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COVID-19 vaccine and post-pandemic recovery: Evidence from Bitcoin cross-asset implied volatility spillover

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**Abstract**

This paper examines implied volatility spillovers and connectedness between Bitcoin and a broad range of traditional financial assets (U.S. equity market, gold, crude oil, emerging markets and developing markets) from January 8, 2019 to January 20, 2022. Vector Auto-Regression and Generalized Forecast Error Variance Decomposition are used to compare results before COVID-19, during COVID-19 and after the vaccine becomes available. Results indicate higher connectedness during COVID-19 but very low connectedness after the vaccine is available, signaling recovery in financial markets. We also find that Bitcoin is a strong transmitter of volatility during COVID-19.

1. Introduction

Since the Novel Coronavirus (COVID-19) outbreak we have seen changes in many aspects of our lives. According to the World Health Organization, there have been more than 198 million cases of COVID-19 and at least 4 million deaths worldwide. In the beginning, countries around the world were sent scrambling into a state of damage mitigation, even at the cost of shutting down most non-essential production worldwide. From February 19, 2020 to March 23, 2020, the S&P 500 index declines about 34%. In an effort to stabilize the market, many countries made large monetary injections and cut interest rates. In such a turbulent market, Bitcoin is considered as a risk hedging tool because of its independence from monetary policy and weak correlation with traditional financial assets (Baur et al., 2018; Bouri et al., 2017; Dyhrberg, 2016; Maghyereh and Abdoh, 2022; Urquhart and Zhang, 2019). However, Bouri et al. (2021), Cheng et al. (2022) and Benlagha and El Omari (2022) among others find that there is a much higher level of connectedness among financial assets including Bitcoin during COVID-19. In this paper, we intend to explore Bitcoin's connectedness with traditional financial assets during the pandemic recovery period.

The availability of the COVID-19 vaccine allows non-essential businesses to reopen and speeds up the economic recovery from the pandemic. It would be interesting to explore Bitcoin's connectedness with other markets during the pandemic recovery period. In this paper, we investigate whether the COVID-19 vaccine has restored confidence in a strong financial markets recovery through a reduction in inter-market connectedness among Bitcoin and other traditional financial markets.

Castillo et al. (2021), Zhang and Hamori (2021) and Díaz et al. (2022) are all papers that study the impact of the pandemic on the financial market. Volatility during the COVID-19 pandemic surpasses that of the 2008 financial crisis and is of particular interest. In times of financial uncertainty investors always seek to hedge their risks. Corbet et al. (2020) find that cryptocurrencies satisfy the safe haven property in periods of severe financial uncertainty. Cheng et al. (2022) find that COVID-19 strengthens volatility...
connectedness in global stock and commodity markets and that connectedness stays high throughout 2020. Benlagha and El Omari (2022) also find higher connectedness during COVID-19 while focusing on gold and oil. Other papers that study the effects of COVID on financial markets include Choi (2022), Baig et al. (2021), and Bouri et al. (2021). We contribute to this fast expanding literature by examining the COVID recovery period after the availability of the COVID-19 vaccine. To the best of our knowledge, our paper is the first to study the impact of the COVID-19 vaccine on financial market recovery.

Our research most closely resembles that of Elsayed et al. (2022) which examines return and volatility connectedness between Bitcoin and traditional financial assets during COVID-19. Consistent with their finding, we find that there is higher connectedness and Bitcoin plays a major role in volatility transmission during COVID-19. More importantly, we find that the inter-market connectedness reduces to the pre-COVID-19 level after the availability of COVID-19 vaccine, signaling a financial market recovery from the pandemic.

Bouri et al. (2018) examine the inter-connectedness of Bitcoin and other assets in different market conditions. They find that there is some return connectedness in Bitcoin but relatively low volatility connectedness. It is evident that systematic risk is the cause of the aforementioned findings of higher connectedness during COVID-19. Shocks in the financial markets during times of great economic uncertainty can propagate extensively, making it more difficult to hedge. This has very important implications for portfolio diversification as well as policy effects during periods of global uncertainty and crisis.

