Return and volatility spillovers between Bitcoin and other asset classes in Turkey
Evidence from VAR–BEKK–GARCH approach

Gulin Vardar and Berna Aydogan
Izmir University of Economics, Balcova, Turkey

Abstract
Purpose – With a substantial return and volatility characteristic of Bitcoin, which may be seen as a new category of investment assets, better understanding of the nature of return and volatility spillover can help investors and regulators in achieving the potential goal from portfolio diversification. The paper aims to discuss these issues.

Design/methodology/approach – This paper explores the return and volatility transmission between the Bitcoin, as the largest cryptocurrency, and other traditional asset classes, namely stock, bond and currencies from the standpoint of Turkey over the period July, 2010–June, 2018 using the newly developed multivariate econometric technique, VAR–GARCH, in mean framework with the BEKK representation.

Findings – The empirical results reveal the existence of the positive unilateral return spillovers from the bond market to Bitcoin market. Regarding the results of shock and volatility spillovers, there exists strong evidence of bidirectional cross-market shock and volatility spillover effects between Bitcoin and all other financial asset classes, except US Dollar exchange rate.

Originality/value – The important extention is the adoption of a newly developed multivariate econometric technique, VAR–GARCH, in mean framework with the BEKK representation, proposed by Engle and Kroner (1995), which is employed for the first time specifically to examine the extent of integration in terms of volatility and return between Bitcoin and key asset classes. Second, Bitcoin has experienced a rapid growth since around a decade and a number of investors are showing interest in its potential as an integrative part of portfolio diversification. The information provided by empirical results gives empirical bases from which to address topics concerning hedging purposes and optimal portfolio allocation. It is also increasingly important to analyze the current behavior of Bitcoin in relation to other assets to provide policy makers and regulatory bodies with guidance on the role of the Bitcoin as an investment asset in Turkey. Thus, this is the first serious attempt at exploring the potential for Bitcoin to offer diversification opportunities in the context of Turkey.

Keywords Volatility, Bitcoin, Cryptocurrency, Multivariate GARCH

Paper type Research paper

1. Introduction
Regarded as a new class of investment, cryptocurrencies have grown in popularity immensely since 2008, rapidly becoming a new phenomenon on the global financial market. With a substantial market capitalization of about $140bn[1], Bitcoin has emerged as the most popular virtual currency, and maintains the greatest share ahead of its competitors; the Ethereum, Ripple, Litecoin and Bitcoin Cash. As a new kind of cryptocurrency, Bitcoin is mainly used as an alternative currency due to its low transaction costs, its peer-to-peer, global characteristics and free from government intervention, and has quickly gained ground as an investment asset. Several important stylized facts of Bitcoin are common in financial assets, such as leptokurtosis (Chan et al., 2017), heteroscedasticity (Gkillas and Katsiampa, 2018) and long memory (Phillip et al., 2019). Therefore, Bitcoin is regarded as a new asset class, rather than traditional currency and its popularity as an investment asset has attracted many speculators and investors due to its high volatility and large returns (Glaser et al., 2014; Baek and Elbeck, 2015). These specific characteristics could affect other...
asset classes, and thereby, the stability of the financial system (European Central Bank, 2012). Interestingly, Bitcoin returns are essentially uncorrelated with all major asset classes in normal and extreme times (Baur, Hong and Lee, 2018). Due to the existence of a remarkably low correlation between Bitcoin and other major financial assets, it is a potentially valuable tool for diversification and hedging in risk management (Briere et al., 2015; Dyhrberg, 2016a; Bouri, Molnár, Azzi, Roubaud and Hagfors, 2017; Bouri, Gupta, Tiwari and Roubaud, 2017; Guesmi et al., 2019; Feng et al., 2018; Chan et al., 2019; Selmi et al., 2018; Giudici and Abu-Hashish, 2019; Ji et al., 2018; Corbet et al., 2018).

