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Portfolio diversification during the COVID-19 pandemic: Do vaccinations matter?

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A B S T R A C T

The COVID-19 vaccine rollout expects to mitigate the severe negative impacts of the pandemic on global financial markets. Our study provides supporting evidence for this expectation. We find robust evidence that vaccinations significantly reduce the cross-country stock volatility connectedness among G7 nations, suggesting that the diversification benefits of an international equity portfolio may be enhanced during the pandemic when vaccinations accelerate. We present two explanations for this result. First, the vaccine deployment improves stock market return and decreases individual stock market volatility. Second, the vaccine rollout helps a country's stock market be more resilient to exogenous shocks. We further demonstrate that a global portfolio using a tactical allocation rule based on the intensity of vaccinations can outperform a buy-and-hold portfolio in terms of risk-adjusted returns.

1. Introduction

The global outbreak of the coronavirus disease 2019 (COVID-19) has caused enormous damage to the world economy and left detrimental impacts on global financial markets. The existing studies have shown that the effects of the pandemic are not limited to the volatility of an individual asset class or a country-specific market,[1] but also include cross-asset and cross-country volatility interdependence (e.g., Bissoondoyal-Bheenick et al., 2021; Foglia et al., 2022). In particular, these studies show that the pandemic significantly increases return and volatility connectedness, thereby dampening the benefits of international portfolio diversification. In a global effort to reduce the adverse effects of the outbreak, the COVID-19 vaccination programs have been deployed worldwide since late 2020. These programs are expected to contribute to mitigating the severe negative effect of the pandemic on global financial markets. Recent research has focused on assessing the role of vaccinations in stabilizing individual stock markets (e.g., Acharya et al., 2020 and Rouatbi et al., 2021). We extend this emerging strand of the literature by giving insights into a stabilizing effect of COVID-19 vaccinations on the volatility connectedness among the G7 stock markets.[2]

The main motivations of our empirical research are threefold. First, according to the portfolio theory proposed by Markowitz (1952), non-systematic risks can be minimized through diversification. However, increases in the interconnectedness of global stock markets during the COVID-19 pandemic may significantly reduce the portfolio

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[1] See, e.g., Al-Awadhi et al. (2020); Albulescu (2021); Baek et al. (2020); Zaremba et al. (2020) for evidence of the effects of the pandemic on individual financial assets or markets.

[2] G7 is the abbreviation of the Group of Seven industrialized countries including Canada, France, Germany, Italy, Japan, the United Kingdom (UK), and the United States (US). Interest in understanding the risk transmissions among these stock markets has been shown in various aspects. For example, BenSaïda (2019) investigates their good and bad volatility spillovers, and Finta and Aboura (2020) examine their volatility and skewness risk premium spillover effects.

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diversification benefit.[3] Thus, diminishing the damaging effect of COVID-19 on the global stock market has important implications for international risk management and asset allocation. As a result, studies on how COVID-19 vaccinations affect volatility connectedness across stock markets should be among the primary interests of portfolio managers and investors. Second, our study aims to design an international stock portfolio based on a comprehensive understanding of the effect of vaccinations on stock volatility connectedness. This proposed trading strategy is deemed to help portfolio managers achieve more diversification benefits during the uncertain times. Third, our research focuses on the G7 stock markets as they represent a significant proportion of global market capitalization. As of 2020, five G7 countries, including the US, the UK, Japan, Canada, and France, were among the 10 largest markets in terms of stock market capitalization.[4] Besides, focusing on the G7 countries also allows us to have a longer history of vaccination data.

Our study employs the popular measure of stock volatility, the so-called realized volatility,[5] calculated from intraday equity data. Meanwhile, we collect the data on global vaccination from Our World in Data, which is a comprehensive and well-trusted database.[6] The volatility connectedness across G7 stocks markets is constructed by integrating Diebold and Yilmaz (2012, 2014) connectedness approach into the multivariate Heterogeneous Autoregressive (Vector-HAR or VHAR) model.[7] We examine the effect of the COVID-19 vaccinations on the stock volatility connectedness using different proxies, including the scaled daily new vaccinations, the dummy variable based on the increase or decrease in new vaccinations, and the dummy variable based on vaccination periods. We find strong evidence that massive COVID-19 vaccinations have significantly negative effects on the stock market volatility connectedness after controlling for the effects of the pandemic and other economic variables. This implies that the diversification benefits of an international portfolio of G7 stock markets might improve following the development and deployment of vaccinations. We provide empirical evidence supporting two plausible reasons which help explain the negative effect of vaccine deployment on the global stock volatility connectedness.

First, numerous studies have shown that the transmission of shock across markets tends to strengthen with shock's size (e.g., Bouri et al., 2021b; Jena et al., 2021; Saeed et al., 2021) and becomes more severe during periods of market downturn and bear market (e.g., Bekaert et al., 2003; Karolyi, 2003; Benhmad, 2013; Baruník et al., 2016; among others). Therefore, we hypothesize that the COVID-19 vaccine deployment can reduce cross-country volatility connectedness by lowering individual stock market volatility (i.e., smaller volatility shocks) and improving stock market return. By restoring normalcy to economies, we expect the COVID-19 vaccine rollout will reduce market uncertainty, raise investors' expectations of corporate profits, and in turn, enhance stock market returns. We test this conjecture by examining the time-varying effects of COVID-19 vaccinations on the realized volatility and return of the selected stock markets. We find that the impact of COVID-19 vaccinations on stock market volatility is negative and statistically significant for all G7 countries. Meanwhile, the COVID-19 vaccine rollout significantly improves stock market returns for all countries except Japan.

Second, we expect that mass vaccination program helps a country's stock market be less vulnerable to volatility shocks from outside, thereby reducing the cross-country volatility shock transmission. We test this conjecture by investigating the impact of COVID-19 vaccinations on the volatility dependence index of a market. The volatility dependence index of a market indicates the directional volatility connectedness received by that market from all other markets. The lower this index is, the less volatility is transmitted from the outside world to the considered market. In other words, the considered market is more resilient to outside shocks. Consistent with this conjecture, we find robust results of significant negative relationships between the daily COVID-19 vaccinations and the daily volatility dependence indexes.

From a portfolio perspective, a lower volatility dependence index of a market implies that this market is more attractive in terms of risk diversification as its volatility is less sensitive to other markets' volatility. Based on our empirical result that COVID-19 vaccinations reduce the volatility dependence index of a stock market, we propose a simple vaccination-driven diversification strategy for global investors who seek to gain potential diversification benefits from investing in G7 stock markets. This strategy involves increasing weights in stock markets exhibiting the highest monthly measure of new vaccinations. Our simulation results show that the vaccination-based portfolios outperform the buy-and-hold portfolio in every aspect of portfolio performance. Specifically, the average monthly return of the vaccination-based portfolio increases by 12.29%, whereas its standard deviation reduces by 12.15% compared to the buy-and-hold portfolio. The reduction in the standard deviation of the vaccination-based portfolios corroborates our main finding that COVID-19 vaccinations help reduce volatility connectedness across stock markets, thereby leading to higher diversification benefits. In terms of risk-adjusted returns, we reveal that the Sharpe ratio of the vaccination-based portfolio improves by 25.94% in comparison with the buy-and-hold portfolio. Noteworthy, the benefits of the vaccination-based portfolio hold when we re-apply our simulation to a sample of emerging stock markets.

Our study makes several contributions to the extant literature. First, we are the first to investigate the relationship between COVID-19 vaccinations and global stock markets' volatility connectedness. While the existing studies have extensively documented the role of the pandemic itself, including infections, casualties, and the pandemic-related government policy responses (e.g., Albulescu, 2021; Baek et al., 2020; Bai et al., 2021; Engelhardt et al., 2021, and Zaremba et al., 2021), our paper contributes to a newly emerging strand of literature related to the effects of COVID-19 vaccinations on financial markets (e.g., Acharya et al., 2020; Rouatbi et al., 2021; Khalfaoui et al., 2021, and Chan et al., 2022).

Second, our finding that the COVID-19 vaccine rollout helps attenuating the volatility connectedness among global stock markets is novel and has practical implications for investors and policymakers worldwide. Specifically, based on our empirical finding of stock market volatility connectedness depending on vaccine rollout, we propose a potential vaccination-based trading strategy, which helps portfolio managers better manage their portfolio risk and enhance their portfolio risk-adjusted return performance through the period of the COVID-19 pandemic. In addition, as the outbreak of the COVID-19 pandemic has substantially heightened the contagion risk across global financial markets (e.g., Bouri et al., 2021a; Farid et al., 2021), our study suggests that vaccinations could act as a "game changer" to reinstate financial stability. Therefore, policymakers should consider the importance of vaccinations when formulating financial market stabilization policies.

[3] Evidence on increases in interconnectedness among global stock markets during the pandemic can be found in several recent studies such as Bissoondoyal-Bheenick et al. (2021), Le et al. (2021), Liu et al. (2021).

[4] The data on the market capitalization of listed domestic companies is updated by World Bank.

[5] See for example Andersen and Bollerslev (1998) and Andersen et al., (2001, 2003).

[6] https://ourworldindata.org/. The database has been well trusted by top-notch research journals and media such as Science, Nature, BBC, Financial Times, The New York Times, and The Wall Street Journal. Besides, it has also been used by top academic institutions such as Harvard University, Stanford University, University of Cambridge, and University of Oxford.

[7] Inheriting features of the univariate HAR (see, Corsi, 2009), the VHAR model effectively captures the long-memory behavior of realized volatility. Therefore, an incorporation of the Diebold and Yilmaz connectedness index into the VHAR model helps empirical research on volatility connectedness avoid inconsistency in estimated parameters caused by the strong persistence of volatility and hence achieve better measurement of volatility transmission.

Finally, our paper contributes the literature by documenting two channels that explain the reducing effect of COVID-19 vaccinations on global stock markets' volatility connectedness. The first channel is through the impacts of vaccinations on individual stock market's return and volatility. Consistent with Acharya et al. (2020), Chan et al. (2022), and Rouatbi et al. (2021), we find that the COVID-19 vaccine rollout reduces the volatility of a single market and improves its return, thereby, decreasing the cross-market contagion risk. The second channel relates to the resilience of a stock market to outside shocks when the vaccine rollout intensifies. We find intriguing result that the COVID-19 vaccinations help reduce the vulnerability of a country's stock market to external shocks during the pandemic period. The result implies that investors are highly watchful about the deployment of COVID-19 vaccinations in a specific stock market in making their investment decisions. This implication supports the recent theoretical and empirical findings about the role of investor attention index as a key driver of stock market volatility and performance (Fisher et al., 2022; Ma et al., 2022a; Ma et al., 2022b).

The remainder of the article proceeds as follows. Section 2 discusses the related literature. Section 3 describes the methodology used. Section 4 presents the data. Empirical findings and robustness checks are provided in Section 5. Section 6 provides analyses on the two plausible mechanisms which help explain the main empirical findings. Section 7 discusses the financial and policy implications, and we conclude the paper in Section 8.