In this paper, we examine implied volatility connectedness between Bitcoin and traditional financial assets before COVID-19, during COVID-19 and after the COVID-19 vaccine becomes available. Vector Auto-Regression (VAR) is used alongside Generalized Forecast Error Variance Decomposition (GFEVD) to measure implied volatility spillover. We find volatility spillover increases drastically during COVID-19, however, the spillover reduces to extremely low levels after the availability of COVID-19 vaccine.

Our results indicate that, during COVID-19, systematic risk propagating through global economies drastically decreases diversification benefits. Furthermore, these reduced diversification benefits on volatility dissipate after the vaccine is available, making hedging volatility much more effective and signaling recovery in financial markets. As the COVID-19 vaccine becomes available and business gradually reopens, investors are more confident about a strong economic recovery from COVID-19.

2. Data

Data for this study spans from January 8, 2019 to January 20, 2022. First we obtain the VIX series from Choe (2022) which we use to represent volatility in the U.S. equity market. Following Badshah (2018), we use VXEEM and VXEFA which are aggregate implied volatility indices for emerging and developing markets worldwide. The benefit of using these indices as opposed to using implied volatility directly from markets in specific countries is that the trading hours line up perfectly with that of the VIX and our other series. The VXEEM is derived from the iShare MSCI Emerging Markets ETF which is comprised of 26 emerging stock markets. The VXEFA is based on the iShares MSCI EAFE ETF which is comprised of European, Australian, Asian and East Asian markets.

Two commodity implied volatilities are also used: gold and crude oil. The gold implied volatility is derived from the SPDR Gold shares ETF (NYSEArca: GLD) and crude oil implied volatility is calculated using prices from the United States Oil Fund (USO). Data for VXEEM, VXEFA, gold implied volatility and crude oil implied volatility are obtained from Choe (2022). Data for Bitcoin implied volatility is obtained from T3 Index (2022) and has been cross-referenced with data from Deribit which is the largest crypto options exchange. Additionally, we use nominal broad (trade-weighted) U.S. dollar index obtained from FRED. In the rest of this paper, we will refer to VXEEM, VXEFA, gold implied volatility, oil implied volatility, Bitcoin implied volatility and the U.S. dollar index as VEM, VDM, GVX, OVX, BVOL and USD.
Table 1
Descriptive statistics and ADF stat.

| Variable | N  | Mean  | Std. Dev. | Min  | Max  | ADF stat | P-value |
|----------|----|-------|-----------|------|------|----------|---------|
| BVOL     | 748| 86.701| 21.654    | 44.84| 190.28| −1.028   | 0.304   |
| VIX      | 748| 21.518| 9.553     | 11.54| 82.69 | −0.998   | 0.319   |
| GVX      | 748| 16.925| 5.537     | 8.88 | 48.98 | −0.787   | 0.432   |
| OVX      | 748| 45.976| 29.899    | 24.00| 325.15| −2.415   | 0.016   |
| VEM      | 748| 23.682| 8.786     | 7.77 | 92.46 | −1.191   | 0.234   |
| VDM      | 748| 18.942| 8.393     | 7.77 | 75.17 | −1.191   | 0.234   |
| USD      | 748| 115.528| 2.973    | 110.54| 126.14| −0.005   | 0.996   |

Panel B: Summary statistics of differenced series

| Variable | N  | Mean  | Std. Dev. | Min  | Max  | ADF stat | P-value |
|----------|----|-------|-----------|------|------|----------|---------|
| ΔBVOL    | 747| −0.020| 6.623     | −36.24| 57.53| −19.9949| 0.000   |
| ΔVIX     | 747| 0.007 | 2.530     | −17.64| 24.86| −20.7189| 0.000   |
| ΔGVX     | 747| 0.005 | 1.167     | −9.50 | 7.25 | −19.6891| 0.000   |
| ΔOVX     | 747| −0.007| 9.143     | −90.61| 130.22| −23.9101| 0.000   |
| ΔVEM     | 747| 0.005 | 3.310     | −34.09| 35.35| −26.4795| 0.000   |
| ΔVDM     | 747| 0.007 | 3.168     | −21.91| 40.42| −21.8751| 0.000   |
| ΔUSD     | 747| 0.000 | 0.347     | −2.36 | 2.24 | −16.7965| 0.000   |

Daily observations of implied volatility and USD series are summarized in Panel A. Panel B presents the summary statistics in the differenced series. The ADF test null hypothesis is that there is a unit root.