Bitcoin’s increasing popularity and importance, as well as its volatility, has triggered interest not only among virtual currency users and investors, but also in the economics of cryptocurrencies literature. With a market capitalization close to $71bn (see footnote 1), and with no need for intermediaries, Bitcoin offers a more efficient and secure mechanism to transfer money, allowing for cheaper and faster payments. Due to its specific characteristics and the lack of regulatory framework, the literature primarily concentrates on its price mechanism, as well as its capacity for the development of an alternative monetary system (Becker et al., 2013; Rogojanu and Badea, 2014; Segendorf, 2014; Dwyer, 2015; Brandvold et al., 2015; Ciaian et al., 2016). The technical aspects and stylized facts of cryptocurrencies market raised a new debate on whether Bitcoin is used as a currency or commodity (Buchholz et al., 2012; Yermack, 2015; Polasik et al., 2015; Selgin, 2015; Cheah and Fry, 2015; Dyhrberg, 2016a, b; Chourou et al., 2018; Katsiampa, 2017; Pieters and Vivanco, 2017). In contrast to these debates over the financial characteristics of Bitcoin, a more recent study, Baur, Dimpfl and Kuck (2018) take a different approach, arguing that Bitcoin is in fact neither commodity nor currency, but has distinctively different time series patterns compared to other asset classes, such as gold and the US Dollar. With the recent fluctuations in Bitcoin prices, the focus of research has expanded from the technical aspects to speculative characteristic of Bitcoin (Glaser et al., 2014; Baek and Elbeck, 2015; Kristoufek, 2015; Yermack, 2015; Dyhrberg, 2016b; Blau, 2017), and market efficiency (Urquhart, 2016; Nadarajah and Chu, 2017; Bariviera, 2017; Vidal-Tomás and Ibañez, 2018).

As mentioned above, many studies in the literature have addressed the technical, legal and ethical aspects of Bitcoin, as well as its economic and financial aspects. Moreover, the existence of long memory and persistent volatility characteristics of Bitcoin justifies the usage of various GARCH-type models; linear GARCH (Glaser et al., 2014; Gronwald, 2014), the Threshold GARCH (TGARCH) (Dyhrberg, 2016a; Bouoiyour and Selmi, 2015a, 2016; Bouri, Azzi and Dyhrberg, 2017), the Exponential GARCH (EGARCH) (Dyhrberg, 2016b; Bouoiyour and Selmi, 2015a, 2016; Bouri, Jalkh, Molnár and Roubaud, 2017; Kokkinaki et al., 2018). Bitcoin has become significant in financial markets and in portfolio management as a hedge and safe haven and a small number of studies have analyzed the linkages between Bitcoin and other financial assets (Bouoiyour and Selmi, 2015b; Baur et al., 2015; Briere et al., 2015; Bouri, Jalkh, Molnár and Roubaud, 2017; Ji et al., 2018). However, all these foregoing studies rely on unconditional correlation, and overlooking the existence of long memory and persistent volatility characteristics of Bitcoin. Dyhrberg (2016a) analyzed the hedge properties of Bitcoin using a selection of explanatory variables such as gold (cash and future), the dollar–euro and dollar–pound exchange rates and the FTSE 100 index. The results of the GARCH model showed that Bitcoin can be used in hedging against the dollar and the UK stock market, showing similar hedging capabilities to gold. Dyhrberg (2016b) also explores the financial asset capabilities of Bitcoin against gold and dollar using asymmetric GARCH model and finds that Bitcoin could serve as a hedging tool.