2. Literature review and hypothesis development

2.1. COVID-19 pandemic and stock market's volatility and volatility connectedness

Research into the effects of the COVID-19 pandemic on financial markets has grown significantly since its outbreak in early 2020. Earlier studies mostly address the impacts of the outbreak on the return and volatility of financial markets with a focus on the stock market.[8] Al-Awadhi et al. (2020) and Topcu and Gulal (2020) show that the confirmed COVID-19 cases and fatalities have a negative correlation with stock returns. Regarding the effects of the pandemic on stock market volatility, Albulescu (2021) documents that the realized volatility of the S&P 500 index varies proportionately with the COVD-19 new cases and new deaths figures. In a similar vein, Bai et al. (2021) find a positive linkage between the development of the outbreak and stock market volatility, and this relationship could persist in the long term. Pertaining to the time-varying effect of the pandemic on stock volatility, Xu (2022) employs the Realized Exponential GARCH (REGARCH) model to examine the time-varying impacts of the COVID-19 pandemic on the volatility of the Canadian stock market. He reveals that the country's stock market volatility became more sensitive to both good and bad news during the pandemic. Other research investigates the role of a country's financial conditions, firm-specific factors, industry characteristics, government responses, and societal trust as the mechanisms that fuel the impacts of COVID-19 on stock markets.[9]

Concerning the volatility connectedness across markets, Bouri et al. (2021a) employ the time-varying vector autoregressive model (TVP-VAR) to investigate dynamic interconnectedness across five asset classes during the COVID-19 pandemic. The authors find that the total connectedness has spiked in response to the COVID-19 outbreak. Benlagha and Omari (2021) find that the COVID-19 pandemic has significantly increased the volatility connectedness between stock markets, gold, and oil. Rai and Garg (2021) show that the dynamic correlations and volatility connectedness between stock prices and exchange rates in BRICS countries have strengthened during the outbreak. In line with these aforementioned studies, Farid et al. (2021) reveal that the volatility connectedness across precious metals, energy, and US stocks has peaked during the outbreak.

Turning to volatility connectedness across sectors, Laborda and Olmo (2021) reveal the volatility connectedness among US stock sectors spiked during the COVID-19 pandemic crisis. Similarly, Dong et al. (2022) find a dramatic rise in the global stock sectors' interconnectedness following the outbreak of COVID-19. Meanwhile, Shahzad et al. (2021) reveal that both good and bad volatility transmission among Chinese stock market sectors is substantially intense during the COVID-19 outbreak.

In addition, the impacts of the pandemic on the cross-country volatility connectedness have been also investigated. Bissoondoyal-Bheenick et al. (2021) investigate the effect of COVID-19 on stock return and volatility connectedness of G20 economies and document that both stock return and volatility connectedness have increased through the phases of the COVID-19.

In summary, these studies reviewed above reveal that the COVID-19 pandemic has diminished the diversification benefits of investing in different stock sectors, or in different geographic stock markets or in multiple asset classes since it increases the volatility connectedness across markets.

2.2. COVID-19 vaccinations and stock market's volatility connectedness

Recently, with the development of COVID-19 vaccines in the middle of 2020 and the start of the global deployment of COVID-19 vaccinations in late 2020, researchers have shifted their attention to the effects of COVID-19 vaccinations on financial markets. Acharya et al. (2020) investigate the implication of vaccine development for asset pricing using a "vaccine progress indicator". The authors document that a one-year decrease in the vaccine development and deployment time would add 4–8% to the stock market return. Chan et al. (2022) study the impacts of human clinical trials for COVID-19 vaccine candidates on global stock market returns and reveal positive abnormal returns after each phase of the clinical trial. Their results suggest a probable positive impact of the vaccine rollout on stock returns. Khalfaoui et al. (2021) employ the wavelet coherence approach to investigate the time-varying impact of the COVID-19 vaccine rollout on the return of the S&P 500 index. The authors uncover a positive and significant connectedness between S&P 500 return and COVID-19 vaccination rate. Regarding the effect of vaccinations on stock market volatility, Rouatbi et al. (2021) provide empirical evidence that vaccination programs help reduce the stock market volatility and the reducing effect is more severe in developed countries than in emerging countries.

Notwithstanding the extant studies on the effects of vaccinations on the volatility of stock markets, the role of vaccinations in mitigating the interconnectedness across stock markets has not been investigated in the literature. As such, our study turns to this left-over issue. Specifically, we hypothesize that the COVID-19 vaccine rollout contributes to reducing the volatility connectedness among G7 stock markets, leading to our first hypothesis as follows,

H1. . COVID-19 vaccinations help reduce volatility connectedness among G7 stock markets.

We contemplate two possible explanations for this relationship. First, we hypothesize that vaccinations could help decrease volatility and increase return of each G7 stock market, thereby reducing cross-market volatility connectedness among G7 countries. Our conjecture is built-up upon various studies showing that the spillover of shocks in financial markets varies proportionally with their magnitude (e.g., Bouri

[8] In addition to the stock market, various studies examine the impact of COVD-19 on other asset classes, such as bonds (Falato et al., 2020), commodities (Sharif et al., 2020; Gharib et al., 2021; Mensi et al., 2020; Wu et al., 2021), cryptocurrencies (Conlon and McGee, 2020; Demir et al., 2020), and real estate (Ling et al., 2020; Milcheva, 2021).

[9] See, e.g., Albuquerque et al. (2020); Baek et al. (2020); Engelhardt et al. (2021); Ramelli and Wagner (2020); Zaremba et al. (2020).

et al., 2021b; Jena et al., 2021; Saeed et al., 2021; Tiwari et al., 2022; among others). For instance, Bouri et al. (2021b) find that the connectedness among cryptocurrencies is most significant when volatility shocks are at extreme levels. Tiwari et al. (2022) document that the volatility connectedness among the commodity futures is stronger with larger magnitudes of shocks. Based on these findings, volatility connectedness might be weakened if vaccinations contribute to decreasing individual volatility (i.e., volatility shocks) of each G7 stock market.

In addition, financial contagion risk tends to be more pronounced during times of market crisis or bear market (Bekaert et al., 2003). For example, Benhmad (2013) conducts a wavelet rolling correlation analysis between S&P 500 index and the international stocks markets index. He finds that correlation is substantially higher during a bear market than a bull market. Based on Diebold and Yilmaz's (2012) connectedness framework, Barunik et al. (2016) compare the magnitude of good volatility connectedness (i.e., positive return) and bad volatility connectedness (i.e., negative return) among US stocks. The authors find that bad volatility connectedness is higher than good volatility connectedness, emphasizing the role of return in driving the transmission of volatility shocks. By restoring normalcy of the economies, we expect the COVID-19 vaccine rollout will raise investors' expectations of corporate profits, and in turn enhance stock market returns. Through this mechanism, COVID-19 vaccinations would reduce the volatility connectedness among G7 stock markets. Based on the above discussion, we formulate the second hypothesis as follows,

H2. The vaccine rollout reduces individual volatility and enhances the returns of G7 stock markets.

Second, we conjecture that the vaccine rollout in a country may have increased the resilience of its stock market to outside shocks during the pandemic period, thereby lowering the total volatility connectedness across the system. The COVID-19 pandemic has significant impacts on financial markets as it is documented to intensify stock market volatility (e.g., Albulescu, 2021; Bai et al., 2021), increase economic policy uncertainties (e.g., Baker et al., 2020; Sharif et al., 2020), and lower corporate financial performance (e.g., Shen et al., 2020). Considering that the COVID-19 vaccine rollout is aimed to restore the normalcy of the economy, it could reverse the damaging effects of the pandemic on a specific country by improving its economic activity, mitigating economic policy and social uncertainties, and enhancing consumers and investors' confidence. Thus, vaccination-related news has important implications for investors about the stock market outlook. Along this line, we conceive that when investors become more engaged in domestic factors following the deployment of vaccinations, such as the impacts of vaccinations on domestic economic activities and corporate businesses. An increase in vaccination rate would make them less sensitive to outside shocks, hence increasing the stock market's resilience. The above explanation leads to our third hypothesis as follows,

H3. . The vaccine rollout makes a G7 country's stock market more resilient to outside shocks.

3. Methodologies

3.1. The realized volatility estimator

We use the realized variance (RV) introduced by Andersen and Bollerslev (1998) to estimate the daily volatility of a stock market. This measure is constructed using the high-frequency intraday financial returns. First, consider ith Δ-period intraday return within day t as,

$$r_{i,t} = \left(\log P_{t-1+i\Delta} - \log P_{t-1+(i-1)\Delta}\right) \times 100\% \quad (1)$$

The realized variance *(RV)* is then computed as the sum of squared intraday return:

$$RV_{\neg t} = \sum_{i=1}^{M} r_{t,i}^2 \quad (2)$$

where $M \equiv 1/\Delta$ is the number of observations within a trading day and Δ is the sampling frequency. As $\Delta \to 0$ or $M \to \infty$, Eq. (2) is an effective and consistent estimator for unobservable integrated variance (Andersen et al., 2003).

3.2. The VHAR model with DCC-GARCH

The Heterogeneous Autoregressive (HAR) model proposed by Corsi (2009) has gained its popularity in modelling time-varying return volatility using RV due to its effectiveness and simplicity in capturing the high persistence of volatility process through a hierarchical structure of short-, medium-, and long-term components of past RV. In this study, we rely on the multivariate framework of the Heterogeneous Autoregressive, the so-called VHAR model, to estimate $m\times 1$ vector of realized volatility with m is the number of considered stock indexes as follows,

$$RV_t = c^{(d)} + \beta^{(d)} RV_{t-1} + \beta^{(w)} RV_{t-1|t-5} + \beta^{(m)} RV_{t-1|t-22} + \varepsilon_t^{(d)} \quad (3)$$

where $c^{(d)}$ denotes $m\times 1$ vector of intercepts; RV_t is $m\times 1$ vector of realized volatility at day t; RV_{t-1}, $RV_{t-1|t-5} = \frac{1}{5}\sum_{j=1}^{5} RV_{t-j}$and $RV_{t-1|t-22} = \frac{1}{22}\sum_{j=1}^{22} RV_{t-j}$ denote the daily, weekly and monthly lagged $m\times 1$ vector of realized volatility, respectively; $\beta^{(d)}$, $\beta^{(w)}$, $\beta^{(m)}$ are the $m\times m$ matrices of autoregressive coefficients; and $\varepsilon_t^{(d)}$ is $m\times 1$ vector of error terms.

Corsi et al. (2008) show empirical evidence that the residual series obtained from the HAR model exhibit volatility clustering and then propose the HAR-GARCH model to capture this property. We follow the spirit of Corsi et al. (2008) to allow the vector residual ε_t from the VHAR model in Eq. (3) to follow the DCC-GARCH model proposed by Engle (2002). The incorporation of the DCC-GARCH model into the VHAR model enables us to capture the variance of realized volatility effects. We specify the VHAR – DCC-GARCH as follows,

$$\varepsilon_t = H_t^{1/2} z_t \quad (4)$$

$$z_t \sim NID(0, I)$$

where $z_{it} = \varepsilon_{it}/\sqrt{h_{it}}$ are standardized residuals that have mean zero and variance one for each series; ε_t is the $m \times 1$ vector of error term from the VHAR model; H_t is $m\times m$ conditional variance-covariance matrix of vector error term and is modelled by the standard DCC-GARCH (Engle, 2002) as follows,

$$\varepsilon_t \sim N(0, H_t)$$

$$H_t = D_t R_t D_t \quad (5)$$

where $D_t = diag(h_{1,t}^{1/2}, \ldots, h_{m,t}^{1/2})$,$D_t$ is the $m\times m$ diagonal matrix of conditional standard deviations, with conditional variances $h_{i,t}$ (i = 1,…,m) are defined by GARCH(1,1)

$$h_{i,t} = \omega_i + \alpha_{i,1}\epsilon_{i,t-1}^2 + \gamma_{i,1} h_{i,t-1} \quad (6)$$

and R_t is $m\times m$ conditional correlation matrix of standardized residuals,$z_{it} = \varepsilon_{it}/\sqrt{h_{it}}$; $R_t$can be estimated as,

$$E_{t-1}(z_t z_t') = D_t^{-1} H_t D_t^{-1} = R_t$$

$$R_t = diag\left(q_{(11,t)}^{(-1/2)}, .., q_{(mm,t)}^{(-1/2)}\right) ?Q?_{(t)} diag\left(q_{11,t}^{-1/2}, .., q_{mm,t}^{-1/2}\right) \quad (7)$$

where $m\times m$ symmetric positive definite matrix $Q_t = (q_{ij,t})$ follows the correlation equation as,

$$Q_t = (1 - a - b)\overline{Q} + a z_{t-1} z_{t-1}' + bQ_{t-1} \quad (8)$$

with $\overline{Q} = \mathrm{E}\,[z_t' z_t]$ stands for $m \times m$ unconditional variance matrix of z_t, a and b are non-negative scalar parameters satisfying $a + b < 1$, that guarantees the positive definiteness of Q_t and hence of R_t.

