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ДИНАМИЧЕСКИЙ УСЛОВНО-КОРРЕЛЯЦИОННЫЙ АНАЛИЗ ФИНАНСОВОГО РАСПРОСТРАНЕНИЯ: БУДУЩЕЕ ЕВРОДОЛЛАРА И БИТКОИН НА ФОРЕКС-РЫНКАХ

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В данной статье рассматриваются изменяющиеся во времени условные корреляции между будущим рынком евродоллара и семью Форекс-рынками биткоина. Автор применяет двумерную динамическую условную корреляционную модель DCC-GARCH, чтобы зафиксировать потенциальные эффекты финансового распространения между этими рынками в 2017–2019 гг. Эмпирические результаты за исследуемый период показывают финансовое распространение в отношении семи двумерных моделей и потенциальные каналы передачи волатильности между рынками, что имеет решающее значение для директивных органов, которые обеспечивают регулирование вышеуказанных рынков производных финансовых инструментов.

Ключевые слова: модель DCC-GARCH; Форекс-рынки; биткоин; рынок евродоллара; коэффициент финансового распространения; динамически условная коинтеграция.

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DYNAMIC CONDITIONAL CORRELATION ANALYSIS OF FINANCIAL CONTAGION: EURODOLLAR FUTURE AND FOREX BITCOIN MARKETS

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This paper examines the time-varying conditional correlations between eurodollar future market and seven Forex bitcoin markets. We apply a bivariate dynamic conditional correlation DCC-GARCH model in order to capture potential contagion effects between the markets for the period 2017–2019. Empirical results reveal contagion during the under investigation period regarding the seven bivariate model, showing potential volatility transmission channels among the markets. Findings have crucial implications for policymakers, who provide regulations for the above derivative markets.

Keywords: DCC-GARCH model; bitcoin Forex markets; eurodollar future market; financial contagion; dynamic conditional correlations.

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Introduction

This paper investigates the potential volatility spillover and contagion effects of eurodollar future market and seven Forex bitcoin markets. By employing a bivariate DCC-GARCH model, we show significant volatility spillover effects. Moreover, we use the definition of contagion suggested by Forbes and Rigobon[1] according to [1]. Dynamic conditional correlations reveal contagion effects in sub-periods between eurodollar future market and the seven Forex bitcoin markets.

The motivation for this paper is analysed as follows. In the literature, this is the first empirical research exploring the potential conditional second moments of the distribution between eurodollar future market and the seven Forex bitcoin markets [2–4]. Second, we provide new evidence to financial market theory regarding the potential contagion effects between eurodollar future market and the seven Forex bitcoin markets. Third, we use data for Forex bitcoin markets from 2017, when first appeared in datastream database.

There are some empirical studies exploring the conditional volatility of bitcoin market [5–9]. In addition, many researchers support the use of bitcoin market as a speculative market [2; 10–12]. In the literature, there are studies investigating the volatility spillover effects between bitcoin market and different financial markets [7; 9; 13–18]. Moreover, some empirical studies have investigated the effects of future bitcoin markets [11; 19; 20] and the effects between different future and financial markets [21–23]. In this paper, we provide evidence of potential spillovers between markets unexplored before.

The paper is organised as follows. Section two shows the methodology and data. Section three provides the empirical results. The last section of the paper concludes.

Methodolody and data

In the first stage, we filter our linear structure of the returns series and decouple of from the conditional variance by employing the VAR model. We generate the daily logarithmic returns.

$$y_t = \gamma + \sum_{s=1}^{n} \alpha_s r_{t-s} + \varepsilon_t, \text{ with } t = 1, ..., T \text{ and } \varepsilon_t = \sqrt{h_t} u_t,$$

where r_{t-s} is the 2×1 column vector of future and Forex markets, γ and α_s are respectively, a 2×1 vector and 2×2 matrices of parameters and ε_t are 2×1 vectors of innovations. The lag length is choses by information criteria[2]. u_t is standardised errors, h_t is conditional variance depending on h_t and ε_t for each market lagged one period, generated by the univariate GARCH(1,1) model [24]:

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + bh_{t-1},$$

where ω is constant, a and b are ARCH and GARCH effects.