Employing quantile-on-quantile regressions, Demir et al. (2018) examine the relationship between Bitcoin and the economic policy uncertainty index, and find that Bitcoin can be used for hedging purposes against uncertainty. Gajardo et al. (2018) apply MF-ADCCA to investigate the existence and asymmetry of the cross-correlation among the major currency
rates, Bitcoin, DJIA, gold price and oil crude market. Their results indicate differences between Bitcoin’s relationship with commodities and its relationship with stock market indices. However, there is little empirical evidence of the return and volatility spillovers between Bitcoin and other assets classes. Symitsi and Chalvatzis (2018) explore volatility spillovers between Bitcoin, and energy and technology companies, noting significant return spillovers from energy and technology stocks to Bitcoin. Guesmi et al. (2019) investigate the conditional cross effects and volatility spillover between Bitcoin and a set of financial assets using DCC-GARCH models. They found that hedging strategies involving gold, oil, emerging stock markets and Bitcoin reduce considerably a portfolio’s risk (variance), as compared to the risk of a portfolio composed of gold, oil and stocks from emerging stock only. Trabelsi (2018) examines connectedness within cryptocurrency markets, as well as across the Bitcoin index and widely traded asset classes such as traditional currencies, stock market indices and commodities, such as gold and Brent oil. Bouri et al. (2018) analyze return and volatility spillovers between Bitcoin and four asset classes (equities, commodities, currencies and bonds), employing a smooth transition, VAR–GARCH, in mean model. Klashorst (2018) investigates the volatility spillovers and other market dynamics between stock indices and cryptocurrencies, and finds the evidence that volatility of cryptocurrencies is highly affected by the dynamics of the stock market.

In the existing literature, however, little is known about the actual market dynamics between Bitcoin and other financial assets in a particular country context. Such insight is becoming increasingly important, as Bitcoin gradually establishes its position within the regulated markets. Given the increasing popularity of Bitcoin, a better understanding of the nature of spillover effects provide information for investors and regulators in realizing the relationship between these assets, and in achieving potential gain from portfolio diversification. This study aims to extend earlier research efforts through a comprehensive framework to investigate the return and volatility spillover among the largest cryptocurrency – Bitcoin – and Borsa Istanbul 100 stock index (BIST 100 hereafter) as a proxy of stock index, Turkish five-year government bonds as a proxy of bond, US Dollar and Euro currencies over the period July, 2010–June, 2018. This will lead to a better understanding of Bitcoin’s potential to act as a diversifier or hedge against these selected financial assets in Turkey.

The major contribution of this study to the existing literature is threefold. First, this is a pioneering study, to the best of author’s knowledge, in the examination of the return and volatility spillovers between Bitcoin and key traditional asset classes in Turkey. It employs a newly developed multivariate econometric technique, VAR–GARCH, in mean framework with the BEKK representation. Second, Bitcoin has experienced a decade of rapid growth and an increasing number of investors are showing interest in its potential as an integrative part of portfolio diversification. The results provide empirical bases from which to address topics concerning hedging purposes and optimal portfolio allocation. Thus, this is the first serious attempt at exploring the potential for Bitcoin to offer diversification opportunities in the context of Turkey. Finally, it is also increasingly important to analyze the current behavior of Bitcoin in relation to other assets to provide policy makers and regulatory bodies with guidance on the role of the Bitcoin as an investment asset in Turkey.

The reminder of this paper is organized as follows. The data and methodology are introduced in Section 2. Section 3 discusses the empirical findings. Section 4 provides some concluding remarks.

2. Data and methodology
The data used in this analysis are daily prices of Bitcoin, BIST-100 stock index, TR five-year government bond yield, US Dollar and Euro currencies. The sample is spanning from July 19, 2010[2] to June 26, 2018, which corresponds to a total of 2072 observations. The data for
Bitcoin prices were obtained from CoinDesk, and the data for the other asset classes, from DataStream. The daily returns of each series were calculated as the first difference of the natural logarithm of prices multiplied by 100.

The graph of daily returns of the variables and the conditional variance of Bitcoin over the sample period is displayed in Figure 1. As seen from Figure 1, Bitcoin shows a different volatility pattern compared to other traditional asset classes. Therefore, potential differences in diversification benefits for Bitcoin and for other asset classes may be a crucial outcome for the investors. Additionally, the graph of bond represents periods of relatively low volatility, and a relatively uncommon characteristic among the financial asset classes over the sample period in Turkey.