In general, the estimation of the VHAR – DCC-GARCH model involves two steps. Step 1 estimates the coefficients $(c^{(d)}, \beta_t^{(d)}, \beta^{(w)}, \beta^{(m)})$ of the VHAR model. Step 2 estimates the coefficients of DCC-GARCH using the vector error terms generated from step 1. The set of parameters including $(\omega_i, \alpha_i, \gamma_i | \, i = 1, \dots, m)$ are estimated by GARCH(1,1) in Eq. (6) and the correlation coefficients (a,b) are estimated by the DCC model in Eq. (8).

3.3. Measurement of volatility connectedness

We incorporate the generalized connectedness index by Diebold and Yilmaz (2012, 2014) into the VHAR model to measure the volatility connectedness indices. First, we transform the VHAR specification in Eq. (3) to the restricted VAR(22) process as follows,

$$RV_t = c^{(d)} + \Phi_1 RV_{t-1} + \Phi_2 RV_{t-2} + \dots + \Phi_{22} RV_{t-22} + \varepsilon_t \quad (9)$$

where $\varepsilon_t = H_t^{\frac{1}{2}} z_t$ and $z_t \sim NID(0, I)$; $c^{(d)}$ is $m \times 1$ intercept vector estimated by the VHAR model; Φ_i $(i = 1,\dots,22)$ are $m \times m$ restricted coefficient matrices, and satisfy the following conditions,

$$\Phi_1 = \beta^{(d)} + \frac{1}{5}\beta^{(w)} + \frac{1}{22}\beta^{(m)} \quad (10)$$

$$\Phi_6 = \dots = \Phi_{22} = \frac{1}{22}\beta^{(m)}$$

where $\beta^{(d)}$, $\beta^{(w)}$, $\beta^{(m)}$ are estimated by the VHAR model in Eq. (3). As such, the VAR(22) model in Eq. (9) embodies the restricted coefficient matrices estimated by the VHAR model and the vector error term estimated by the DCC-GARCH model. Given the stationary VAR(22) process in Eq. (9), we rewrite the restricted VAR(22) into the infinite moving average representation specified as,

$$RV_t = \sum_{j=1}^{\infty} A_j \varepsilon_{t-j} \quad (11)$$

where the $m \times m$ coefficient matrices of moving average A_j follow the recursion $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \dots + \Phi_p A_{j-p}$, with A_0 being an $m \times m$ identity matrix and $A_j = 0$ for $j < 0$. These moving average coefficients are used to construct the forecast error variance *(FEV)* decompositions (Diebold and Yilmaz, 2012).

We can compute the fractions of the h-step-ahead error variance in forecasting x_i as follows,

$$\theta_{ij,t} = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h H_t e_j\right)^2}{\sum_{h=0}^{H-1} e_i' A_h H_t A_h' e_i} \quad (12)$$

where H_t is the conditional variance-covariance matrix of the vector error term ε_t estimated by the DCC-GARCH model; σ_{jj} is the standard deviation of the error term for the jth equation, and e_i is the selection vector with one as the ith element and zeros otherwise.

Then each entry of the variance decomposition matrix is normalized by the row sum and used to calculate the total connectedness index (*TCI*) as follows,

$$\widetilde{\theta}_{ij} = \frac{\theta_{ij}}{\sum_{j=1}^{m} \theta_{ij}} \quad (13)$$

$$TCI = \frac{\sum_{i,j=1; i \neq j}^{m} \widetilde{\theta}_{ij}}{m} .100 \quad (14)$$

The so-called Volatility Dependence Index *(VDI)* used in this study is calculated as the fraction of volatility that one market receives from all other markets in the system. The higher is the value of $VDI_{i.}$, the more volatility-dependent is market i on other markets. We compute *VDI* as follows,

$$VDI_{i.} = \sum_{j=1; i \neq j}^{m} \widetilde{\theta}_{ij} .100 \quad (15)$$

From Eqs. (14) and (15), we infer the relationship between the $VDI_{i.}$ and the *TCI* as,

$$TCI = \frac{\sum_i^m VDI_{i.}}{m} \quad (16)$$

Further, directional spillover index transmitted by market i to all other markets j is computed as,

$$S_{.i} = \sum_{j=1; i \neq j}^{m} \widetilde{\theta}_{ji} .100 \quad (17)$$

While Bubák et al. (2011) have employed the VHAR – DCC-GARCH model in computing spillover index of Diebold and Yilmaz (2009), we extend to apply the VHAR – DCC-GARCH model as the underlying function to compute generalized connectedness indices. As such, we can measure the time-varying stock volatility connectedness without applying a rolling-window approach as in the traditional Diebold and Yilmaz connectedness index. Thus, our results of connectedness indices can overcome the potential subjectivity bias in window length selection.

3.4. Baseline regression models

Based on the daily time series of *TCI* as computed in Eq. (14), we investigate the impact of COVID-19 vaccinations on the time-varying volatility connectedness among G7 stock markets using the following baseline model:

$$TCI_{t+1} = \beta_0 + \beta_v Vax_t + \beta_c Control_t + \varepsilon_{t+1} \quad (18)$$

where $Control_t$ is a vector of four control variables, which are used in prior studies to explain stock volatility connectedness or reflect the intensity of the COVID-19 pandemic, including: (1) VIX_t, the daily implied volatility of the S&P 500 Index's option (CBOE VIX); (2) ER_t, the daily cross-country average of exchange rates against the US dollar[10]; (3) $DEATH_t$, which is the cross-country average daily natural logarithm of new deaths of COVID-19 per one million people in G7 countries; and (4) R_t, which is the cross-country average reproduction rate of the disease in the seven countries.[11] The first two control variables account for the effects of the foreign exchange market and investors' sentiment on stock volatility connectedness. The last two control variables consider the possible impact of the pandemic dynamics on the volatility connectedness.[12] The reproduction rate is the average number of people who become infected by an infectious person. It is considered a rough summary of the actual development of the pandemic and has been documented to affect stock market volatility (Díaz et al., 2022).

Our primary regressors in Eq. (18), Vax_t, which reflect the intensity

[10] For the United States, we use the Dollar Index as its exchange rate.

[11] The reproduction rate (R number) has widely used in recent research to reflect the transmissibility of the pandemic (see, Bissoondoyal-Bheenick et al., 2021; Díaz et al., 2022; Su, 2020).

[12] Several other macroeconomic variables that are likely to influence stock markets' volatility transmission, such as EPU and global economic activity as mentioned in Su (2020), are not included in Eq. (18) as their data are not available on a daily basis. Su (2020) also included WTI, the crude oil price as a determinant of volatility connectedness among G7 stock markets, however, in our study we excluded this variable as it causes severe multicollinearity problem in Eq. (18) with its variance inflation factor above 5. Our choice of variables in Eq. (18) ensures that none of independent variables exhibit evidence of multicollinearity as shown by the unreported variance factors.

Table 1
Summary Statistics.

Panel A. The whole sample

	Obs.	Mean	Std. Dev	10th percentile	90th percentile	Kurtosis	Skewness
RV	2905	1.1458	3.0703	0.1320	1.9357	102.74	8.54
RV^w	2905	1.1467	2.6287	0.1761	1.8560	39.29	5.86
RV^m	2905	1.1480	2.0954	0.2151	1.8593	16.65	4.03
R	2905	1.0104	0.4941	0.5800	1.4300	5.61	1.03
DEATH	2905	2.4925	3.5923	0.0080	7.4190	6.36	2.29
VIX	415	24.9563	10.7328	16.1100	36.8200	7.18	2.35
ER	2905	14.2531	32.6091	0.0094	92.0770	2.18	2.04
New_Vax	2905	4764	3231	1019	9281	-0.76	0.482
Vax_Increase	2905	0.2594	0.4384	0.0000	1.0000	-0.79	1.09
Vax_Period	2905	0.4839	0.4998	0.0000	1.0000	-1.99	0.06

Panel B. By country

	RV	RV^w	RV^m	R	DEATH	ER	New_Vax	Vax_Increase	Vax_Period
CA	0.8193	0.7995	0.7895	0.9711	1.1955	0.7709	4841	0.2922	0.4831
	(2.2585)	(1.9993)	(1.6533)	(0.4465)	(1.274)	(0.0325)	(4049)	(0.4554)	(0.5003)
FR	1.3811	1.3383	1.3516	1.0268	3.1329	1.1658	4749	0.2732	0.4878
	(3.0551)	(2.6161)	(2.1814)	(0.4987)	(3.9641)	(0.0427)	(2939)	(0.4461)	(0.5004)
GE	1.3687	1.3341	1.3532	1.0357	2.1361	1.1658	4333	0.2378	0.4854
	(3.0736)	(2.6125)	(2.1881)	(0.5172)	(3.2152)	(0.0427)	(3057)	(0.4263)	(0.5001)
IT	1.4551	1.4078	1.4257	1.0104	3.4896	1.1658	4802	0.2639	0.4826
	(3.5472)	(2.8861)	(2.3431)	(0.5001)	(4.0113)	(0.0427)	(2949)	(0.4413)	(0.4999)
JP	0.8801	0.8570	0.8224	0.9782	0.2432	0.0093	5826	0.1787	0.4237
	(2.2868)	(1.8234)	(1.2986)	(0.4319)	(0.2639)	(0.0002)	(4278)	(0.3836)	(0.4325)
UK	1.2909	1.2802	1.2890	1.0215	3.3923	1.3297	5062	0.2754	0.4811
	(4.0957)	(2.9800)	(2.4540)	(0.4830)	(5.0969)	(0.0588)	(2067)	(0.4472)	(0.5001)
US	1.4013	1.3632	1.3515	1.0293	3.8647	93.94	3948	0.2947	0.4831
	(3.9322)	(3.3597)	(2.7588)	(0.5683)	(3.1209)	(3.14)	(2604)	(0.4564)	(0.5003)

This table reports the descriptive statistics of the main variables used in this study. These variables include: 1) daily realized variance (RV); 2) weekly realized variance (RVw); 3) monthly realized variance (RVm); 4) the daily reproduction rate of the outbreak(R); 5) the daily number of deaths of COVID-19 per 1 million people (DEATH); 6) the daily CBOE volatility index of the S&P 500 Index (VIX); 7) daily exchange rates (ER); 8) the new vaccinations per 1 million people (New_Vax); 9) the dummy variable for increase in new vaccinations (Vax_Increase); 10) the dummy variable for vaccination period (Vax_Period). Panel A shows the statistics for the whole sample and Panel B presents the mean and the standard deviation of the variables for each country. The numbers in the parentheses in Panel B are the standard deviation. CA, FR, GE, IT, JP, UK, and US denotes Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States, respectively. Std. Dev denotes the standard deviation.

of COVID-19 vaccine rollout in G7 countries, consist of three different vaccination-related variables: (1) New_Vax_t, defined as the cross-country average natural logarithm of the daily number of COVID-19 vaccinations per 1 million people in the seven markets; (2) $Vax\_Increase_t$, which is an indicator variable that equals 1 if the daily change in $New_Vax_t$is strictly positive, and zero otherwise; and (3) Vax_Period_t, which is a dummy variable that equals 1 for the period starting the G7′s first vaccination day on December 18, 2020,[13] and zero otherwise. As above discussed, we expect that the coefficients of the three vaccination-related variables would be negative, implying that the volatility connectedness across stock markets declines with the intensity of vaccinations and when the countries get access to COVID-19 vaccines.