Next, we use the R. F. Engle as written in [25] representation of the bivariate GARCH model in order to estimate the bivariate conditional variance matrix (H_t is $N \times N$ matrix, with N the number of markets, $i = 1, \dots, N$) as follows:

$$H_t = D_t R_t D_t$$

where D_t is the conditional variance matrix given by

$$D_t = \left(h_{11t}^{\frac{1}{2}} \dots h_{NN,t}^{\frac{1}{2}} \right),$$

where R_t is the condition correlation matrix of $N \times N$ dimension and defined as follows:

$$R_t = \left(p_{iit}\right) = diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}} \right) Q_t diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}} \right),$$

where the $N \times N$ symmetric positive definite matrix $Q_t = \left(q_{ii,t}\right)$ is given by

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1},$$

where $\bar{Q}$ is the $N \times N$ unconditional variance matrix of u_t, and α and β are non-negative scalar parameters, satisfying $\alpha + \beta < 1$.

[1]They defined contagion as a significant increase in cross-market linkages after a shock.

[2]The VAR order length is selected by the final predicted error and the Akaike criterion. The results are available upon request.

We use daily data for eurodollar future market (CME-EURO_GLOBEX_CONT._-_SETT._PRICE) and seven Forex bitcoin markets (USD/BITCOIN, EUR/BITCOIN, NZD/BITCOIN, AUD/BITCOIN, CAD/BITCOIN, CHF/BITCOIN, JPY/BITCOIN). We downloaded data from datastream database. We set the period from 18 December 2017 to 20 May 2019 (371 observations) and use the market returns generated by the equation $r_t = \log(p_t) - \log(p_{t-1})$, where p_t is the price of future market on day t and p_{t-1} is the price of future market on day $t-1$.

In table 1 we see the summary statistics for the market returns. CME-EURO_GLOBEX_CONT._-_SETT._PRICE exhibits the highest mean value (–6,4221e-005). Based on the highest maximum (0,178 18), the minimum (–0,135 49) and the highest standard deviation (0,037 612) values, EUR/BITCOIN presents the largest fluctuations among all the markets. Additionally, all market returns are negatively skewed, except the case of EUR/BITCOIN. Furthermore, we observe that all market returns show excess kurtosis. In addition, Jarque – Bera statistic results indicate the rejection of the null hypothesis of normality for all market returns except the cases of SGX-KRW/USD CONT.AVG - SETT. PRICE and DGCX-EUR/USD CONTINUOUS AVG. - SETT. PRICE. ADF (Dickey and Fuller 1979) test results reject the null hypotheses of unit root at 1 % level, showing that the daily market returns appropriate for further testing.

Figure 1 graphs the logarithmic returns for CME-EURO_GLOBEX_CONT._-_SETT._PRICE, USD/BITCOIN, EUR/BITCOIN, NZD/BITCOIN, AUD/BITCOIN, CAD/BITCOIN, CHF/BITCOIN and JPY/BITCOIN. Based on the virtual observation of the graph, we see time varying levels of fluctuations, indicating the presence of heteroskedasticity and appropriate the use of DCC-GARCH model.

Empirical results

In this section, we present the empirical results generated by the bivariate DCC-GARCH model. Sub-section «Results of the univariate GARCH(1,1) model» shows the results of the univariate GARCH model while in sub-section «Results of the bivariate DCC-GARCH(1,1) model, diagnostic tests and selected information criteria», we analyse the results of the multivariate DCC-GARCH model. In sub-section «Analysis of the dynamic conditional correlations», we report an analysis of the generated dynamic conditional correlations (DCC).

Results of the univariate GARCH(1,1) model. Table 2 shows the estimated values for univariate GARCH(1,1) model. Empirical results report statistically significant ω for CME-EURO_GLOBEX_CONT._-_SETT._PRICE and EUR/BITCOIN. Moreover, ARCH (*a*) and GARCH (*b*) terms are highly significant for all the markets returns.

In figure 2, we observe the behaviour of conditional variances for CME-EURO_GLOBEX_CONT._-_SETT._PRICE, USD/BITCOIN, EUR/BITCOIN, NZD/BITCOIN, AUD/BITCOIN, CAD/BITCOIN, CHF/BITCOIN and JPY/BITCOIN. We see strongly volatile conditional variances for all the market returns over time. Additionally, results indicate a common movement of conditional volatilities.