Table I presents a wide range of descriptive statistics for all the variables in the sample, along with Jarque–Bera (JB) statistics for normality. Among all return series, Bitcoin has the highest mean, followed by US Dollar and Euro currencies, while the stock market return has the lowest mean. Regarding the statistics of standard deviation, Bitcoin has the highest volatility, followed by bond yield. All return series are skewed negatively, except for the US Dollar and Euro currencies, and also all series have excess kurtosis, implying the existence of

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<tr>
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<th>Bitcoin</th>
<th>Stock</th>
<th>Bond</th>
<th>USD/TL</th>
<th>Euro/TL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.542</td>
<td>0.023</td>
<td>0.031</td>
<td>0.053</td>
<td>0.048</td>
</tr>
<tr>
<td>SD</td>
<td>6.477</td>
<td>1.367</td>
<td>1.981</td>
<td>0.705</td>
<td>0.692</td>
</tr>
<tr>
<td>Min.</td>
<td>-47.000</td>
<td>-11.063</td>
<td>-47.621</td>
<td>-3.876</td>
<td>-3.143</td>
</tr>
<tr>
<td>Max.</td>
<td>49.966</td>
<td>6.237</td>
<td>45.317</td>
<td>4.612</td>
<td>4.286</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.008</td>
<td>-0.561</td>
<td>-0.827</td>
<td>0.319</td>
<td>0.208</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>12.086</td>
<td>7.298</td>
<td>295.367</td>
<td>5.969</td>
<td>5.946</td>
</tr>
<tr>
<td>Jarque–Bera</td>
<td>7125.397*</td>
<td>1702.969*</td>
<td>737.632*</td>
<td>795.8659*</td>
<td>764.1554*</td>
</tr>
</tbody>
</table>

Note: *Significance level of 1 percent
leptokurtic distribution. This leptokurtic excess and asymmetry is in line with the JB test results, justifying the rejection of normality at 1 percent significance level for all the series over the sample period. The unit root test results and the LM test statistics, available upon request, coincide with the descriptive statistics findings. This highlights the importance of using a time-varying volatility model for the implementation of an empirical analysis of spillover effects among variables. The unconditional correlation matrix in Table II shows that Bitcoin has a weak and positive correlation with all asset classes with the exception of US Dollar.

The present study specifies the positive definite covariance matrix, therefore multivariate GARCH with BEKK specification developed by Engle and Kroner (1995) appears well suited to the inspection of volatility spillover effects between Bitcoin and each asset class. A notable feature of the BEKK specification is that it imposes no restriction on the correlation structure between the variables.

For the empirical analysis on volatility spillover, the conditional mean equation is modeled through a vector autoregressive (VAR) model. Based on the principle of minimum Akaike Information Criterion values, VAR (1) model is chosen, and it can be described as:

\[ R_t = \mu + \delta R_{t-1} + \epsilon_t, \]

(1)

where \( R_t = (r_t^B, r_t^A)' \) with \( r_t^B \) and \( r_t^A \) being the returns on Bitcoin and the other assets, namely, stock, bond, US Dollar and Euro currencies at time \( t \), respectively; \( \delta \) is a \((2 \times 2)\) matrix of coefficients of the form \( \delta = (\delta_{11}, \delta_{12}, \delta_{21}, \delta_{22})' \); \( \mu \) is a \((2 \times 1)\) vector of constant terms of the form; \( \epsilon_t = (\epsilon_t^B, \epsilon_t^A)' \) with \( \epsilon_t^B \) and \( \epsilon_t^A \) being the error terms from the mean equations of the two asset markets, B and A (bitcoin and asset classes), respectively. The coefficients \( \delta_{11} \) and \( \delta_{22} \) measure own-mean spillovers; whereas the coefficients \( \delta_{12} \) and \( \delta_{21} \) provide the measures of the cross-mean spillovers.