4. Data and preliminary analyses

4.1. Data source

Our study employs high-frequency trading data of G7 stock market indices, including Canada (S&P/TSE Composite Index), France (CAC 40 Index), Germany (DAX Index), Italy (FTSE Italia All-Share Index), Japan (Nikkei 225 Index), United Kingdom (FTSE 100 Index), and United States (S&P 500 Index). The data are extracted from the Thomson Reuters Tick History database maintained by the SIRCA (Security Industry Research Centre of Asia-Pacific). The sample period spans from January 01, 2020, to October 29, 2021. Following Andersen et al. (2001), we choose the sampling frequency of 5-minute to balance the costs of measurement errors and market microstructure noise in calculating realized volatility. The 5-minute return series are computed as the logarithmic difference between the trading prices of each index. The intraday returns are subsequently used to calculate daily realized variance, weekly realized variance, and monthly realized variance using formulas in Section 3.2.

The data on the dynamics of the COVID-19 pandemic and vaccinations comes from Our World in Data,[14] which tracks the intensity of the COVID-19 pandemic and the vaccine rollout across 169 countries in the world.

The source of other data in our study (e.g., macro-economic control variables) is Thomson Reuters DataStream.

4.2. Preliminary analyses

We report the descriptive statistics of variables used in the baseline regression models in Table 1 Panel A. All variables are winsorized at the 1st and the 99th percentiles to mitigate the impact of outliers. To facilitate the readability of data, the pandemic and vaccination-related variables in Table 1 are not in natural logarithm form. We find that the average realized variance is lowest at the daily frequency (RV= 1.1458) and increases gradually for weekly (RV^w=1.1467) and monthly frequency (RV^m=1.1480) for the whole sample. As evidenced by their skewness and kurtosis, all stock markets exhibit asymmetry and heavier tail in their volatility distribution compared to the normal distribution.

[13] United States had administered the first COVID-19 vaccine dose among G7 countries on December 18, 2020.

[14] https://ourworldindata.org/covid-vaccinations

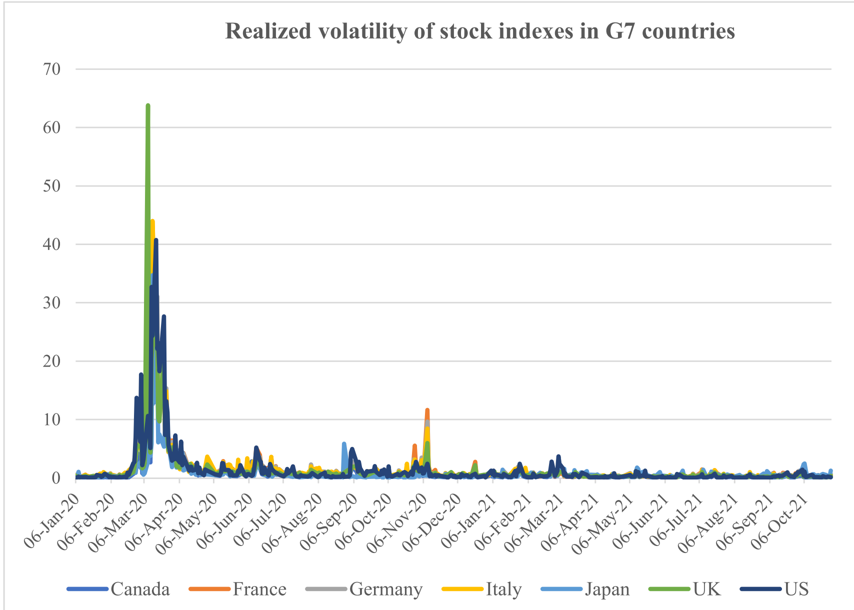

Fig. 1. The Evolution of Realized Volatility of G7 Stock Markets during the COVID-19 Pandemic. The figure shows the time evolution of realized variances of G7 stock markets.

Pertaining to the pandemic dynamics, the average reproduction rate (*R*) is at 1.01, implying that during the research period, about 1 person will become infected by an infectious person in the G7 countries. The G7 average new vaccinations per one million people (*New_Vax*) are relatively low at 4764 for the whole research period since the vaccination period represents only a part of the research period.[15]

Panel B Table 1 shows the mean values of variables for each member country of G7. We find that the stock index of Italy has the highest realized volatility (1.4551), followed by the US's S&P 500 Index (1.4013) and France's CAC 40 Index (1.3811). By contrast, Canada and Japan are the most stable stock markets during the pandemic with the daily average realized volatilities of 0.8193 and 0.8801, respectively. The relatively low volatility of Canada and Japan's stock markets during the pandemic may imply the contribution of the governments' pandemic-response policy to diminishing the damaging effects of the pandemic in these countries. In addition, Canada and Japan also have the lowest infection rates and death rates among G7 countries. The average reproduction rates (R) in Canada and Japan are recorded at 0.9711 and 0.9782, respectively while the death rates are 1.1955 and 0.2432, respectively. On the contrary, the pandemic is highly infectious and calamitous in other G7 countries with their average reproduction rates all above 1 and most death rates all above 3.

In terms of COVID-19 vaccinations, the pace of the vaccine rollout is strongest in Japan and the UK. The daily average number of vaccine doses administered per one million people (New_Vax_t) in the two countries are 5826 and 5062, respectively. While being the first G7′s country that has jabbed its population, the average daily new vaccinations of the US was the lowest among the group at 3948.

Fig. 1 displays the time evolution of the daily realized variance (*RV*) of G7 stock markets. The figure shows that the realized volatility was highest in March 2020 when the COVID-19 outbreak started to spread worldwide. After this period, the realized volatilities of all seven stock markets have declined significantly. However, they have increased again during October 2020 because of the uncertainty of the U.S. presidential election, rising COVID-19 cases in many countries, and raising concerns among investors about reintroduced national lockdown measures in response to the pandemic intensity.[16]

Table 2
Diagnostic Tests of Realized Variances.

	LB-Q (20)	JB-Test	ADF-Test
RV^{CA}	1821***	31,826***	-3.46**
RV^{FR}	1556***	32,386***	-5.14***
RV^{GE}	1550***	38,979***	-5.15***
RV^{IT}	1187***	84,855***	-7.09***
RV^{JP}	751.5***	287,033***	-6.27***
RV^{UK}	672.7***	342,754***	-9.17***
RV^{US}	1510***	38,546***	-4.25***

This table reports the diagnostic tests of the realized variance for each stock market. LB Q(20) indicates the Ljung-Box Q statistics up to 20th order autocorrelation. JB-Test shows the Jarque-Bera test for normal distribution of the time series. ADF test shows the augmented Dickey-Fuller unit root test. * ** denotes the cases where the null hypothesis of no autocorrelation (for LB Q test) and a normal distribution (for JB test) and a presence of unit root (for ADF test) is rejected at the 1%.

We further conduct diagnostic tests for the time series of daily realized variances and report their results in Table 2. First, the Ljung-Box Q statistics up to 20 lags indicate that there is a significant autocorrelation in all realized volatility series. Second, the Jarque-Bera statistics significantly reject the null hypothesis of normal distribution for all variances. Third, the augmented Dickey-Fuller (ADF) statistics statistically significantly reject the null hypothesis that the realized variance time series is non-stationary with a unit root.

To examine the long-memory characteristics in realized volatility of the seven selected stock markets, we plot their auto-correlograms of realized volatility from lag 1 to lag 50 in Fig. 2. The plots of the autocorrelation functions of all stock markets exhibit a hyperbolic slow rate of decay, implying the long-memory behaviour of the volatility process in all cases. This evidence confirms the appropriateness of our choice of

[15] The research period spans from January 1, 2020, to September 29, 2021, whereas the start date of vaccination in the US is administered to be December 18, 2020.

[16] https://www.schroders.com/en/insights/economics/monthly-markets-review—october-2020/

Fig. 2. The Long-memory Characteristic of Realized Volatility. These figures show the auto-correlogram up to 50 lags of the realized volatility of G7 stock markets.

the VHAR model to estimate the volatility of G7 stock markets.

5. Empirical results

5.1. Regression results of the VHAR – DCC-GARCH model

Table 3 reports the estimation results of the VHAR model in Eq. (3) using the ordinary least square procedure. The effects of past realized variance (including daily, weekly, and monthly effects), which influence the present realized variance are defined by the estimated coefficients β^d, β^w, β^m, respectively. The results show that for each stock market, its past own components of realized volatility contain information that affects its present realized variance. Further, we point out that the effect of the short-term volatility component (β^d) on their own current volatilities is most prevalent as its coefficient is statistically significant for 5 out of 7 stock markets (Canada, France, Italy, Japan, and the US). Additionally, the effect of the middle-term component (β^d) is less pronounced as it is statistically significant in explaining the own current volatilities in the only cases of Canada, Germany, and the US. Final, among the own-variance components, the role of the long-term component is least impressive as evidenced by only one statistically significant coefficient of β^m in the case of Germany.

Regarding the cross-volatility transmission, we preliminarily show that G7 stock markets are highly interconnectedness as the present volatility of one market is likely to be affected by the past components of the volatility of other markets. Specifically, for each stock market represented by one column in Table 3, the results of estimated coefficients of past volatility components of all other markets are statistically

Table 3
Regression Results of VHAR Model.

