Figure A1 in Appendix). Currently, more than 50 000 transactions are handled daily on BTC exchanges.5 We use weekly BTC closing exchange rates against the USD retrieved from the Bitcoincharts Website for the period from 23 July 2010 to 27 December 2013. BTC has already experienced two major speculative crises in its short history (see Figure A2 in Appendix). The first started in June 2011 and ended in a crash after the first major BTC theft in July 2011. The second coincided with the Cyprus crisis (Rushe, 2013). A period of price inflation started in March 2013 just after the United States published legislative guidance on virtual currencies, and ended in April 2013 when BTC lost nearly half of its value in a couple of hours. Our sample period covers both crises.

We consider the situation of a US investor holding a diversified portfolio comprising both traditional assets (worldwide stocks, bonds, hard currencies) and alternative investments (commodities, hedge funds, real estate). Each asset class is represented by several liquid financial indices.6 The weekly returns of these indices are retrieved from Datastream (total return indices in USD). Figure 1 draws cumulative performances for the 13 assets under study, and Table 1 provides descriptive statistics. BTC returns are exceptional in many regards. The average return is skyrocketing (404 per cent annually), but so is volatility (176 per cent annually). These exceptionally high figures reflect the risks in BTC investment, including nonsurvival risk.7 Financial innovations are hard to value and assets linked to these financial innovations are likely to exhibit bubble-like features (Frehen et al, 2013). The returns observed on our sample may thus be linked to novelty and may not be reached again in subsequent periods. In other words, BTC past returns should be used with care when assessing future expected returns.8 The presence of significant extreme risks is reflected in kurtosis values of up to 9.10, comparable with those of emerging government bonds (8.96). Even more striking is the extremely high skewness (1.85), a real curiosity for financial analysts. Positive skewness levels of this magnitude are known to be reachable only by sophisticated strategies such as volatility investments meant to hedge financial portfolios against crises (Brière et al, 2010).9 This evidence, though still frail, suggests that BTC could act as a partial hedge against crises. Overall, it looks like something new in the investment universe.10

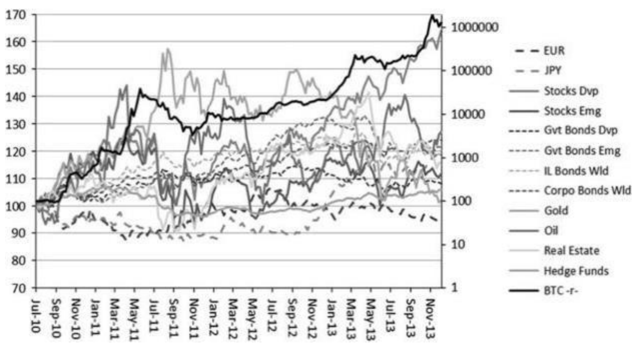

Figure 3. Performances of BTC and traditional investment.

Table 1. Correlations (in %)

Hedge funds		Real estate	Oil Gold Corpo bonds bonds	wld	IL wld	Gvt bonds emg	Gvt bonds dvp	Stocks Stocks emg dvp Yen Euro BTCs
BTCs								— — — — — — — — — — — — —
Euro	−4							— — — — — — — — — — — —
Yen	−6	21***						— — — — — — — — — — —
Stocks dvp	5	−53***	4					— — — — — — — — — —
Stocks emg	4	−45***	6	80***				— — — — — — — — —
Gvt bonds dvp	8	−64***	−74***	16**	20***			— — — — — — — —
Gvt bonds emg	3	−27***	−5	34***	53***	39***		— — — — — — —
IL bonds wld	14*	−60***	−44***	23***	30***	84***	48***	— — — — — —
Corpo bonds wld	10	−70***	−38***	38***	49***	81***	61***	81*** — — — — —
Gold	14*	−38***	−36***	21***	31***	49***	31***	50*** 48*** — — — —
Oil	−1	−34***	−6	50***	47***	14*	20***	23*** 30*** — — — 21***
Real estate	0	13*	15**	63***	66***	−11	46***	2 — 28*** 0 14*
Hedge funds	9	−34***	15**	77***	71***	7	32***	23*** 60*** — 49*** 17** 37***

Notes: This table displays the correlation matrix between the weekly returns in USD of the 13 asset classes under study (BTC

4. Concluding Remarks

Investors are always looking for alternative investment instruments as part of diversified investment portfolios. Cryptocurrencies represent such an alternative because of their high average return and low correlation with financial assets. However, only a few studies have examined cryptocurrencies as hedging and diversification tools. To fill this gap in the literature, we examine the conditional cross effects and volatility spillover between Bitcoin and a set of financial assets using various model specifications extended from the DCCGARCH models to identify appropriately the best-fit model.

BTC is a recent concept and subsequently a still rather unexplored financial asset with a short history. Some might even argue that BTC is just a bubble. Figuring out the fundamental value of BTC is a difficult task, and history has shown that assets linked to innovations (financial or real) are more bubble-prone (Frehen et al, 2013). Furthermore, our data is contaminated by early-stage behavior that might compromise the analysis of future performance. Past performance is obviously no forecast for future asset prices, particularly for young and highly risky assets such as BTC. The fact that BTC has low correlations with other assets over the time frame of this study (2010–2013) does not necessarily imply that BTC correlations will remain this low in times of crises, as correlations are known to increase during crises. As such, it is hard to say how BTC will be perceived in future time of crises. The correlations observed would tend to place BTC in the safe-haven category, but history is replete with examples of assets initially presented as safe havens and not fulfilling that promise. Keeping this caveat in mind, we carefully exploit the most recent, most robust spanning testing methodology to explore the diversification potential of BTC.

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