Based on VAR (1) model, the residuals \( \epsilon_{1,t} \) and \( \epsilon_{2,t} \) of the mean equation are derived and the conditional variance-covariance matrix (\( H_t \)) of the residuals are represented as follows:

\[ \epsilon_t = z_t \sqrt{H_t}, \quad z_t \sim N(0, H_t), \]

(2)

\( z_t = (z_t^B, z_t^A) \) refers to \((2 \times 1)\) vector of independently and identically distributed errors. (3)

\( H_t = \text{diag} \left( \sqrt{h_t^B}, \sqrt{h_t^A} \right) \), with \( h_t^B \) and \( h_t^A \) being the conditional variances of \( r_t^B \) and \( r_t^A \), respectively. The BEKK–GARCH specification model defines the conditional variance-covariance matrix \( (H_t) \) as follows:

\[ H_t = C C + A' \epsilon_{t-1} \epsilon_{t-1}' A + B H_{t-1} B, \]

(4)

where \( C \) is a lower triangular matrix to represent constant components; \( A \) and \( B \) are \((2 \times 2)\) matrix of ARCH and GARCH coefficients, respectively. \( A \) is a \((2 \times 2)\) matrix of coefficients that capture the effects of own and cross-market shocks; and \( B \) is a \((2 \times 2)\) matrix of

<table>
<thead>
<tr>
<th>Bitcoin</th>
<th>Stock</th>
<th>Bond</th>
<th>USD/TL</th>
<th>Euro/TL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.000000</td>
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<td></td>
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<tr>
<td>0.027847</td>
<td>1.000000</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>0.006065</td>
<td>-0.283580</td>
<td>1.000000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.007445</td>
<td>-0.501086</td>
<td>0.289069</td>
<td>1.000000</td>
<td></td>
</tr>
<tr>
<td>0.010910</td>
<td>-0.364441</td>
<td>0.249346</td>
<td>0.664734</td>
<td>1.000000</td>
</tr>
</tbody>
</table>

Table II. Unconditional correlation matrix
coefficients that capture the own volatility persistence and the volatility transmissions between returns of Bitcoin and other asset markets, namely, stock, bond, US Dollar and Euro currencies.

To estimate all the model parameters of VAR–BEKK–GARCH specification \((\mu, \delta, C, A, B)\), the study makes use of the quasi-maximum likelihood method with a combination of the standard gradient-search algorithm Broyden–Fletcher–Goldfarb–Shanno (BFGS) and simplex algorithm. The conditional log-likelihood function \(L(\theta)\) are denoted as follows:

\[
L(\theta) = \sum_{t=1}^{T} L_t(\theta),
\]

\[
L_t = -\ln 2\pi - \ln |H_t(\theta)| - \frac{1}{2} \varepsilon_t H^{-1}_t(\theta) \varepsilon_t(\theta),
\]

where \(T\) is the number of observations, \(\theta\) represents the vector of all estimated parameters.

3. Empirical results

The empirical results of return and volatility spillovers between Bitcoin and the other traditional assets, namely, stock, bond, US Dollar and Euro currencies obtained from VAR–BEKK–GARCH model are reported in Panels A and B of Table III, while Table IV