	CA	FR	GE	IT	JP	UK	US
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\beta^{CA,d}$	-0.892***	-0.548***	-0.100	-0.447	0.570***	-0.612	-2.057***
$\beta^{CA,w}$	0.190	-0.620***	-0.785***	-1.883***	-0.353	-2.782***	-0.820*
$\beta^{CA,m}$	0.153	1.264**	1.303**	0.256	-0.272	-0.702	0.361
$\beta^{FR,,d}$	-0.453***	-0.501***	-0.331*	-0.914***	-0.490***	-0.175	-1.188***
$\beta^{FR,w}$	-0.952***	-1.630***	-1.541***	-1.528*	-0.518	-2.611*	-1.824**
$\beta^{FR,m}$	0.653	1.697	1.539	0.744	0.589	-0.695	1.426
$\beta^{GE,d}$	0.321***	0.313*	0.173	0.540***	0.046	-0.133	1.029***
$\beta^{GE,w}$	0.799***	1.526***	1.401***	2.120***	0.737*	2.206*	1.765**
$\beta^{GE,m}$	-0.283	-2.201*	-2.575**	-1.509	-1.590*	0.371	-1.442
$\beta^{IT,,d}$	0.384***	0.621***	0.511***	1.184***	0.759***	0.746***	0.842***
$\beta^{IT,w}$	0.436***	0.674***	0.677***	0.010	0.070	0.957**	0.804***
$\beta^{IT,m}$	-0.660	0.408	0.982	-0.022	0.254	0.380	-1.029
$\beta^{JP,d}$	0.054	-0.162**	-0.121*	-0.828***	-0.536***	-0.305*	-0.060
$\beta^{JP,w}$	0.470***	0.153	-0.003	0.249	0.115	0.032	0.920***
$\beta^{JP,m}$	-0.012	-0.438	-0.125	0.085	0.778	-0.376	-0.056
$\beta^{UK,,d}$	0.001	-0.084**	-0.096***	-0.262***	-0.123***	-0.249	-0.068
$\beta^{UK,w}$	0.587***	0.816***	0.743***	1.269***	0.343**	0.412***	1.027***
$\beta^{UK,m}$	0.083	-0.589	-0.740**	0.388	0.578**	-0.342	0.507
$\beta^{US,d}$	0.228***	0.235***	0.128*	0.230**	0.133**	0.247*	0.597***
$\beta^{US,w}$	-0.384***	-0.244***	-0.091	0.037	-0.395	1.299	-0.380*
$\beta^{US,m}$	0.066	0.034	-0.056	0.281	0.002	1.281	0.266
Intercept	-0.240**	0.145	0.133	0.103	0.088	-0.051	-0.337*
N. Obs.	415	415	415	415	415	415	415
Adj. R-squared	0.889	0.849	0.862	0.761	0.844	0.463	0.821
LB (20) Test of Residuals	33.66**	47.12***	96.51***	125.40***	46.54***	52.81***	46.47***

This table reports the estimated parameters of the VHAR model as shown in Eq. (3) for seven time series of realized variances of G7 stock markets. The last row of the table shows the Ljung-Box Q statistics up to 20th order autocorrelation of the residuals from the VHAR model. For the sake of brevity, the t-statistics and standard errors of the estimated parameters are not reported in this table. * ** , * * and * indicate that the estimated parameters are statistically significant at 1%, 5% and 10% significance level, respectively.

Table 4
Summarized Statistics of Connectedness Indices using Realized Variance.

Panel A. The whole sample

	CA	FR	GE	IT	JP	UK	US	Spillover from others (*VDI*)
CA	24.30%	9.90%	8.32%	9.27%	0.69%	7.56%	39.95%	75.70%
FR	4.30%	26.25%	21.96%	20.64%	1.13%	15.76%	9.95%	73.75%
GE	3.99%	24.46%	26.52%	20.67%	1.36%	13.97%	9.03%	73.48%
IT	3.36%	17.87%	16.04%	34.64%	4.44%	15.16%	8.48%	65.36%
JP	0.75%	2.50%	2.80%	12.35%	75.88%	3.95%	1.78%	24.12%
UK	3.55%	17.14%	13.52%	18.75%	1.59%	38.21%	7.23%	61.79%
US	17.23%	9.88%	8.12%	10.03%	0.74%	6.57%	47.43%	52.57%
Spillover to others	33.19%	81.74%	70.76%	91.71%	9.95%	62.97%	76.44%	
Net spillover	-42.51%	7.99%	-2.71%	26.35%	-14.17%	1.18%	23.87%	
Total Connectedness Index (*TCI*)	60.97%							

Panel B. Pre-vaccination (Before the first dose of vaccine on Dec 18, 2020)

	CA	FR	GE	IT	JP	UK	US	Spillover from others
CA	23.84%	10.12%	8.78%	10.08%	0.60%	8.39%	38.20%	76.16%
FR	4.78%	25.17%	21.51%	21.16%	0.82%	15.47%	11.09%	74.83%
GE	4.50%	23.57%	26.16%	21.21%	1.03%	13.60%	9.94%	73.84%
IT	3.83%	17.33%	15.86%	34.87%	3.39%	15.34%	9.38%	65.13%
JP	1.01%	2.80%	3.27%	14.66%	70.59%	5.62%	2.04%	29.41%
UK	3.99%	16.27%	12.99%	19.30%	1.23%	38.07%	8.17%	61.93%
US	16.61%	10.03%	8.30%	10.45%	0.55%	7.12%	46.94%	53.06%
Spillover to others	34.72%	80.11%	70.71%	96.85%	7.62%	65.53%	78.82%	
Net spillover	-41.44%	5.28%	-3.13%	31.72%	-21.79%	3.60%	25.76%	
Total Connectedness Index (*TCI*)	62.05%							

Panel C. Post-vaccination period (After the first dose of vaccine on Dec 18, 2020)

	CA	FR	GE	IT	JP	UK	US	Spillover from others
CA	24.52%	9.79%	8.10%	8.89%	0.74%	7.16%	40.79%	75.48%
FR	4.08%	26.77%	22.18%	20.40%	1.28%	15.89%	9.41%	73.23%
GE	3.75%	24.88%	26.70%	20.41%	1.51%	14.15%	8.60%	73.30%
IT	3.13%	18.13%	16.13%	34.53%	4.94%	15.08%	8.06%	65.47%

(*continued on next page*)

Table 4 (*continued*)

Panel C. Post-vaccination period (After the first dose of vaccine on Dec 18, 2020)								
	CA	FR	GE	IT	JP	UK	US	Spillover from others
JP	0.62%	2.35%	2.57%	11.24%	78.41%	3.15%	1.66%	21.59%
UK	3.35%	17.56%	13.78%	18.49%	1.76%	38.28%	6.79%	61.72%
US	17.53%	9.81%	8.03%	9.84%	0.83%	6.30%	47.67%	52.33%
Spillover to others	32.45%	82.52%	70.79%	89.26%	11.05%	61.75%	75.31%	
Net spillover	-43.02%	9.28%	-2.51%	23.79%	-10.54%	0.03%	22.97%	
Total Connectedness Index (*TCI*)	60.45%							

This table shows the average connectedness indices among G7 stock market using realized variances. Panel A presents the results for the whole period from January 1, 2020, to October 29, 2021. Panel B reports the results for the pre-vaccination period from January 1, 2020, to December 18, 2020. Panel C shows the results for the post-vaccination period from December 18, 2020, to October 29, 2021.

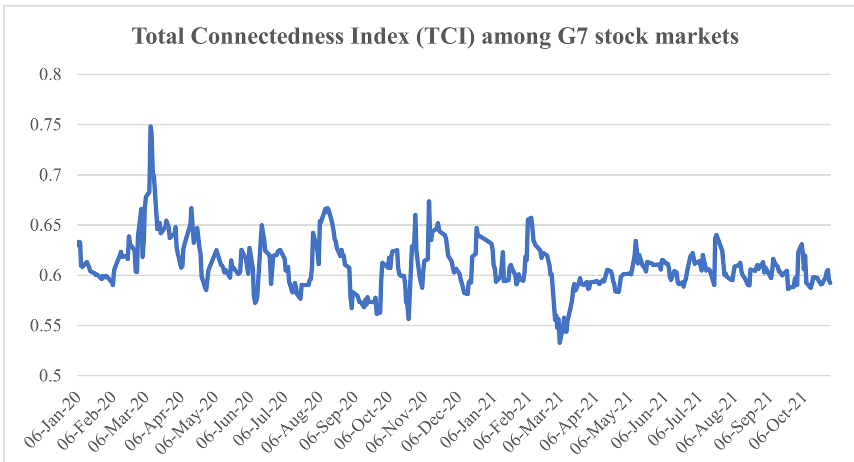

Fig. 3. Dynamics of the Total Connectedness Index. The figure plots the Total Connectedness Index among G7 stock markets between January 2020 and October 2021.

significant in the short-term, medium-term, or long-term. However, it is worth noting that the connectedness is mostly driven by the effects of short-term and medium-term volatility components as evidenced by significant β^d and β^w in each column, whereas the effect of long-term volatility components is least pronounced. [17]

5.2. Analysis of dynamic volatility connectedness

Panel A Table 4 reports the average dynamic volatility connectedness among G7 stock markets for the whole sample period using the connectedness framework of Diebold and Yilmaz (2012) within the VHAR – DCC-GARCH model. First, the results indicate there is significant volatility connectedness among G7 stock markets as shown by the average Total Connectedness Index of 60.97%. Our result is higher than the volatility connectedness index among G7 stock markets as documented in the earlier studies for pre-COVID-19 pandemic periods (e.g., Liow, 2015; Su, 2020; Tsai, 2014), implying that that the connectedness effect has increased during the COVID-19 crisis.

Further, among the seven markets, Canada's stock market receives the most volatility from other G7 members whereas Japan is least sensitive to volatility shocks from outside. This finding is represented by the Volatility Dependence Indices of Canada and Japan, which are 75.70% and 24.12%, respectively. Similarly, the past volatility of the Nikkei 225 plays a less significant role in affecting other markets' volatility as evidenced by its lowest value of the "*Spillover to others*" index of 9.95%. In addition, the "*Net spillover*" row reveals that the most-affected countries by the pandemic, such as Italy and the US, are the main volatility transmitters while the least-affected countries like Canada and Japan are the net volatility receivers.

We go further to examine the dynamic volatility connectedness for two sub-sample periods, including the pre-vaccination and post-vaccination, and demonstrate the results in Panels B and C of Table 4, respectively. The pre-vaccination period is from January 1, 2020, to December 18, 2020, which is the first day that the US administered its first dose of the COVID-19 vaccine. The post-vaccination period is from December 18, 2020, to October 29, 2020. The results show that the Total Connectedness Index has declined from 62.05% in the pre-vaccination period to 60.45% in the post-vaccination period. A decline in the Volatility Dependence Index in the post-vaccination period is also observed for 6 out of 7 countries, except in the case of Italy. We may infer that during the post-vaccination period, the decline in TCI was attributed to the decrease in VDI of 6 out of 7 markets in G7 group. In other words, the individual stock market seems to be more resilient to outside shocks after the vaccinations build up, leading to a reduction in volatility connectedness across G7 stock markets. These findings provide preliminary supporting evidence to our expectation that COVID-19 vaccinations could help reduce the volatility transmission among G7 stock markets.

[17] The Ljung-Box Q test at the end row of Table 3 indicates all residuals resulted from the VHAR model exhibit significant autocorrelation. As such, they need to be modelled by the DCC-GARCH model as described in Section 3.2 to meet the i.i.d. requirement of the VAR(22) model for Diebold and Yilmaz (2012) connectedness framework. For the sake of brevity, the results of the DCC-GARCH model are presented in Panel A of Appendix A1. The diagnostic test results of Engle's LM Test on the ARCH effect and Li-Mak's (1994) test on squared standardized residual series shown in Pane B of the appendix indicate that the residual series derived from the DCC-GARCH model exhibit no remaining ARCH effects and no serial autocorrelation.

Table 5
Vaccinations and Total Connectedness Index: Main Regression Results.

	(1)	(2)	(3)
VIX	0.05**	0.09***	0.05***
	(2.31)	(3.00)	(2.50)
ER	0.02	0.06	0.02
	(0.31)	(0.70)	(0.35)
R	1.80***	2.60***	1.80***
	(2.80)	(2.58)	(2.77)
DEATH	0.06	0.09	0.07
	(1.12)	(1.18)	(1.14)
New_Vax	-0.21**		
	(−2.34)		
Vax_Increase		-0.43*	
		(−1.87)	
Vax_Period			-0.61*
			(−1.72)
Intercept	56.10***	-59.70***	56.40***
	(11.14)	(−7.82)	(11.15)
Number of observations	415	415	415
Adjusted R-squared	0.190	0.186	0.188

This table reports the OLS regression results of Eq. (18) to examine the impact of COVID-19 vaccinations of the Total Connectedness Index (TCI) among G7 stock markets. T-statistics which are calculated using heteroskedasticity-consistent standard errors are in the parentheses beneath the coefficient estimates. * ** , * * and * indicate that the estimated parameters are statistically significant at 1%, 5% and 10% significance level, respectively.