Fig. 2. Daily number of new cases (7-day moving average). Figure 2 plots a 7-day moving average of daily new COVID-19 cases globally in millions.

Table 2
Correlation of volatility shocks.

|         | ΔBVOL | ΔVIX  | ΔGVX  | ΔOVX  | ΔVEM  | ΔVDM  | ΔUSD  |
|---------|-------|-------|-------|-------|-------|-------|-------|
| ΔBVOL   | 1     | 0.112 | 0.230 | −0.010| 0.143 | 0.042 | −0.006|
| ΔVIX    | 0.112 | 1     | 0.333 | 0.266 | 0.583 | 0.528 | 0.238 |
| ΔGVX    | 0.230 | 0.333 | 1     | 0.190 | 0.332 | 0.273 | 0.109 |
| ΔOVX    | −0.010| 0.266 | 0.190 | 1     | 0.179 | 0.199 | 0.172 |
| ΔVEM    | 0.143 | 0.583 | 0.332 | 0.322 | 1     | 0.421 | 0.230 |
| ΔVDM    | 0.042 | 0.528 | 0.273 | 0.199 | 0.421 | 1     | 0.205 |
| ΔUSD    | −0.006| 0.238 | 0.109 | 0.172 | 0.230 | 0.205 | 1     |

Correlations of the first difference of data series used in models.

In Table 1, summary statistics and Augmented Dickey–Fuller (ADF) unit-root test results are provided in levels and in first difference. We can see that GVX exhibits the smallest variance whereas BVOL and OVX exhibit the highest. The ADF test statistics show that they are stationary after one difference. Despite being able to reject the presence of a unit root in OVX using the entire data, we are not able to reject this in any of the three subsamples used in our analysis.

In Fig. 1, the series are plotted in levels and the shock to the volatility indices caused by COVID-19 are readily apparent. Fig. 2 plots the number of new daily COVID-19 cases globally. We can see that before the vaccine, the number of cases is steadily rising. After the vaccine becomes available there is a brief drop in cases, but then the series begins an oscillating pattern until the Omicron variant hits and new cases spike. Table 2 provides the correlation table of the differenced series.
Table 3
VAR(2) before COVID-19.