<table>
<thead>
<tr>
<th>Panel A – mean equation</th>
<th>Stock</th>
<th>Bond</th>
<th>USD/TL</th>
<th>Euro/TL</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\delta(1)_{11})</td>
<td>0.035 [1.434]</td>
<td>–0.010 [–0.528]</td>
<td>0.043 [1.751]***</td>
<td>0.033 [1.347]</td>
</tr>
<tr>
<td>(\delta(1)_{12})</td>
<td>–0.025 [–0.363]</td>
<td>0.066 [0.763]</td>
<td>–0.081 [–0.792]</td>
<td>–0.003 [–0.025]</td>
</tr>
<tr>
<td>(\mu_1)</td>
<td>0.291 [3.234]*</td>
<td>0.471 [3.853]*</td>
<td>0.267 [2.901]*</td>
<td>0.277 [3.337]*</td>
</tr>
<tr>
<td>(\delta(1)_{21})</td>
<td>–0.003 [–0.673]</td>
<td>0.013 [2.103]**</td>
<td>–0.001 [–0.499]</td>
<td>–0.000 [–0.188]</td>
</tr>
<tr>
<td>(\delta(1)_{22})</td>
<td>–0.018 [–0.815]</td>
<td>0.039 [1.515]</td>
<td>0.051 [2.259]**</td>
<td>0.062 [2.726]*</td>
</tr>
<tr>
<td>(\mu_2)</td>
<td>0.066 [2.154]**</td>
<td>0.012 [0.459]</td>
<td>0.031 [2.157]**</td>
<td>0.026 [1.937]***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B – variance equation</th>
<th>Stock</th>
<th>Bond</th>
<th>USD/TL</th>
<th>Euro/TL</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_{11})</td>
<td>0.885 [8.994]**</td>
<td>0.921 [2.662]*</td>
<td>0.790 [5.766]*</td>
<td>0.671 [7.188]*</td>
</tr>
<tr>
<td>(c_{21})</td>
<td>–0.227 [–7.744]**</td>
<td>0.557 [10.773]*</td>
<td>0.082 [–3.215]***</td>
<td>–0.140 [–0.140]***</td>
</tr>
<tr>
<td>(c_{22})</td>
<td>–0.000 [–0.000]</td>
<td>–0.000 [–0.000]</td>
<td>–0.024 [–0.498]</td>
<td>–0.140 [3.401]***</td>
</tr>
<tr>
<td>(a_{11})</td>
<td>0.387 [0.397]*</td>
<td>0.086 [–1.823]***</td>
<td>0.375 [10.050]*</td>
<td>0.331 [16.008]*</td>
</tr>
<tr>
<td>(a_{12})</td>
<td>–0.014 [–0.496]***</td>
<td>–0.096 [–20.897]***</td>
<td>–0.001 [–0.301]***</td>
<td>–0.002 [–1.665]***</td>
</tr>
<tr>
<td>(a_{21})</td>
<td>–0.207 [–3.019]**</td>
<td>0.133 [1.860]***</td>
<td>–0.067 [–3.587]***</td>
<td>–0.313 [–2.440]***</td>
</tr>
<tr>
<td>(a_{22})</td>
<td>0.153 [8.890]**</td>
<td>0.293 [12.058]*</td>
<td>0.256 [12.219]*</td>
<td>0.305 [8.820]***</td>
</tr>
<tr>
<td>(b_{11})</td>
<td>0.919 [95.171]***</td>
<td>0.612 [12.979]*</td>
<td>0.924 [65.557]***</td>
<td>0.942 [140.734]***</td>
</tr>
<tr>
<td>(b_{12})</td>
<td>0.006 [6.525]*</td>
<td>0.131 [22.062]*</td>
<td>0.001 [1.257]</td>
<td>0.001 [2.375]***</td>
</tr>
<tr>
<td>(b_{21})</td>
<td>0.130 [5.927]*</td>
<td>–0.047 [–23.150]***</td>
<td>0.270 [3.941]***</td>
<td>0.275 [2.657]***</td>
</tr>
<tr>
<td>(b_{22})</td>
<td>0.970 [168.887]**</td>
<td>0.624 [24.082]***</td>
<td>0.961 [122.826]**</td>
<td>0.919 [36.717]**</td>
</tr>
</tbody>
</table>

Notes: \(\mu_1 \) and \(\mu_2\) are constant term of the mean equation. \(\delta(1)_{11}\) and \(\delta(1)_{22}\) capture variables’ own lagged effects in mean, which variable 1 denotes Bitcoin 2 denotes stock, bond, USD/TL, Euro/TL Exchange Rates, respectively. \(\delta(1)_{ij}\) stands for lagged spillover effects in mean from bitcoin to stock, bond, USD/TL, Euro/TL Exchange Rates and \(\delta(1)_{ij}\) indicates the same effect in the opposite direction. \(c_{ij}\) and \(c_{ij}\) are constant terms of the variance equation. \(a_{ij}\) and \(a_{ij}\) represent the ARCH effect in two variables. \(a_{ij}\) measures the spillover effect of a previous shock in bitcoin on the current volatility of stock, bond, USD/TL, Euro/TL Exchange Rates, and \(a_{ij}\) measures the spillover effect in the opposite direction. \(b_{ij}\) and \(b_{ij}\) indicate the GARCH terms, which measure volatility persistence of each series. \(b_{ij}\) measures the spillover effect of the last period’s variance of bitcoin on the current variance of stock, bond, USD/TL, Euro/TL Exchange Rates and \(b_{ij}\) measures the spillover effect in the opposite direction. Numbers in square brackets correspond to \(t\)-statistics. ***, *** Statistical significance at the 1, 5 and 10 percent levels, respectively.