Results of the bivariate DCC-GARCH(1,1) model, diagnostic tests and selected information criteria. Table 3 presents the results of the bivariate DCC model estimations. the estimated average correlations are statistically significant for the pairs of markets: CME-EURO_GLOBEX_CONT._-_SETT._PRICE – NZD/BITCOIN and CME-EURO_GLOBEX_CONT._-_SETT._PRICE – CHF/BITCOIN. We see statistically significant β-parameters, indicating strong GARCH effects for the pairs of markets: CME-EURO_GLOBEX_CONT._-_SETT._PRICE – USD/BITCOIN, CME-EURO_GLOBEX_CONT._-_SETT._PRICE – NZD/BITCOIN and CME-EURO_GLOBEX_CONT._-_SETT._PRICE – CAD/BITCOIN. Additionally, we provide the estimates of the degrees of freedom and of the log-likelihood.

In table 4 we report the results of diagnostic tests and information criteria. $x^2(4)$ statistic results suggest that the null hypothesis of no spillovers is rejected at 1 % significance level. Ljuing – Box test results [26–27] provide evidence of no serial autocorrelation, suggesting the absence of misspecification errors of the estimated multivariate GARCH model. Moreover, the estimated AIC and SIC information criteria are presented.

Figure 3 plots the conditional covariances for all the pairs of market returns during the whole period. We observe for all the conditional covariances a tremble trend. Additionally, conditional covariances seem to be extreme volatile.

Analysis of the dynamic conditional correlations. Table 4 shows the descriptive statistics of the dynamic conditional correlations of the seven pairs of markets. We observe the highest mean value (0,659 38) is for the pair of markets CME-EURO_GLOBEX_CONT._-_SETT._PRICE – NZD/BITCOIN. The highest standard deviation value for the pair of markets CME-EURO_GLOBEX_CONT._-_SETT._PRICE – CHF/BITCOIN indicates that the specific DCC experiences larger flunctuations. The statistical significant skewness, excess kyrtosis and the Jarque – Bera test statistics indicate that the DCCs for all the pairs of markets are not normally distributed.

Table 1

Summary statistics of the daily market logarithmic returns

Criterion	CME-EURO_GLOBEX_CONT._-_SETT._PRICE	USD/BITCOIN	EUR/BITCOIN	NZD/BITCOIN	AUD/BITCOIN	CAD/BITCOIN	CHF/BITCOIN	JPY/BITCOIN
Mean	–6.4221e-005	–0.001 010 8	–0.001 857 8	–0.000 915 17	–0.000 873 46	–0.000 944 96	–0.000 968 36	–0.001 021 4
Minimum	–0.006 860 7	–0.109 17	–0.135 49	–0.110 73	–0.112 54	–0.112 55	–0.114 34	–0.113 1
Maximum	0.005 153	0.090 37	0.178 18	0.099 148	0.100 65	0.099 186	0.094 779	0.094 567
Standard deviation	0.001 829 9	0.020 898	0.037 612	0.021 073	0.021 021	0.020 991	0.020 999	0.020 963
Skewness	–0.135 53*	–0.354 31**	0.679 04***	–0.294 52**	–0.280 27**	–0.290 43**	–0.372 28**	–0.358 37**
t-Statistic	1.068 6	2.793 5	5.353 9	2.322 2	2.209 8	2.289 9	2.935 3	2.8255
p-Value	0.285 27	0.005 213 5	8.6086e-008	0.020 223	0.027 118	0.022 027	0.003 332 6	0.004 720 0
Excess Kyr-tosis	0.404 83*	3.673 9***	3.713 2***	3.923 3***	4.167 8***	4.065 2***	4.122 5***	4.140 9***
t-Statistic	1.600 2	14.522	14.677	15.508	16.474	16.068	16.295	16.368
p-Value	0.109 56	8.7966e-048	9.0247e-049	3.0827e-054	5.6314e-061	4.2452e-058	1.0695e-059	3.2443e-060
Jarque-Bera	3.659 2***	215.83***	241.00***	242.65***	272.64***	259.97***	270.56***	272.27***
p-Value	0.160 48	1.3575e-047	4.6570e-053	2.0430e-053	6.2619e-060	3.5285e-057	1.7769e-059	7.5253e-060
ADF Test	–11.220 2***	–10.524 7***	–9.837 84***	–10.311 7***	–10.353 6***	–10.475 8***	–10.378 2***	–10.518 2***

Note. * – statistical significance at the 10 % level; ** – statistical significance at the 5 % level; *** – statistical significance at the 1 % level.

Source: Datastream® Database.