| Dependent variable: | ΔBVOL | ΔVIX | ΔGVX | ΔOVX | ΔVEM | ΔVDM |
|---------------------|-------|------|------|------|------|------|
| ΔBVOL.l1            | -0.052 | -0.011 | -0.016** | -0.059*** | -0.026* | -0.047*** |
| (−0.484)            | (−0.795) | (−2.185) | (−2.77) | (−1.772) | (−2.021) |
| ΔVIX.l1             | -0.754 | -0.248* | 0.089 | -0.191 | 0.019 | 0.461 |
| (−1.45)             | (−1.921) | (1.106) | (−1.152) | (0.16) | (1.601) |
| ΔGVX.l1             | 0.015 | -0.034 | -0.182** | -0.025 | -0.058 | 0.221 |
| (0.038)             | (−0.331) | (−2.42) | (−0.129) | (−0.621) | (0.9) |
| ΔOVX.l1             | -0.045 | 0.039 | 0.018 | -0.070 | 0.002 | 0.072 |
| (−0.29)             | (1.051) | (0.68) | (−0.91) | (0.061) | (0.957) |
| ΔVEM.l1             | 0.768 | 0.018 | -0.076 | 0.226 | -0.176 | 0.219 |
| (0.993)             | (0.122) | (−0.974) | (1.336) | (−1.219) | (0.888) |
| ΔVDM.l1             | 0.158 | 0.090* | 0.002 | 0.017 | 0.072* | -0.700*** |
| (1.608)             | (1.824) | (0.075) | (0.529) | (1.737) | (−7.718) |
| ΔBVOL.l2            | -0.018 | -0.014 | -0.008 | -0.021 | -0.028*** | 0.03 |
| (−0.252)            | (−1.048) | (−0.944) | (−1.238) | (−2.617) | (0.763) |
| ΔVIX.l2             | -0.528 | -0.247* | 0.022 | 0.041 | -0.075 | 0.007 |
| (−1.033)            | (−1.939) | (0.309) | (0.276) | (−0.581) | (0.026) |
| ΔGVX.l2             | -0.031 | 0.373*** | -0.065 | 0.194 | 0.249*** | -0.079 |
| (−0.055)            | (3.46) | (−0.704) | (1.147) | (2.743) | (−4.441) |
| ΔOVX.l2             | 0.075 | -0.026 | -0.043 | -0.069 | -0.006 | 0.036 |
| (0.511)             | (−0.668) | (−1.474) | (−0.858) | (−0.185) | (0.631) |
| ΔVEM.l2             | 0.314 | 0.040 | 0.042 | -0.140 | -0.030 | -0.004 |
| (0.594)             | (0.312) | (0.587) | (−0.819) | (−0.236) | (−0.016) |
| ΔVDM.l2             | 0.219** | 0.008 | -0.014 | 0.007 | 0.002 | -0.279*** |
| (2.332)             | (0.184) | (−0.491) | (0.181) | (0.048) | (−3.047) |
| ΔUSD                | 0.106 | 1.706*** | -0.173 | 1.239** | 1.639*** | 0.851 |
| (0.088)             | (4.694) | (−0.563) | (2.093) | (4.939) | (1.383) |
| Obs.                | 268 | 268 | 268 | 268 | 268 | 268 |
| R²                  | 0.024 | 0.211 | 0.069 | 0.074 | 0.197 | 0.404 |

*Note: p < 0.1.
**p < 0.05.
***p < 0.01.

VAR(2) is run on the differenced implied volatility series with USD shocks as an exogenous variable using data from January 11th, 2019 to February 21st, 2020. Estimates and t-values (calculated using White heteroskedastic standard errors) are presented in this table. The .l1 and .l2 suffixes are used to denote the first and second lag of the series.

3. Method and results

In this section, we consider the effect of the COVID-19 vaccine on post-pandemic recovery of the Bitcoin market. We split our sample into three subsamples: before COVID-19 restrictions, after restrictions, and after the COVID-19 vaccine is available. The three samples can be seen graphically in Fig. 1, split by the dashed vertical line segments. The same subsamples are also plotted in Fig. 2, although the first subsample is not fully shown in the figure. We can see that in the first subsample there are very few daily new cases, but as we move throughout the second subsample the number of new cases rises steadily. After the vaccine, in the third subsample, an oscillating behavior is exhibited in the number of new daily cases. The Omicron spike is shown, but without more data, its effect cannot be observed accurately.

A VAR model is used to model inter-market volatility spillovers and GFEVD is used to compare connectedness more directly. The Bayesian Information Criterion (BIC) suggests that VAR(1) is suitable for all the subsample models, but with residual analysis, we still find some autocorrelation and that VAR(2) provides a better fit. All implied volatility series are included in the VAR alongside...
**Table 4** VAR(2) during COVID-19.