Table III. Estimated results of volatility spillover between Bitcoin and asset classes based on the full VAR–BEKK–GARCH model.
summarizes the estimated results of the model. For coefficients $\delta(1)_{11}$ and $\delta(1)_{22}$ in VAR-mean Equations (1) and (2), respectively, represents Bitcoin return, and proxies of financial asset return, namely, stock return, bond yield, US Dollar and Euro currencies. Both coefficients are positive and statistically significant only on US Dollar, implying that the lagged return of each variable helps to forecast its current short-term returns. The return spillover effects in the direction from Bitcoin to each asset and vice versa are, respectively, captured by the parameters, $\delta(1)_{12}$ and $\delta(1)_{21}$. Interestingly, among all these asset classes, the results reveal the existence of the positive unilateral return spillovers from the bond market to the Bitcoin market. In other words, current period returns in bond market are influenced by last period returns in Bitcoin market. This implies that bond returns can be predicted using past Bitcoin returns over time. As seen, the relationship is quite evident. An argument could be made that in the current circumstances, Bitcoin may be a leading indicator of interest rates, with major downward swings in Bitcoin accompanied by similar negative sentiment toward the interest rate.

As to the coefficients associated with own conditional ARCH ($a_{ij}$) and GARCH ($b_{ij}$) effects, which capture short and long-term persistence in the variance-covariance equation, respectively, all the parameters were found to be statistically significant at 1 percent level. The off-diagonal elements of matrices $A$ and $B$, $a_{12}, a_{21}, b_{12}, b_{21}$, capture the cross-market effects such as shock and volatility spillovers among Bitcoin and other asset classes, namely, stock, bond, US Dollar and Euro currencies. Regarding the extent of shock and volatility spillovers, the empirical results provide strong evidence of bidirectional cross-market shock and volatility transmission between Bitcoin and all other assets. The sole exception is the US Dollar, which offers interesting results. Hence, it can be concluded that the volatility of Bitcoin is highly affected by the dynamics of other financial assets, except the US dollar, and moreover, the effect occurs in the opposite direction. There is an unidirectional spillover effect from US Dollar to Bitcoin, highlighting that past shocks and conditional volatility in the US Dollar are crucial in explaining the conditional volatility of Bitcoin returns. US Dollar apparently serves as sources of information transmission among the other main financial assets. These empirical findings are partially consistent with those of Bouoiyour and Selmi (2015a, b), Kristoufek (2015), Bouri et al. (2018), Guesmi et al. (2019), Symitsi and Chalvatzis (2018), Gajardo et al. (2018), Klashorst (2018). However, the results are interestingly inconsistent with those of Trabelsi (2018), who finds no spillover effects between Bitcoin and other traditional asset classes.

Turning to the coefficient estimates of DCC between Bitcoin and the other assets, namely stock, bond, US Dollar and Euro currencies, Figure 2 displays the graphical exposition of the dynamic conditional correlation between variables. Significant fluctuations in the conditional correlations evolve over time, experiencing phases of increase and decrease.

<table>
<thead>
<tr>
<th></th>
<th>Stock</th>
<th>Bond</th>
<th>USD/TL</th>
<th>Euro/TL</th>
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<tbody>
<tr>
<td><strong>Panel A – mean spillovers</strong></td>
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<td>Bitcoin</td>
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<tr>
<td><strong>Panel B – shock transmission</strong></td>
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<td><strong>Panel C – volatility spillovers</strong></td>
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**Notes:** ← indicates a bidirectional volatility transmission; → or ← indicates a unilateral volatility transmission, and – indicates no volatility transmission. ← means the related commodity on the first column is volatility receiver, while → is the indication of volatility transmitter.