Table 2

Estimates of univariate GARCH(1,1) model

Critetion	CME-EURO_ GLOBEX_ CONT._-_ SETT._PRICE	USD/BITCOIN	EUR/BITCOIN	NZD/BITCOIN	AUD/ BITCOIN	CAD/ BITCOIN	CHF/BITCOIN	JPY/ BITCOIN
Constant (ω)	1.885 387**	0.018 679	9.787 036***	0.022 837	0.015 968	0.015 335	0.021 960	0.023 981
t-Statistic	2.288	0.509 7	5.215	0.540 9	0.414 1	0.409 0	0.618 6	0.612 9
p-Value	0.022 7	0.610 6	0.000 0	0.588 9	0.679 0	0.682 8	0.536 6	0.540 3
ARCH (*a*)	–0.083 052*	0.087 080***	0.288 417**	0.082 228***	0.084 434**	0.088 373***	0.090 383***	0.085 605**
t-Statistic	–1.708	3.033	2.703	3.203	2.284	3.303	3.135	2.862
p-Value	0.088 5	0.002 6	0.007 2	0.001 5	0.022 9	0.001 1	0.001 9	0.004 5
GARCH (*b*)	0.633 162***	0.908 741***	–0.043 610	0.913 403***	0.913 877***	0.910 357***	0.906 721***	0.909 705***
t-Statistic	3.422	34.81	–0.725 7	39.96	28.30	40.27	37.67	34.52
p-Value	0.000 7	0.000 0	0.468 5	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0

Note. * – statistical significance at the 10 % level; ** – statistical significance at the 5 % level; *** – statistical significance at the 1 % level.

Source: Datastream® Database.

Table 3

Estimates of the bivariate DCC-GARCH(1,1) model, degrees of freedom, log-likelihood

Critetion	CME-EURO_ GLOBEX_CONT._-_ SETT._PRICE – USD/ BITCOIN	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – EUR/ BITCOIN	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – NZD/ BITCOIN	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – AUD/ BITCOIN	CME-EURO_ GLOBEX_CONT._-_ SETT._PRICE – CAD/ BITCOIN	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – CHF/ BITCOIN	CME-EURO_ GLOBEX_CONT._-_ SETT._PRICE – JPY/BITCOIN
Average COR *ij*	–0.025 859	0.003 014	0.064 134*	0.065 718	0.034 294	0.056 540*	0.027 894
t-Statistic	–0.517 3	0.060 00	1.305	0.862 2	0.702 2	1.095	0.517 4
p-Value	0.605 2	0.952 2	0.192 9	0.389 1	0.483 0	0.274 1	0.605 2
alpha (α)	0.000 000 8	0.000 000 0	0.000 000 1	0.091 887	0.000 000 9	0.094 385	0.086 607
t-Statistic	0.096 38	0.00	0.135 0	0.117 9	0.043 10	0.505 0	0.219 5
p-Value	0.923 3	1.000 0	0.892 7	0.906 2	0.965 6	0.613 8	0.826 4
beta (β)	0.829 406***	0.237 771	0.640 912*	0.000 000	0.671 466**	0.000 000	0.000 000
t-Statistic	3.008	0.434 9	1.679	0.00	2.058	0.00	000
p-Value	0.002 8	0.663 9	0.094 1	1.000 0	0.040 3	1.000 0	1.000 0
Degrees of freedom (df)	4.233 330***	4.874 488***	4.382 709***	4.235 011***	4.308 371***	4.262 997***	4.353 704***
t-Statistic	6.301	5.294	6.229	6.429	6.392	6.318	6.313
p-Value	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0	0.000 0
Log-likelihood	2772.508	2535.800	2765.063	2768.983	2768.140	2770.719	2768.663

Note. * – statistical significance at the 10 % level; ** – statistical significance at the 5 % level; *** – statistical significance at the 1 % level.

Source: Datastream® Database.