| Dependent variable: | \( \Delta \text{BVOL} \) | \( \Delta \text{VIX} \) | \( \Delta \text{GVX} \) | \( \Delta \text{OVX} \) | \( \Delta \text{VEM} \) | \( \Delta \text{VDM} \) |
|---------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| \( \Delta \text{BVOL} \) | \(-0.018\) | \(0.112^{**}\) | \(0.062^{**}\) | \(0.000\) | \(0.068^{**}\) | \(-0.041^{*}\) |
| (\(-0.165\)) | (8.154) | (8.592) | (0.023) | (4.719) | (1.772) |
| \( \Delta \text{VIX} \) | \(0.190\) | \(-0.338^{***}\) | \(0.216^{**}\) | \(0.365^{**}\) | \(0.191\) | \(0.212\) |
| (0.365) | (2.623) | (2.681) | (1.999) | (1.630) | (0.735) |
| \( \Delta \text{GVX} \) | \(1.134^{***}\) | \(0.147\) | \(-0.061\) | \(-0.946^{***}\) | \(0.279^{***}\) | \(0.308\) |
| (2.796) | (1.416) | (0.810) | (4.852) | (2.999) | (1.256) |
| \( \Delta \text{OVX} \) | \(-0.035\) | \(-0.010\) | \(-0.003\) | \(0.085\) | \(-0.013\) | \(0.006\) |
| (\(-0.223\)) | (\(-0.276\)) | (\(-0.106\)) | (1.113) | (\(-0.463\)) | (0.082) |
| \( \Delta \text{VEM} \) | \(-0.179\) | \(-0.120\) | \(-0.089\) | \(-0.453^{***}\) | \(-0.43^{***}\) | \(-0.189\) |
| (\(-0.231\)) | (\(-0.833\)) | (\(-1.146\)) | (\(-2.683\)) | (\(-2.979\)) | (\(-0.767\)) |
| \( \Delta \text{VDM} \) | \(0.132\) | \(-0.009\) | \(-0.122^{**}\) | \(-0.233^{***}\) | \(-0.049\) | \(-0.503^{**}\) |
| (1.344) | (\(-0.176\)) | (\(-0.500\)) | (\(-7.136\)) | (\(-1.178\)) | (\(-5.552\)) |
| \( \Delta \text{BVOL} \) | \(-0.103\) | \(0.057^{***}\) | \(0.017^{*}\) | \(0.127^{**}\) | \(0.007\) | \(-0.106^{***}\) |
| (\(-1.421\)) | (4.213) | (1.909) | (7.397) | (0.68) | (\(-2.659\)) |
| \( \Delta \text{VIX} \) | \(0.576\) | \(0.219^{*}\) | \(0.112\) | \(0.782^{***}\) | \(0.532^{***}\) | \(0.591^{**}\) |
| (1.128) | (1.721) | (1.566) | (5.227) | (4.133) | (2.229) |
| \( \Delta \text{GVX} \) | \(-0.478\) | \(-0.169\) | \(-0.194^{**}\) | \(0.959^{***}\) | \(-0.186^{**}\) | \(0.023\) |
| (\(-0.841\)) | (\(-1.570\)) | (\(-2.113\)) | (5.665) | (\(-2.048\)) | (0.130) |
| \( \Delta \text{OVX} \) | \(-0.060\) | \(-0.004\) | \(0.010\) | \(-0.270^{***}\) | \(-0.027\) | \(-0.034\) |
| (\(-0.407\)) | (\(-0.104\)) | (0.334) | (\(-3.343\)) | (\(-0.822\)) | (\(-0.59\)) |
| \( \Delta \text{VEM} \) | \(0.193\) | \(-0.178\) | \(0.045\) | \(-0.118\) | \(-0.199\) | \(-0.329\) |
| (0.366) | (\(-1.390\)) | (0.626) | (\(-0.688\)) | (\(-1.561\)) | (\(-1.328\)) |
| \( \Delta \text{VDM} \) | \(0.190^{**}\) | \(0.011\) | \(-0.026\) | \(-0.389^{***}\) | \(0.032\) | \(-0.205^{**}\) |
| (2.026) | (0.248) | (\(-0.931\)) | (\(-10.052\)) | (0.790) | (\(-2.241\)) |
| \( \Delta \text{USD} \) | \(-0.726\) | \(2.264^{***}\) | \(0.164\) | \(5.848^{***}\) | \(2.776^{***}\) | \(2.642^{***}\) |
| (\(-0.601\)) | (6.23) | (0.535) | (9.877) | (8.368) | (4.294) |

**Obs.** 193  
**R²** 0.171 0.314 0.233 0.159 0.357 0.365

*Note: p < 0.1.