5.3. The effect of vaccinations on total connectedness index and robustness checks

Fig. 3 plots the dynamic Total Connectedness Index among the seven stock markets over the research period. The index was highly volatile for the whole research period and peaked in March 2020, the early stage of the pandemic. Our study aims to investigate the impact of COVID-19 vaccinations on the volatility transmission among G7 stock markets using the baseline regression model specified in Eq. (18).

We estimate the coefficients of Eq. (18) using the heteroskedasticity consistent standard errors to compute their *t*-statistics and report the regression results in Table 5. Columns (1), (2), and (3) of Tables 6, 7, 8 report the estimation results of three different regressions in each of which the main proxy of vaccination is, in turn, *New_Vax*, *Vax_Increase*, and *Vax_Period*, respectively. First, in Column (1) Table 5, the coefficient of *New_Vax* is negative and statistically significant, implying that there is a reducing effect of COVID-19 vaccinations on the volatility connectedness. The coefficient estimate of *New_Vax*, which is equal to − 0.21, suggests that a 10% increase in the average daily vaccination rate in G7 countries leads to a 2.1% reduction in their Total Connectedness Index. Column (2) Table 5 show that the Total Connectedness Index is negatively and significantly correlated with the average increase in daily vaccination rate as evidenced by the coefficient of *Vax_Increase* of − 0.43. Final, the estimated parameter of *Vax_Period* is also statistically significant and negative (−0.61). These results corroborate our preliminary observation that the volatility spillover significantly reduces in the post-vaccination period compared to the pre-vaccination one.

Besides, the coefficient estimates of other control variables in Eq. (18) are noteworthy. First, we find that the investors' uncertainty, which is proxied by *VIX*, is positively correlated with the Total Connectedness Index. This increasing effect of *VIX* on the volatility spillover is in line with the work of Su (2020), who shows that investors' uncertainty has significantly increased the volatility connectedness among G7 stock markets. In addition, we find that the Total Connectedness Index increases as the COVID-19 pandemic build-ups as evidenced by the significant positive coefficient estimate of the reproduction rate (R) across different model specifications. This result is in line with previous literature that has explored the impact of the COVID-19 outbreak's dynamics on the stock market's volatility and volatility connectedness (e.g., Bissoondoyal-Bheenick et al., 2021; Bouri et al., 2021a; Liow et al., 2018; Youssef et al., 2021).

Table 6
Vaccinations and Total Connectedness Index: Different Sampling Periods.

Panel A. From March 11, 2020			
	(1)	(2)	(3)
VIX	0.02	0.05*	0.03
	(1.03)	(1.62)	(1.22)
ER	0.001	0.02	0.001
	(0.10)	(0.25)	(0.07)
R	2.21***	3.32***	2.24***
	(3.42)	(3.30)	(3.40)
DEATH	0.31**	0.61**	0.32**
	(2.17)	(2.29)	(2.12)
New_Vax	-0.21**		
	(−2.02)		
Vax_Increase		-0.11**	
		(−2.38)	
Vax_Period			-0.73*
			(−1.89)
Intercept	57.4***	-56.7***	57.66***
	(11.42)	(−7.29)	(11.32)
Number of observations	372		372
Adjusted R-squared	0.1510	0.143	0.149
Panel B. From June 6, 2020			
	(1)	(2)	(3)
VIX	0.07**	0.03*	0.08**
	(2.35)	(1.70)	(2.12)
ER	-0.11	-0.12	-0.11
	(−1.11)	(−0.47)	(−0.99)
R	-0.71	0.55	-0.52
	(−0.82)	(0.38)	(−0.66)
DEATH	0.21	0.43	0.22
	(1.28)	(1.23)	(1.23)
New_Vax	-0.12***		
	(−3.98)		
Vax_Increase		-1.42***	
		(−3.05)	
Vax_Period			-0.24***
			(−3.69)
Intercept	71.62***	-43.83***	71.50***
	(9.51)	(−3.72)	(9.48)
Number of observations	322	322	322
Adjusted R-squared	0.053	0.025	0.043
Panel C. From August 11, 2020			
	(1)	(2)	(3)
VIX	0.14**	0.09*	0.12**
	(2.97)	(1.76)	(2.76)
ER	-0.21**	-0.21*	-0.22**
	(−2.10)	(−1.67)	(−1.94)
R	0.12	1.83	0.21
	(0.11)	(1.38)	(0.27)
DEATH	0.31*	0.63*	0.32*
	(1.89)	(1.91)	(1.84)
New_Vax	-0.14***		
	(−3.97)		
Vax_Increase		-1.52***	
		(−3.24)	
Vax_Period			-1.82***
			(−3.65)
Intercept	81.2***	-26.5*	80.7***
	(9.47)	(−1.95)	(9.40)
Number of observations	281	281	281
Adjusted R-squared	0.076	0.026	0.063

Table 6 Panel A, B, C display the regression results of Eq. (18) for alternative periods that start at March 11, June 6, and August 11, 2020, sequentially. *T*-statistics which are calculated using heteroskedasticity-consistent standard errors are in the parentheses beneath the coefficient estimates. * ** , * * and * indicate that the estimated parameters are statistically significant at 1%, 5% and 10% significance level, respectively.

To check the credibility of our results, we conduct two robustness checks. First, we re-estimate Eq. (18) using different sampling periods and report the results in Table 6. Following Rouatbi et al. (2021), we use three sampling periods with different starting dates of the global

Table 7
Vaccinations and Total Connectedness Index: Different Forecasting Steps.

Panel A. Using 3-step ahead forecast			
	(1)	(2)	(3)
VIX	0.04**	0.09***	0.04***
	(2.23)	(2.88)	(2.45)
ER	0.01	0.05	0.01
	(0.28)	(0.68)	(0.33)
R	1.69***	2.49***	1.70***
	(2.73)	(2.48)	(2.71)
DEATH	0.06	0.09	0.07
	(1.02)	(1.16)	(1.04)
New_Vax	-0.19**		
	(−2.12)		
Vax_Increase		-0.41*	
		(−1.77)	
Vax_Period			-0.59*
			(−1.70)
Intercept	55.73***	-58.55***	55.81***
	(10.41)	(−7.32)	(10.49)
N. Obs	415	415	415
Adjusted R-squared	0.187	0.182	0.185
Panel B. Using 10-step ahead forecast			
	(1)	(2)	(3)
VIX	0.05**	0.08***	0.05***
	(2.37)	(3.21)	(2.67)
ER	0.02	0.06	0.02
	(0.31)	(0.70)	(0.35)
R	1.82***	2.72***	1.87***
	(3.10)	(2.85)	(3.07)
DEATH	0.07	0.10	0.07
	(1.42)	(1.31)	(1.44)
New_Vax	-0.22***		
	(−2.54)		
Vax_Increase		-0.45*	
		(−1.92)	
Vax_Period			-0.64*
			(−1.75)
Intercept	56.88***	-59.89***	57.56***
	(11.34)	(−7.79)	(11.45)
N. Obs	415	415	415
Adjusted R-squared	0.196	0.191	0.192

Table 7 Panel A, B display the regression results of Eq. (18) for alternative forecasting steps. *T*-statistics which are calculated using heteroskedasticity-consistent standard errors are in the parentheses beneath the coefficient estimates. * ** , * * and * indicate that the estimated parameters are statistically significant at 1%, 5% and 10% significance level, respectively.

COVID-19 outbreak. Specifically, the starting date in Panel A is March 11, 2020, when the WHO declared the COVID-19 a pandemic. In Panel B, the study period starts on June 6, 2020, which is considered the end of the initial post-crisis rebound period (Bae et al., 2021). In Panel C, we present the results for the period beginning on August 11, 2020, when Russia officially approved the world's first COVID-19 vaccine. The results show that the coefficient estimates of different measures of COVID-19 vaccinations continue to be negative and statistically significant across different sampling periods. This indicates that our principal conclusions are independent of our chosen study periods.

As another robustness test, we re-calculate the Total Connectedness Index using 3-step ahead and 10-step ahead instead of 5-step ahead. Table 7. As seen in Table 7 Panel A and B, there are no qualitative changes in the relationship between vaccine-related variables and stock connectedness regardless of different forecasting steps used.

In summary, we find that the deployment of the COVID-19 vaccinations contributes to reducing the volatility connectedness among G7 stock markets, which is consistent with hypothesis H1. More importantly, this decreasing effect is robust to controlling for effects of the pandemics' severity, different sampling periods employed, and alternative forecasting steps applied.

6. Exploring the underlying mechanisms

As discussed earlier, we contemplate two possible mechanisms, which would help explain the negative impact of the COVID-19 vaccine rollout on the volatility connectedness across stock markets. In this section, we perform analyses to examine these two mechanisms.

6.1. Impacts of COVID-19 vaccinations on individual stock market volatility and return

In hypothesis H2, we conjecture that vaccinations reduce interconnectedness among G7 stock markets via their impacts on stock market return and volatility. To test our conjecture, we investigate the time-varying effects of vaccinations on volatility and return in each G7 country by estimating the following time-varying models.[18]

$$RV_{i,t} = \beta_i^0(\tau_t) + \beta_i^d(\tau_t)RV_{i,t-1} + \beta_i^w(\tau_t)RV_{i,t-1|t-5} + \beta_i^m(\tau_t)RV_{i,t-1|t-22} + \beta_i^{Vax}(\tau_t)New\_Vax_{i,t-1} + \varepsilon_{i,t} \quad (19)$$

and

$$Ret_{i,t} = \gamma_i^0(\tau_t) + \gamma_i^d(\tau_t)Ret_{i,t-1} + \gamma_i^w(\tau_t)Ret_{i,t-1|t-5} + \gamma_i^m(\tau_t)Ret_{i,t-1|t-22} + \gamma_i^{Vax}(\tau_t)New\_Vax_{i,t-1} + e_{i,t} \quad (20)$$

where$RV_{i,t}$, $RV_{i,t-1}$, $RV_{i,t-1|t-5}$, $RV_{i,t-1|t-22}$ denote the daily realized volatility, lagged daily realized volatility, lagged weekly realized volatility and lagged monthly realized volatility of stock market *i*, respectively; $Ret_{i,t}$, $Ret_{i,t-1}$, $Ret_{i,t-1|t-5}$,$Ret_{i,t-1|t-22}$ indicate the daily return, lagged daily return, lagged weekly return and lagged monthly return of stock market *i*;$\beta_{t,i} = \beta_i^k(\tau_t)$and $\gamma_{t,i} = \gamma_i^k(\tau_t)$ for $k = 0, d, w, m, Vax,$ are the coefficient functions of the models; $\tau_t = \frac{t}{n}$ with $t = 1, ., n$; $\varepsilon_{i,t}$and $e_{i,t}$ are sequences of stationary errors.