Table 4

Diagnostic tests and information criteria

Critetion	CME-EU-RO_GLOBEX_CONT._-_SETT._PRICE – USD/BITCOIN	CME-EURO_GLOBEX_CONT._-_SETT._PRICE – EUR/BITCOIN	CME-EU-RO_GLOBEX_CONT._-_SETT._PRICE – NZD/BITCOIN	CME-EU-RO_GLOBEX_CONT._-_SETT._PRICE – AUD/BITCOIN	CME-EU-RO_GLOBEX_CONT._-_SETT._PRICE – CAD/BITCOIN	CME-EU-RO_GLOBEX_CONT._-_SETT._PRICE – CHF/BITCOIN	CME-EU-RO_GLOBEX_CONT._-_SETT._PRICE – JPY/BITCOIN
x^2	584.62**	103.74**	442.70**	547.57**	631.75**	519.70**	494.16**
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Hosking (50)	187.941	193.790	195.408	197.594	193.698	196.431	196.566
p-Value	0.7197109	0.6103895	0.5784710	0.5348331	0.6121863	0.5580847	0.5553876
$Hosking^2$ (50)	155.988	142.113	156.666	151.207	152.251	151.778	151.622
p-Value	0.9877142	0.9990083	0.9863842	0.9943476	0.9932513	0.9937679	0.9939316
Li-McLeod (50)	189.902	195.818	197.108	199.168	195.358	198.127	198.226
p-Value	0.6844528	0.5703171	0.5445508	0.5033225	0.5794607	0.5241589	0.5221782
$Li\text{-}McLeod^2$ (50)	158.881	146.652	159.689	154.424	155.655	155.130	154.903
p-Value	0.9811695	0.9975265	0.9788984	0.9903752	0.9883283	0.9892417	0.9896178
Akaike	0.013550	0.017008	0.013659	0.013601	0.013614	0.013576	0.013606
Schwarz	0.119320	0.122778	0.119429	0.119372	0.119384	0.119346	0.119376

Note. ** – statistical significance at the 5 % level.

Source: Datastream® Database.

Table 5

Statistical properties of the Multivariate GARCH-DCC's

Criterion	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – USD/ BITCOIN	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – EUR/ BITCOIN	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – NZD/ BITCOIN	CME-EURO_ GLOBEX_ CONT._-_SETT._ PRICE – AUD/ BITCOIN	CME-EURO_ GLOBEX_CONT._-_ SETT._PRICE – CAD/BITCOIN	CME-EURO_ GLOBEX_CONT._-_ SETT._PRICE – CHF/ BITCOIN	CME-EURO_ GLOBEX_CONT._-_ SETT._PRICE – JPY/ BITCOIN
Mean	–0.025 859	0.003 014 1	0.064 134	0.063 136	0.034 294	0.053 631	0.025 399
Minimum	–0.025 859	0.003 014 1	0.064 134	0.297 11	0.034 294	–0.312 05	–0.329 45
Maximum	–0.025 859	0.003 014 1	0.064 134	0.287 25	0.034 294	0.285 76	0.243 98
Standard deviation	1.3411e-009	2.8696e-019	7.4978e-018	0.067 811	4.9471e-018	0.069 185	0.064 401
Skewness	–1.429 0***	–0.111 95	0.000 00	–0.836 41***	–2.185 2***	–0.883 98***	–0.890 86***
p-Value	1.9060e-029	0.377 43	1.000 0	4.2601e-011	1.5946e-066	3.1739e-012	2.1557e-012
Excess kyrtosis	6.984 9***	–0.377 69*	0.425 93*	6.037 7***	2.533 9***	6.199 2***	6.806 2***
p-Value	8.5871e-168	0.135 47	0.092 267	7.0067e-126	1.3008e-023	1.3583e-132	2.0257e-159
Jarque – Bera	878.10***	2.971 9	2.796 8	605.15***	393.46***	640.64***	763.11***
p-Value	2.1051e-191	0.226 28	0.246 99	3.9282e-132	3.6477e-086	7.6923e-140	1.9583e-166

Note. * – statistical significance at the 10 % level; *** – statistical significance at the 1 % level.

Source: Datastream® Database.