**p < 0.05.

***p < 0.01.

VAR(2) is run on the differenced implied volatility series with USD shocks as an exogenous variable using data from February 24th, 2020 to December 3rd, 2020. Estimates and t-values (calculated using White heteroskedastic standard errors) are presented in this table. The .l1 and .l2 suffixes are used to denote the first and second lag of the series.

USD as an exogenous variable. Tables 3–5 present the results of the three subsample periods. We test for heteroskedasticity and apply White heteroskedasticity-robust standard errors. The estimates and t-values are presented in Tables 3–5.²

Following Diebold and Yilmaz (2012), a VAR(p) model written as:

\[
Y_t = \sum_{i=1}^{p} \beta_i Y_{t-i} + \epsilon_t
\]  

(1)

can be written in the following moving average representation:

\[
Y_t = \sum_{j=0}^{\infty} A_j \epsilon_{t-j}
\]  

(2)

² Additional diagnostic tools such as Variance Inflation Factors, Ljung–Box tests, OLS-CUSUM tests and ADF-tests for subsamples with two structural breaks have been conducted. Results are available upon request.
where $\varepsilon \sim (0, \Sigma)$ is independently and identically distributed and $A_{ij}$ is an $N \times N$ dimensional matrix. The estimates from the moving average representation and then used to calculate Generalized Forecast Error Variance Decomposition using Generalized Impulse Response Functions developed by Pesaran and Shin (1998). The corresponding H-step-ahead GFEVD function can be written as:

$$\hat{\theta}_{ij}(H) = \frac{\sum_{h=1}^{H-1} \xi_{ij}^2}{\sum_{j=1}^{N} \sum_{h=1}^{H-1} \xi_{ij}^2}$$  \hspace{1cm} (3)$$

where $\xi_{ij}$ is the response of variables $j$ to a shock in variable $i$. It is by construction that $\sum_{j=1}^{N} \hat{\theta}_{ij}(H) = 1$ and $\sum_{i=1}^{N} \hat{\theta}_{ij}(H) = 1$. Our Total Connectedness Index (TCI), which Diebold and Yilmaz (2012) refers to as a Total Spillover Index is defined as follows:

$$TCI = \frac{\sum_{i=1}^{N} \sum_{j=1,i\neq j}^{N} \hat{\theta}_{ij}(H)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \hat{\theta}_{ij}(H)}$$  \hspace{1cm} (4)$$

In our VAR before COVID, displayed in Table 3, there are only a few significant spillovers. There seems to be only one or two significant influences on $\Delta BVOL$, $\Delta VIX$, $\Delta GVX$ and $\Delta OVX$. This lack of significance, specifically in $\Delta BVOL$ estimates, is consistent with other papers’ findings comparing Bitcoin and traditional financial assets. In Table 4 we can see this changes. $\Delta BVOL$ is significantly