Following Chen et al. (2017), we estimate the coefficient functions in Eqs. (19) and (20) using the nonparametric estimation approach, namely local linear regression. Then the weights of least squares are assigned by the heights of a kernel function with the bandwidth selected by leave-one-out cross-validation (CV bandwidth selection).[19] In Eq. (19), we are interested in estimating $\beta_i^{Vax}(\tau_t)$, which directly measures the time-varying effect of daily new vaccinations on realized volatility. Table 8 reports the summary statistics of the time-varying $\beta_i^{Vax}(\tau_t)$ for the selected stock markets. The results show that all stock markets exhibit negative and statistically significant mean of the time-varying coefficient $\beta_i^{Vax}(\tau_t)$ as evidenced by the *t*-test's statistics in the last row. This supports our hypothesis H2 and is consistent with the finding of Rouatbi et al. (2021) that the COVID-19 vaccine rollout exerts a reducing effect on the stock market volatility. In addition, as shown by the mean absolute value of $\beta_i^{Vax}(\tau_t)$, the average stabilizing effect of the vaccine rollout on realized volatility is highest in France, followed by the US.

In Eq. (20), coefficient $\gamma_i^{Vax}(\tau_t)$ indicates the time-varying impact of daily new vaccinations on stock market return. We report the summary statistics of the time-varying $\gamma_i^{Vax}(\tau_t)$ for the selected stock markets in Table 9. We find that all stock markets, except Japan, exhibit a positive and statistically significant mean of the time-varying coefficient $\gamma_i^{Vax}(\tau_t)$ as shown by the *t*-test's statistics in the last row. This finding conforms to our hypothesis H3 and is in line with Khalfaoui et al. (2021), who reveal

[18] We examine the time-varying effects of vaccinations on stock market volatility and return as we conceive that these effects could be time-dependent and varies by country depending on several country-specific factors. These factors include, but are not limited to, the level of investor confidence in the vaccine, pandemic-related government policies, the economic development of the country or the experience of investors with similar pandemics.

[19] See Chen et al. (2017) for a full reference of the local linear method used to estimate the time-varying coefficient heterogeneous autoregressive model (TVC-HAR) with CV bandwidth selection.

Table 8
Descriptive statistics of Time-varying Stabilizing Effect ($\beta_i^{Vax}(\tau_t)$) of COVID-19 Vaccination on Realized Volatility.

	CA	FR	GE	IT	JP	UK	US
Mean	-0.035	-0.069	-0.008	-0.012	-0.007	-0.008	-0.056
Std. Dev	0.253	0.252	0.00001	0.00001	0.00001	0.016	0.542
1% Percentile	-1.329	-1.347	-0.009	-0.012	-0.007	-0.045	-2.682
99% Percentile	0.646	0.266	-0.009	-0.012	-0.007	0.026	1.295
Kurtosis	14.89	14.69	-1.18	-1.18	-1.19	0.14	10.69
Skewness	-2.545	-3.03	-0.01	-0.01	-0.01	-0.37	-2.046
t-statistics (H0: $\beta_i^{Vax}(\tau_t) = 0$)	-2.73***	-5.52***	-22,341***	-18,983***	-15,259***	-9.61***	-2.06***

The table reports the descriptive statistics of the time-varying coefficient of the effect of vaccinations on the realized volatility ($\beta_i^{Vax}(\tau_t)$) of each selected stock markets as shown in Eq. (19). We estimate Eq. (19) using the local linear method. Std. Dev denotes the standard deviation. The last row presents the t-statistics of the two-tailed t-test with the null hypothesis being that the mean of $\beta_i^{Vax}(\tau_t)$ is equal to 0.

a positive and significant relationship between S&P 500 return and the COVID-19 vaccination rate in the US.

Since the volatility of a stock market is closely interwoven with its trading volume,[20] we also expand our analysis to test whether vaccinations affect stock trading volume. As such, we re-estimate Eq. (19) with the daily realized variance replaced by the logarithm of the daily trading volume. For the sake of brevity, the re-estimation results are presented in Appendices A2. The Appendix A2 indicates that five out of seven G7 countries exhibit a decline in trading volume as the COVID-19 vaccine rollout accelerates.[21] The simultaneous reductions in both trading volume and volatility in reaction to COVID-19 vaccinations are consistent with the abundant empirical evidence showing that the stock market trading volume and stock market volatility are positively correlated (e.g., Chan and Fong, 2006; Chen and Daigler, 2008; Ané and Ureche-Rangau, 2008; Do et al., 2014; Bissoondoyal-Bheenick et al., 2019), which is backed by the Mixture of Distribution Hypothesis (e.g., Clark, 1973, Tauchen and Pitts, 1983), the Differences of Opinion Hypothesis (e.g., Shalen, 1993; Harris and Raviv, 1993), and Sequential Arrival of Information Hypothesis (e.g., Copeland, 1976).

The results of vaccinations on stock market volatility, return and liquidity in this section support our hypothesis H2 and thereby giving explanations for the lower cross-market connectedness following vaccine deployment.

6.2. Did vaccinations make a country's stock market more resilient to outside shocks?

We investigate whether Covid-19 vaccinations make a stock market more resilience to outside shocks, thereby reduce the stock market volatility connectedness. Fig. 4 plots the dynamics of the Volatility Dependence Index for the seven stock markets. The lower VDI indicates that the stock market is more resilient to outside shocks. We observe that the Volatility Dependence Index of the Japanese stock market is the lowest most of the time, indicating the market is least vulnerable to volatility shocks from other G7 markets. In reverse, Canada, France, and Germany's stock markets are highly susceptible to outside fluctuations. To examine whether vaccinations influence the resiliency of a stock market to outside shocks, in turn reduce the stock market volatility connectedness, we estimate the following regression equation:

$$VDI_{i,t+1} = \beta_0 + \beta_v Vax_{i,t} + \beta_c Control_{i,t} + \varepsilon_{i,t+1} \tag{21}$$

where $VDI_{i,t+1}$ is the daily Volatility Dependence Index of the stock market *i*; $Control_{i,t}$ and $Vax_{i,t}$ are specified similarly as in Eq. (18), except that they are country-specific rather than cross-country average numbers.

Following Rouatbi et al. (2021), we estimate Eq. (21) using three estimation methodologies for panel data regression, namely, pooled-OLS, random effects, and country-fixed effects. The corresponding results are reported in Panels A, B, and C of Table 10, respectively. Panel A Column (1) show that the estimated coefficient of *New_Vax* is statistically significant and negative at $-$ 0.13, implying a diminishing effect of COVID-19 vaccinations on the Volatility Dependence Index. Specifically, an 10% increase in the daily vaccine doses administered per 1 million people induces a decrease of 1.3% in the Volatility Dependence Index. The regression results in Columns (2) and (3) conform to the conclusion that the relationship between the vaccine deployment and the Volatility Dependence Index is significantly negative. The estimated coefficients of *Vax_Increase* ($-$2.22) and *Vax_Period* ($-$1.53) in panel A imply the robustness of our main results regardless of alternative vaccination-related variables used in the regression.(Table. 11).

Further, our principal results are not sensitive to different estimation methods employed, as evidenced by the consistent negative coefficients of vaccination-related variables in Panel B and C Table 10. Evidently, we reveal that the COVID-19 vaccine rollout makes a stock market more resilient to the outside shocks. This empirical finding validates our hypothesis H3 that the COVID-19 vaccine rollout makes a country's stock market less sensitive to other stock markets' volatility, leading to lower intermarket volatility connectedness. This emphasizes the crucial implication of the country-specific vaccination-related information for equity investors as this information could indicate the prospects for a return to normalcy in economic activities, which are highly relevant to the stock market outlook in times of the pandemic. As the deployment of the domestic vaccine rollout attracts the attention of investors, they would be less concerned by outside shocks, including the volatility spillover effect of other stock markets.

7. Implications of the study

7.1. Financial implications

In this section, based on our main empirical findings, we demonstrate a vaccination-based tactical trading strategy that is deemed to benefit global equity investors. We conceive a scenario that investors wish to maintain their position in the G7 stock markets for diversification purposes and tactically adjust their portfolio's weights based on vaccination-related news to improve their portfolio performance. This is a highly relevant scenario given the significant role of G7 stock markets in the global equity markets as well as the great attention of media on the pandemic-related information, including the COVID-19 vaccine rollout. Our proposed trading strategy involves two steps as outlined below.

[20] For a discussion of the relationship between stock volatility and trading volume, please see e.g., Foster and Viswanathan (1993), Brooks (1998), Andersen (1996), Chiang et al. (2010), and Park (2010), among others.

[21] Chiah and Zhong (2020) find that the COVID-19 pandemic leads to the popularity of trading from home, and increases global stock market trading volume.

Table 9
Descriptive statistics of Time-varying Effect ($\gamma_i^{Vax}(\tau_t)$) of COVID-19 Vaccination on Stock Market Return.

	CA	FR	GE	IT	JP	UK	US
Mean	0.0007	0.0014	0.000128	0.000949	-0.00265	0.00092	0.0008
STD (* 10^{-6})	1.82	2.82	1.87	2.64	4.76	3.13	244
1% Percentile	0.00067	0.00138	0.000125	0.000945	-0.00267	0.00091	-0.0071
99% Percentile	0.00068	0.00139	0.000131	0.000954	-0.00263	0.00093	0.00296
Kurtosis	-1.1862	-1.1187	-1.1824	-1.1793	-1.189	-1.188	2.000
Skewness	0.016	0.011	-0.011	0.012	0.011	0.015	-1.613
t-statistics (H0: $\gamma_i^{Vax}(\tau_t) = 0$)	7451***	9800***	1367***	7170***	-11,089***	5885***	6.54***

The table reports the descriptive statistics of the time-varying coefficient of the effect of vaccinations on return ($\gamma_i^{Vax}(\tau_t)$) of each selected stock markets as shown in Eq. (20). We estimate Eq. (20) using the local linear method. Std. Dev denotes the standard deviation. The last row presents the t-statistics of the two-tailed t-test with the null hypothesis being that the mean of $\gamma_i^{Vax}(\tau_t)$ is equal to 0.

First, for diversification purposes, investors hold a baseline portfolio with equal weight assigned to each stock market in the G7 group. The simulation period is between December 2020 and October 2021 and the data on new vaccinations in the month (*t-1*) is used to adjust the portfolio's weights in month *t*. We calculate the monthly new vaccinations per 1 million people (monthly *New_Vax*) for seven G7 countries.[22] Then, we rank the countries by their monthly vaccinations.

Second, as discussed in Subsection 6.1, the stock market becomes less sensitive to other stock markets' volatility as the new vaccinations increase, which in turn lower the total volatility connectedness across the whole system. Based on this empirical finding, we form a vaccination-based tactical asset allocation by increasing the weights of three stock markets that exhibit the largest monthly new vaccinations and reducing the weights of three markets with the lowest figures. We expect that this monthly adjustment could reduce the total risk of the portfolio by diminishing the total volatility connectedness among the stock markets. In addition to the risk aspect, the intensity of vaccinations is likely to improve stock market returns, as has been documented in Acharya et al. (2020).

To evaluate the economic significance of our proposed portfolio adjustment, we compare the accumulated return, average monthly return,[23] and standard deviation of the vaccination-based portfolio with those metrics of a Buy-and-Hold portfolio, which involves equally investing in G7 stock markets. Further, we use the Sharpe ratio[24] as a risk-adjusted return to evaluate the portfolio performance. Table 12 reports the description and the evaluation metrics for the mentioned portfolios. Vaccination-based Portfolio 1 involves the lowest weight adjustments, whereas Portfolio 3 entails the largest weight changes. The results show that the vaccination-driven tactical adjustment consistently helps reduce risk and improve return in all cases of vaccination-based portfolios compared to the Buy-and-Hold portfolio. Specifically, the accumulated return of Portfolio 3 is 22.48%,[25] which is improved of 12.46% compared to that of the Buy-and-Hold Portfolio. Concerning risk measurement, the standard deviation of Portfolio 3′s monthly return stands at 6.00, exhibiting a reduction of 12.15%. The robust decline in the risk of vaccination-based portfolios is in line with the negative impact of vaccinations on the volatility connectedness among G7 stock markets as early documented in our study. Finally, we find that the Sharpe ratio of vaccination-based portfolios enhances significantly. In detail, the percentage increase in the Sharpe ratio ranges from 7.89% (Portfolio 1) to 25.94% (Portfolio 3). The outperformance of the vaccination-based portfolios emphasizes the practical implications of our empirical findings in enhancing portfolio risk management based on the effects of vaccinations on stock volatility connectedness. This suggested strategy may help global equity investor better manage their portfolios and gain greater diversification benefits during the period of pandemic uncertainty.