Table IV. Summary of estimated results for the conditional mean and conditional variance equations between Bitcoin and selected financial assets.
The highest peaks correspond to the price crash of 2013 December, with the recovery beginning in the fourth quarter of 2014. In summary, the results indicate relatively weak correlations between Bitcoin and all the asset classes under study, in line with previous works by (Briere et al., 2015; Dyhrberg, 2016b; Baur, Dimpfl and Kuck, 2018; Bouri, Molnár, Azzi, Roubaud and Hagfors, 2017; Bouri, Gupta, Tiwari and Raubaud, 2017; Corbet, 2018).

4. Conclusion
Our study is motivated by the scarce literature on the return and volatility spillovers between Bitcoin and a selection of traditional financial assets, namely, stock, bond and currencies. This study examines the linkages between Bitcoin and other asset classes in the context of Turkey, which enables to draw generalizing conclusions. This study has led to subsequent findings. Firstly, the empirical results provide convincing evidence for the existence of a return spillover effect in the direction from the bond market to Bitcoin market, whereas a vice versa effect is not present. One possible explanation is that profits from the more regular bond market are transferred to the unregulated Bitcoin market. Second, the findings show the existence of bidirectional cross-market shock and volatility spillover effect between Bitcoin and all other financial assets, with the exception of US Dollar. It is, however, important to underline that spillover effects are unidirectional from US Dollar to Bitcoin. The results support the position that cryptocurrencies are regarded as a new investment asset class, since they are interconnected with each other, and have similar patterns of connectedness with other asset classes.

When analyzing the return and volatility spillover effects in the framework of cryptocurrencies – specifically Bitcoin – the behavioral explanation is the most reasonable one since they are international, and also their value is not derived from any underlying economic and financial fundamental. This study on the existence of volatility spillovers between Bitcoin and other traditional asset classes in a specific country context, Turkey, can therefore contribute to the current debate about the speculative nature of the cryptocurrencies. It explores whether Bitcoin offers any diversification and risk management benefits for Turkish as well as international investors.

With respect to the portfolio management, studies focusing on an emerging country’s sensitivities to Bitcoin are of particular interest, since the recent emergence of
cryptocurrencies as a new class of financial assets provides opportunities for diversification swings in asset classes due to higher return and lower correlation with financial assets. Moreover, even if digital currencies are unregulated in many countries, some have effective regulatory frameworks and may have faster process for implementation of the regulations specific to the cryptocurrency market. However, Turkey, as an emerging country with its stock and bond market providing high average returns and low correlation with developed markets, is attracting great interest from overseas investors. Therefore, these combined results underline the importance of investors’ and regulators’ understanding of the volatility transmission mechanism over time and across assets in order to optimize asset allocation, portfolio optimization and hedging. Furthermore, fund manager and investors wary of using Bitcoin in portfolios due to the signs of correlation with the other asset classes (Baek and Elbeck, 2015; Baur et al., 2015; Briere et al., 2015; Bouri, Jalkh, Molnár and Roubaud, 2017; Ji et al., 2018). The continued rapid growth of Bitcoin and the unregulated nature of the market could create new vulnerabilities in the international financial system. Regulators and policy makers should, therefore, closely monitor the Bitcoin market and be aware of the return and volatility spillover effects among the Bitcoin market and other asset classes for selected and specific countries. The current study focuses on solely the spillover effects between Bitcoin and other asset classes in Turkey. It may not be possible to generalize the results of the study to all other countries, since each has different investment alternatives and additionally, the characteristics and investment strategies of Turkish investors may differ from others. Further research should be done to explore the dynamics in different countries. Additionally, with respect to the reported volatility interaction, it is interesting to expand the analysis for the observation of structural breaks in the level of correlation with the separation of high and low volatility periods and asymmetric leverage effect by using different volatility models.

Notes
1. https://coinmarketcap.com
2. Due to the data availability of the Bitcoin price data, the starting date is July 19, 2010.

References


Klashorst, B.P. van de (2018), “Volatility spillovers and other market dynamics between cryptocurrencies and the equity market”, Erasmus School of Economics – Erasmus University, master thesis.


**Corresponding author**
Berna Aydogan can be contacted at: berna.okan@ieu.edu.tr