| Table 5 | VAR(2) after COVID-19 vaccine. | $\Delta BVOL$ | $\Delta VIX$ | $\Delta GVX$ | $\Delta OVX$ | $\Delta VEM$ | $\Delta VDM$ |
|--------|-----------------------------|---------------|---------------|---------------|---------------|---------------|---------------|
| $\Delta BVOL$ | 0.016 | -0.19 | -0.02 | 0.01 | 0.01 | -0.01 |
| (1.18) | (-1.29) | (0.57) | (0.88) | (1.32) | (-0.54) |
| $\Delta VIX$ | 0.009 | -0.16 | -0.01 | -0.18 | 0.10 | 0.01 |
| (0.05) | (-0.43) | (-0.38) | (-2.42) | (3.75) | (0.21) |
| $\Delta GVX$ | 0.022 | -0.03 | 0.00 | 0.09 | -0.61 | -0.03 |
| (0.28) | (-0.16) | (0.06) | (0.05) | (-0.47) | (-0.21) |
| $\Delta OVX$ | 0.015 | 0.01 | -0.01 | -0.15 | 0.25 | 0.30 |
| (1.24) | (1.41) | (-3.29) | (-0.86) | (0.17) | |
| $\Delta VEM$ | 0.081 | -0.07 | 0.02 | 0.19 | 0.25 | 0.30 |
| (0.16) | (0.59) | (0.35) | (1.29) | (1.94) | (1.16) |
| $\Delta VDM$ | 0.684 | -0.11 | -0.09 | 0.16 | -0.21 | -0.02 |
| (1.21) | (-1.04) | (-1.04) | (0.99) | (-2.38) | (-0.23) |
| $\Delta USD$ | 0.008 | 0.00 | 0.01 | 0.02 | -0.25 | -0.00 |
| (0.17) | (-0.11) | (-0.97) | (-2.39) | (-1.21) | (-0.38) |
| Obs. | 280 | 280 | 280 | 280 | 280 | 280 |
| $R^2$ | 0.055 | 0.113 | 0.095 | 0.071 | 0.314 | 0.248 |

*Note: $p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

VAR(2) is run on the differenced implied volatility series with USD shocks as an exogenous variable using data from December 4th, 2020 to January 20th, 2022. Estimates and t-values (calculated using White heteroskedastic standard errors) are presented in this table. The .l1 and .l2 suffixes are used to denote the first and second lag of the series.
Table 6
Generalized Forecast Error Variance Decomposition for subsample models.

|                  | ΔBVOL | ΔVIX | ΔGVX | ΔOVX | ΔVEM | ΔVDM |
|------------------|-------|------|------|------|------|------|
| ΔBVOL            | 0.959 | 0.002| 0.021| 0.002| 0.005| 0.011|
| ΔVIX             | 0.003 | 0.467| 0.110| 0.052| 0.301| 0.067|
| ΔGVX             | 0.027 | 0.122| 0.628| 0.081| 0.129| 0.013|
| ΔOVX             | 0.023 | 0.081| 0.088| 0.701| 0.093| 0.014|
| ΔVEM             | 0.015 | 0.294| 0.108| 0.060| 0.453| 0.070|
| ΔVDM             | 0.019 | 0.103| 0.051| 0.020| 0.103| 0.704|
| Sum others       | 0.087 | 0.601| 0.378| 0.216| 0.631| 0.174|

Panel B: During COVID-19 — TCI: 42.6%

|                  | ΔBVOL | ΔVIX | ΔGVX | ΔOVX | ΔVEM | ΔVDM |
|------------------|-------|------|------|------|------|------|
| ΔBVOL            | 0.641 | 0.076| 0.115| 0.004| 0.128| 0.036|
| ΔVIX             | 0.025 | 0.477| 0.030| 0.033| 0.245| 0.190|
| ΔGVX             | 0.125 | 0.075| 0.562| 0.021| 0.130| 0.086|
| ΔOVX             | 0.020 | 0.055| 0.045| 0.829| 0.028| 0.022|
| ΔVEM             | 0.060 | 0.290| 0.067| 0.010| 0.417| 0.156|
| ΔVDM             | 0.032 | 0.221| 0.048| 0.015| 0.168| 0.516|
| Sum others       | 0.262 | 0.718| 0.304| 0.083| 0.699| 0.491|

Panel C: After vaccine — TCI: 25.7%

|                  | ΔBVOL | ΔVIX | ΔGVX | ΔOVX | ΔVEM | ΔVDM |
|------------------|-------|------|------|------|------|------|
| ΔBVOL            | 0.943 | 0.014| 0.019| 0.001| 0.015| 0.008|
| ΔVIX             | 0.008 | 0.547| 0.075| 0.102| 0.073| 0.195|
| ΔGVX             | 0.017 | 0.105| 0.750| 0.030| 0.022| 0.077|
| ΔOVX             | 0.005 | 0.133| 0.024| 0.758| 0.021| 0.058|
| ΔVEM             | 0.008 | 0.087| 0.024| 0.021| 0.813| 0.048|
| ΔVDM             | 0.001 | 0.208| 0.050| 0.047| 0.048| 0.646|
| Sum others       | 0.039 | 0.547| 0.192| 0.200| 0.180| 0.385|