To address the concern of sampling bias and to gain external validity for our key findings in the paper, we use another sample of seven emerging stock markets[26] and re-conduct two empirical tests. First, we calculate the Total Connectedness Index (TCI) between these markets and investigate whether the vaccination rollout reduces their volatility linkages. Second, we deploy the vaccination-based portfolio using the sample of emerging stock markets. The results of the two empirical tests are presented in Appendices A6 and A7, respectively. In Appendix A6, the results corroborate our key findings that vaccinations contribute to reducing the transmission of volatility shocks among emerging stock markets. Simulation results in Appendix A7 reaffirm that global investors can be better off by incorporating vaccination data in their portfolio allocation strategy. These results suggest that there is no issue of sample bias that would compel our main findings.

7.2. Policy implications

While the literature is replete with empirical works on the impacts of the COVID-19 pandemic, there are limited studies on the effects of COVID-19 vaccinations on global financial markets. By filling this void, our paper provides strong implications for policymakers regarding the deployment of the COVID-19 vaccine. We show that vaccinations help reduce the volatility interconnectedness across global stock markets by reducing individual stock market's volatility and making each stock market more resilient to outside shocks. The deployment of vaccinations also exerts a positive effect on the stock market return. While the COVID-19 outbreak has coincided with spikes in volatility connectedness across the globe (e.g., Bouri et al., 2021a; Farid et al., 2021), our study provides strong evidence that vaccinations could reverse the course and restore financial stability. As a result, policymakers worldwide should take into account the significant impact of vaccinations when formulating policies to stabilize financial markets.

[22] The monthly new vaccinations per 1 million of G7 countries are provided in Appendix A4.

[23] The monthly stock market returns of G7 countries are plotted in Appendix A4.

[24] Sharpe ratio is measured by dividing the excess return of a portfolio by the portfolio's standard deviation. Excess return is calculated as the difference between the average monthly portfolio return and average monthly risk-free rate. Consistent with Basher et al. (2018), we use the 3-month U.S. Treasury bill (T-bill) as the risk-free asset.

[25] Accumulated returns of different portfolios are plotted in Appendix A5.

[26] These emerging stock markets include the largest country components of the MSCI Emerging Markets Index including South Korea (KOSPI Stock Price Index), Taiwan (Taiwan Stock Exchange Weighted TAIEX Price Index), Russia (Russia MOEX Share Price Index), Brazil (Brazil BOVESPA Share Price Index), India (S&P BSE 100 Index), Indonesia (IDX Composite Price Index), and Thailand (Thailand SET Index). China is not included in the sample due to unavailability of vaccination data for the chosen period.

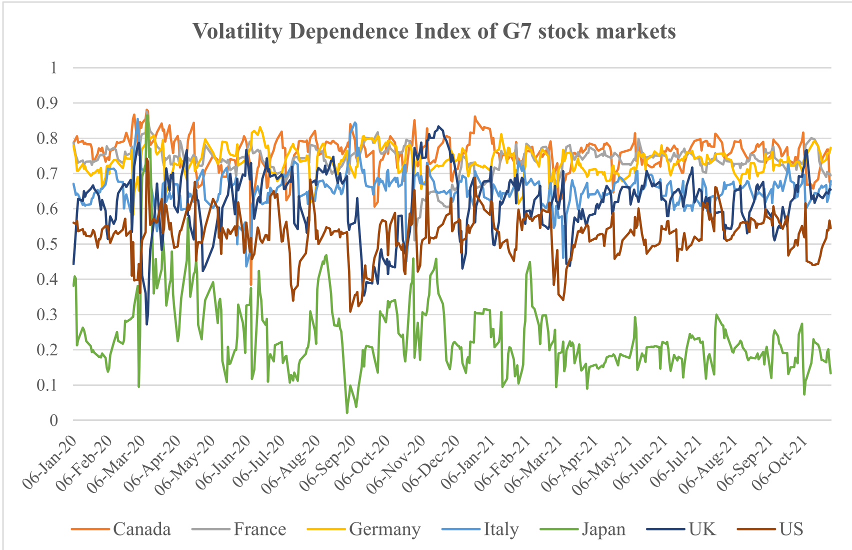

Fig. 4. Dynamics of the Volatility Dependence Index. The figure shows the time evolution of the Volatility Dependence Index (VDI) of G7 stock markets between January 2020 and October 2021.

Table 10
Vaccinations and Volatility Dependence Index.

Panel A. Pooled OLS			
	(1)	(2)	(3)
VIX	0.21***	0.12***	0.22***
	(4.63)	(3.15)	(4.02)
ER	-0.12***	-0.11***	-0.12***
	(−18.55)	(−18.64)	(−18.63)
R	-0.03	0.42	0.63
	(−0.03)	(0.42)	(0.69)
DEATH	-0.02	0.02	0.07*
	(−0.51)	(0.51)	(1.69)
New_Vax	-0.13***		
	(−4.78)		
Vax_Increase		-2.22***	
		(−2.80)	
Vax_Period			-1.53*
			(−1.83)
Intercept	59.1***	58.7***	61.7***
	(59.86)	(54.13)	(48.70)
Number of observations	2905	2905	2905
Adjusted R-squared	0.042	0.039	0.036
Panel B. Random effects			
	(1)	(2)	(3)
VIX	0.12***	0.11***	0.12***
	(5.66)	(6.08)	(5.01)
ER	-0.21*	-0.22*	-0.22*
	(−1.73)	(−1.78)	(−1.84)
R	0.61*	0.62*	0.61**
	(1.76)	(1.80)	(1.89)
DEATH	-0.05	-0.05	-0.05
	(0.42)	(−0.58)	(−1.11)
New_Vax	-0.31***		
	(−3.65)		
Vax_Increase		-0.22***	
		(−3.64)	
Vax_Period			-0.42**
			(−2.17)
Intercept	60.3	60.4	60.8
	(5.66)	(8.81)	(8.82)
Number of observations	2905	2905	2905
Adjusted R-squared	0.058	0.059	0.058
Panel C. Country-fixed effects			
	(1)	(2)	(3)
VIX	0.11***	0.12***	0.11***
	(5.67)	(6.09)	(5.02)
ER	-0.21*	-0.22*	-0.21*
	(−1.70)	(−1.76)	(−1.83)
R	0.61*	0.62*	0.61*
	(1.77)	(1.80)	(1.90)
DEATH	-0.05	-0.05	-0.05
	(−0.51)	(−0.59)	(−1.13)
New_Vax	-0.08***		
	(−3.67)		
Vax_Increase		-0.21***	
		(−3.66)	
Vax_Period			-0.40**
			(−2.19)
Number of observations	2905	2905	2905
Adjusted R-squared	0.163	0.168	0.165

Table 10 reports the regression results of Eq. (21) to examine the impact of COVID-19 vaccinations of the Volatility Dependence Index (VDI) of G7 stock markets using different estimation methodologies, including pooled OLS, random effects, and country-fixed effects regression. * ** , * * and * indicate that the estimated parameters are statistically significant at the 1%, 5% and 10% level, respectively.

8. Concluding remarks

This paper extends the literature by examining the impact of COVID-19 vaccination deployment on the stock volatility connectedness and its financial implications. Using the VHAR – DCC-GARCH model and generalized connectedness index, we find that COVID-19 vaccinations contribute to diminishing the volatility transmission among G7 stock markets. We further provide empirical evidence supporting two explanations of the reducing effects of vaccinations on stock volatility connectedness. First, COVID-19 vaccinations reduce individual stock market volatility and improve stock market return, which in turn lowering the volatility connectedness across the system. Second, the stabilizing effects of vaccinations help individual stock markets become more resilient to outside shocks, thereby reducing total volatility connectedness across stock markets. In addition, the reducing effects of COVID-19 vaccinations on stock volatility connectedness remain robust to alternative proxies of vaccinations, different sampling periods used, and varying forecasting steps applied in our connectedness computation.

Table 11
Portfolio Performance Evaluation of Dynamic Vaccination-driven Investment Strategy.

Portfolios	Portfolio Description	Accu. Ret	Avg. Ret	Std. Dev	Sharpe ratio
Buy-and-hold Portfolio	The portfolio has an equal weight of 14.286% in each stock index at the beginning of the period (Dec 2020). Then the weights are not adjusted.	19.99 (0)	1.82 (0)	6.83 (0)	0.266 (0)
Vaccination-based Portfolio 1	The portfolio has an equal weight of 14.286% in each stock index at the beginning of the period (Dec 2020). Since Jan 2021, the weights are adjusted monthly by increasing (decrease) weights of three countries with last largest (lowest) monthly new vaccinations per 1 million people by 5%, 3%, and 1%, respectively.	20.74 (3.75)	1.89 (3.85)	6.52 (−4.54)	0.287 (7.89)
Vaccination-based Portfolio 2	The portfolio has an equal weight of 14.286% in each stock index at the beginning of the period (Dec 2020). Since Jan 2021, the weights are adjusted monthly by increasing (decreasing) weights of three countries with last largest (lowest) monthly new vaccinations per 1 million people by 7%, 5%, and 3%, respectively.	21.73 (8.70)	1.98 (8.79)	6.23 (−8.79)	0.315 (18.42)
Vaccination-based Portfolio 3	The portfolio has an equal weight of 14.286% in each stock index at the beginning of the period (Dec 2020). Since Jan 2021, the weights are adjusted monthly by increasing (decreasing) weights of three countries with last largest (lowest) monthly new vaccinations per 1 million people by 9%, 7%, and 5%, respectively.	22.48 (12.46)	2.04 (12.29)	6.00 (−12.15)	0.335 (25.94)

This table shows the description and performance evaluation of three vaccination-based portfolios and the buy-and-hold portfolio. Acc. Return refers to the accumulated return of the portfolio between December 2020 and October 2021. Avg. Return denotes the average monthly return of the portfolio. Std. Dev indicates the standard deviation of the portfolio returns. Sharpe ratio is calculated by dividing the excess return of the portfolio by the standard deviation of monthly returns. Excess return is measured by the difference between the average monthly return of the portfolio and the average monthly return of the 3-month U.S. Treasury bill (T-bill). The number in the parentheses indicates the percentage increase (decrease) of the evaluation metrics of the vaccination-based portfolios compared to the buy-and-hold portfolio.

Our empirical findings have practical implications not only for policymakers but also for portfolio managers and investors since they provide potential trading strategies based on the information on vaccine deployment and the knowledge of the effects of vaccinations on stock volatility connectedness. This study suggests that during the pandemic time, equity portfolio managers who hold a global equity portfolio should actively adjust their portfolio weights following the vaccination's deployment news. This proposed vaccination-based strategy would help improve the performance of a global equity portfolio in terms of return, risk, and risk-adjusted return.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jfs.2023.101118.

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