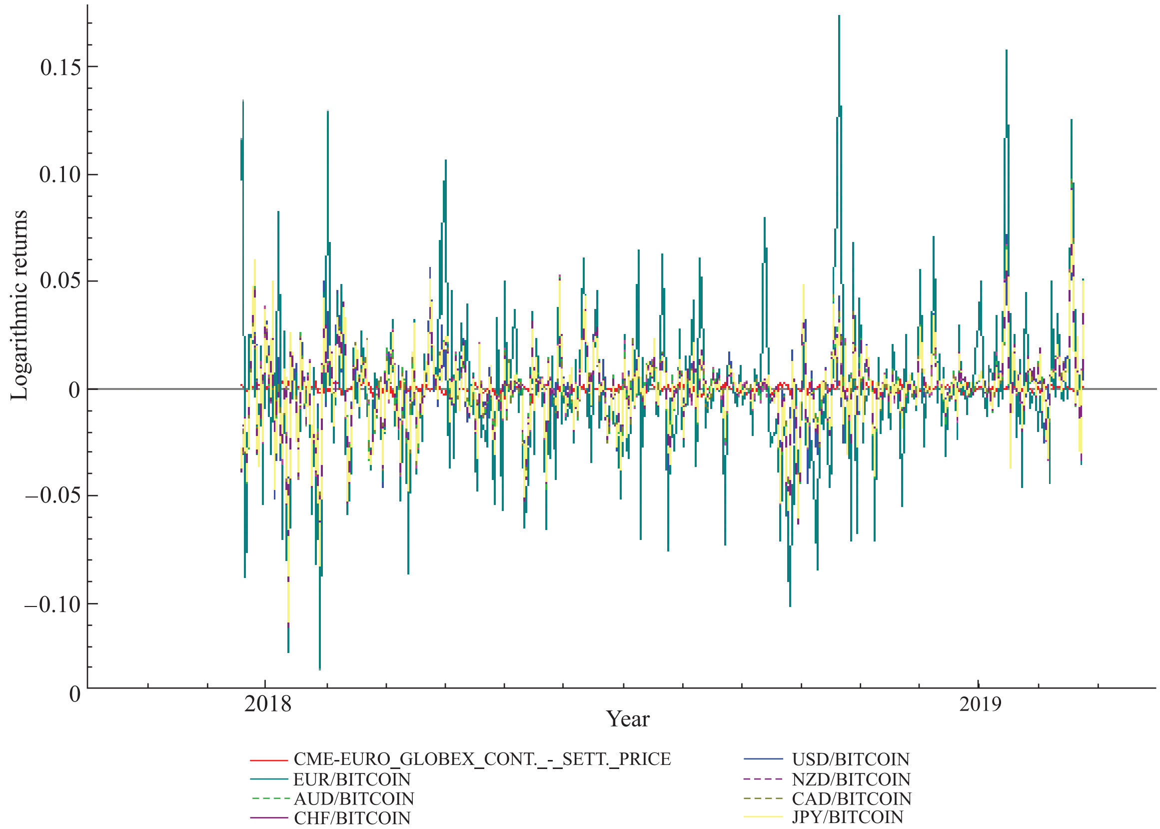

Fig. 1. Actual series of the logarithmic returns of the markets

S o u r c e: Datastream® Database

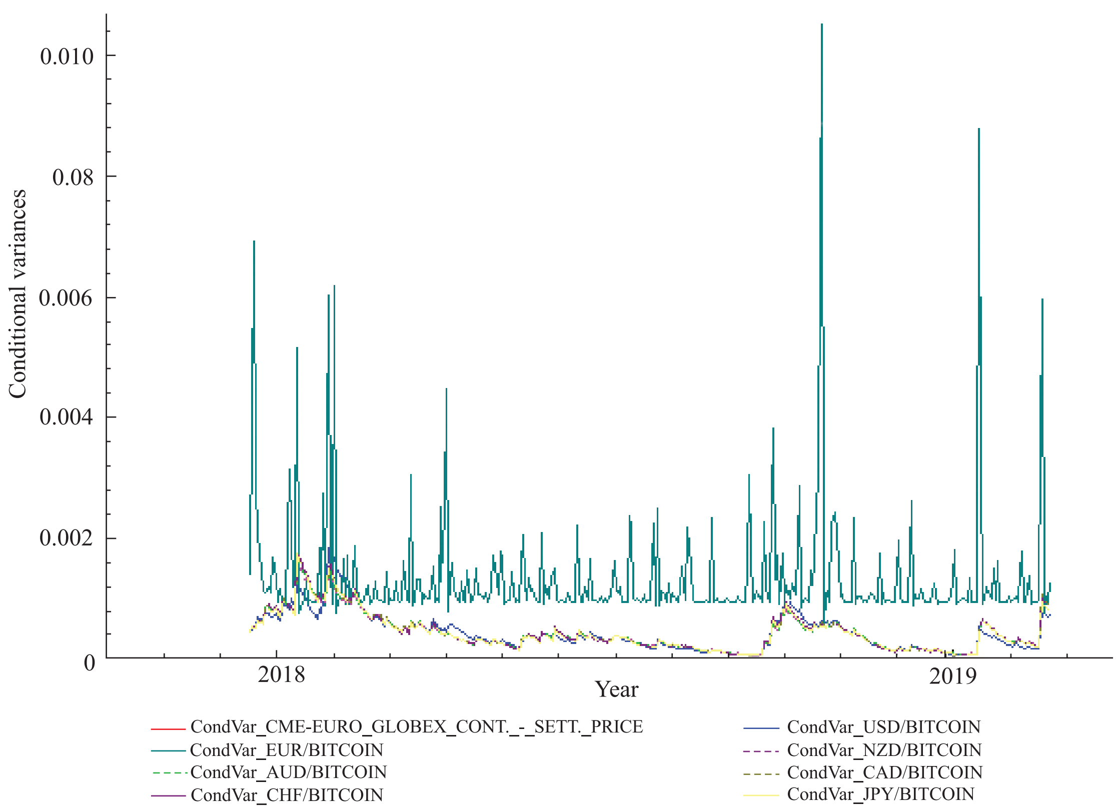

Fig. 2. Conditional variances of the univariate GARCH(1,1) model

S o u r c e: Datastream® Database

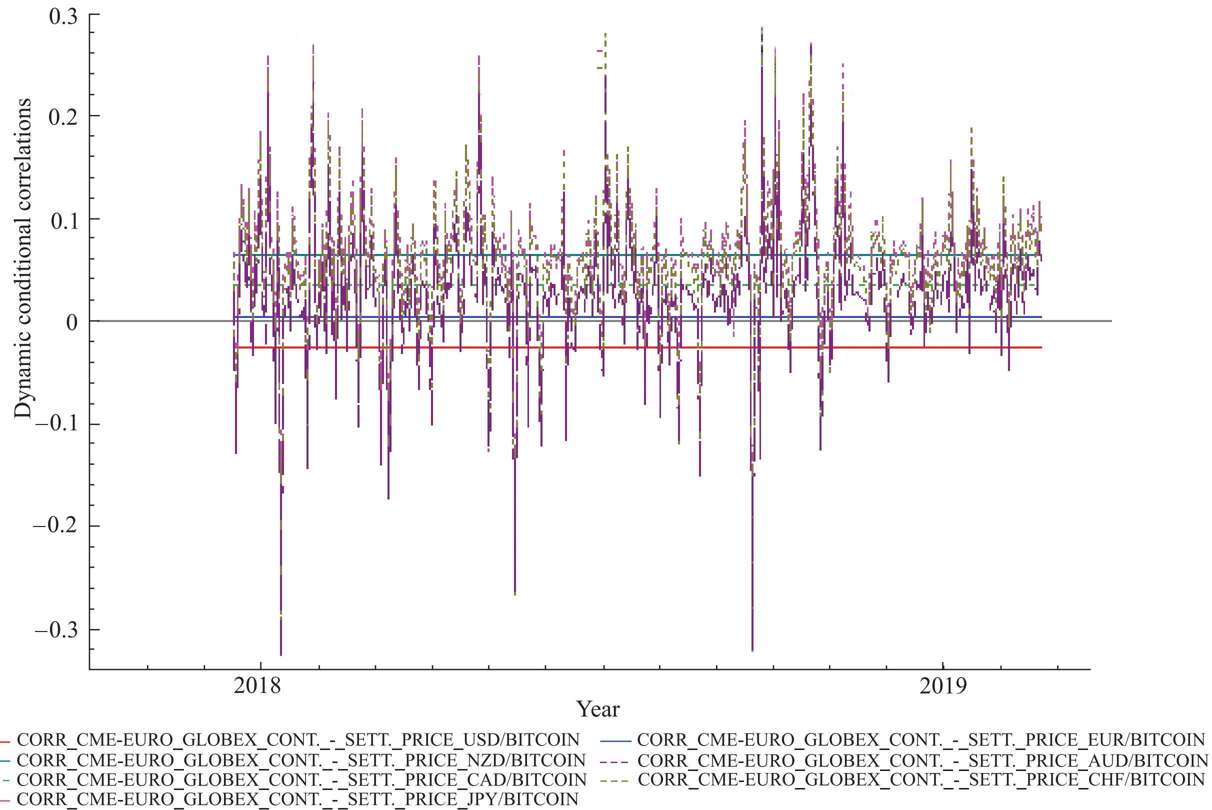

Fig. 3. Conditional covariances of the bivariate DCC-GARCH(1,1) model

S o u r c e: Datastream® Database

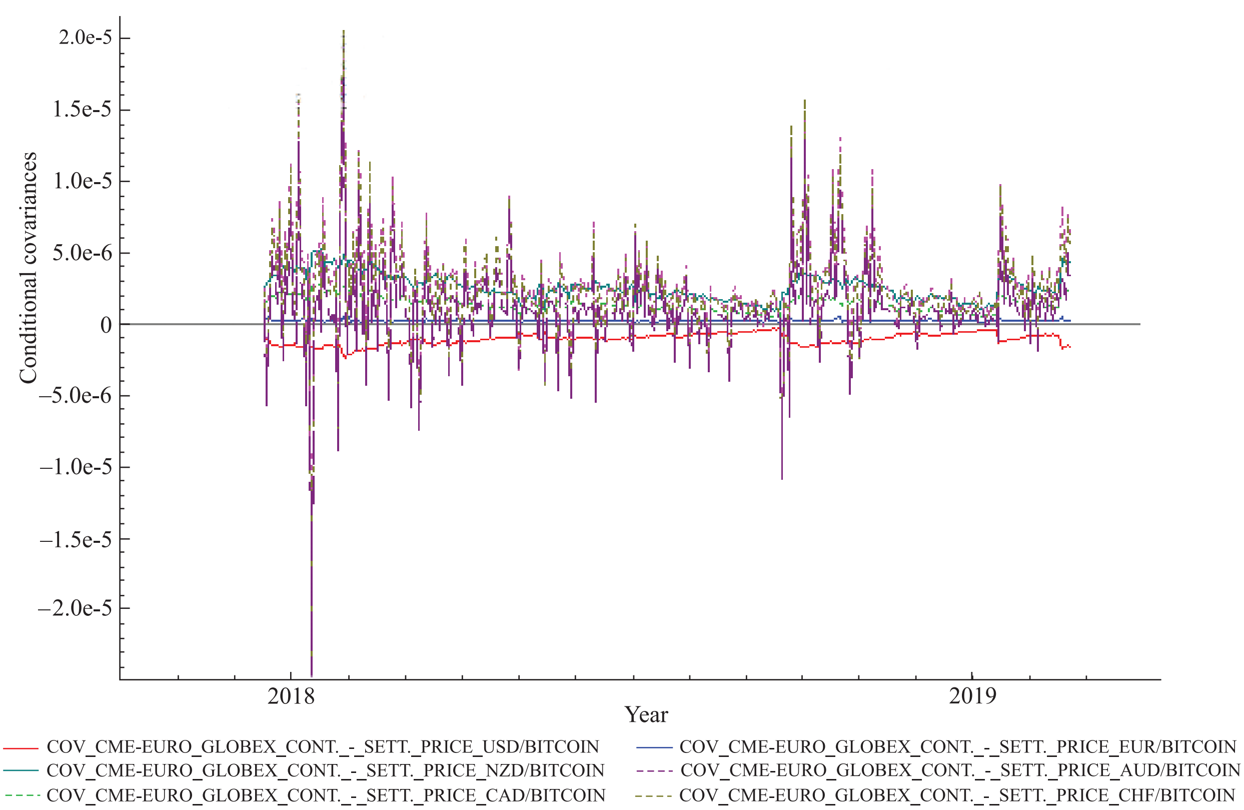

Fig. 4. Dynamic conditional correlations of the bivariate DCC-GARCH(1,1) model

S o u r c e: Datastream® Database

Figure 4 shows the pair-wise DCCs. DCCs present positive values in sub-periods, supporting the existence of contagion, implying the specific correlations risky for any investor. Additionally, we can notice the effects of major economic events on the DCC graphs as we see that the lines are bouncing above and beyond and are extreme volatile for some pairs of markets.

Conclusions

This paper investigates the potential volatility spillovers effects and the existence of contagion effects among eurodollar future market and seven Forex bitcoin markets by employing a bivariate DCC-GARCH model. We set the under investigation period from 2017 until 2019. To the best of our knowledge, this is the first empirical study, investigating volatility spillovers between eurodollar future market and five Forex bitcoin markets.

The main empirical results are summarised as follows. Based on the descriptive statistics, EUR/BITCOIN returns presents the largest fluctuations compared to the rest markets. Furthermore, results of bivariate DCC-GARCH models indicate strong evidence of volatility spillover effects. DCCs analysis shows evidence of strong co-movements for some pairs of markets. Additionally, DCCs reveal contagion for some pairs of markets in sub-periods. The empirical results are of interest to policymakers, who provide regulations for the under investigation derivative markets as well as to market-makers.

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