This table summarizes the empirical results of return spillovers between Bitcoin and traditional financial markets. Results are based on GFEVD for VAR(2) subsample models presented in Tables 3–5. The “Sum others” column sums off-diagonal spillovers vertically to attain total spillovers to the column head. The Total Spillover Index (TCI) measures the proportion of forecast error variance that comes from spillovers.

Results from GFEVD presented in Table 6 further support the connectedness levels found in the subsample models. GFEVD is applied to each subsample period using 5-step-ahead forecast error variance decomposition. The TCIs for the subsamples, defined in Eq. (4) and thoroughly documented Diebold and Yilmaz (2012), are also calculated and presented in Table 6. The TCI represents the average contribution of volatility spillovers across all variables to the total forecast error variance (Elsayed et al., 2022). The “Sum others” row provides the sum of directional spillovers. This is interpreted as the gross directional volatility spillovers to others. The TCI from Panels A-C in Table 6 supports our previous interpretation of VAR estimates. One of the major contributors to the increased TCI in Panel B is Bitcoin. We can see that Bitcoin has much higher directional volatility spillovers during COVID. We also notice that it receives much more directional volatility spillover during the same period. In Panels A and C, it accounts for at least 94% of its own forecast error variance but in Panel B it is only able to account for 64.1% of it. In Panel C, we can see the total directional spillovers for all series other than ΔOVX decreases. This reflects in the TCI which is much lower than the TCI before COVID-19. Our definition of the COVID-19 period begins just before the World Health Organization declared COVID-19 a pandemic. The first recorded case of COVID-19 occurred in December of 2019. In reality, the effect of COVID-19 may have already been present in financial systems, to some degree, before the period we defined to be the COVID-19 period.

While we have focused on implied volatility, we cannot ignore the returns that have been realized in Bitcoin. Bitcoin price has increased more than tenfold since the start of our sample period, and much of this increase was after COVID-19 restrictions were put in place. During COVID-19, many investors turned to Bitcoin as well as Bitcoin options and futures. Open interest in options and futures exceeded 40 billion U.S. dollars at its peak. Corbet et al. (2020) find that Bitcoin exhibits safe haven properties and perhaps this property has increased investors’ interest in Bitcoin. The use of Bitcoin as a possible hedge during COVID-19 seems to have strengthened its connectedness with U.S. equity markets and gold. Thorough sensitivity testing has also been done using traditional methods for VAR and methods developed and presented in Broderick et al. (2020).3

3 Detailed methods and results of sensitivity tests are available upon request. The OVX series in levels is not stationary in any of the three subsamples.
4. Conclusion

This paper examines the impact of COVID-19 vaccine on financial market recovery evidenced by changes in implied volatility spillover between Bitcoin and other traditional financial markets including the U.S. equity market, developed markets, emerging markets, gold and crude oil. Vector Auto-Regression (VAR) and Generalized Forecast Error Variance Decomposition (GFEVD) models are used to measure volatility spillovers and compare spillovers among three sample periods — before COVID-19, during COVID-19 and after the COVID-19 vaccine becomes available.

We find that Bitcoin implied volatility spillover to other financial markets has reduced to an extremely low level after COVID-19 vaccine becoming available. Our results imply that COVID-19 vaccine has a significant positive effect on financial market recovery from the pandemic. The vaccine has injected confidence into the economy and promoted financial market recovery despite the increasing number of new COVID-19 cases caused by Omicron. Vaccination has been a successful tool to support economic recovery and ease tension in the financial market. These findings are valuable for policymakers while considering vaccination campaigns and replacing vaccine hesitancy.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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