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Immunizing markets against the pandemic: COVID-19 vaccinations and stock volatility around the world

Wael Rouatbi [a,b,*], Ender Demir [d,f], Renatas Kizys [c], Adam Zaremba [a,b,e]

[a] Montpellier Business School, 2300 Avenue des Moulins, 34185 Montpellier Cedex 4, France
[b] University of Montpellier, Montpellier Research in Management, Montpellier, France
[c] Department of Banking and Finance, Southampton Business School, University of Southampton, Room 1013, Building 4, Highfield Campus, Southampton SO17 1BJ, United Kingdom
[d] Istanbul Medeniyet University, Dumlupınar D100 Karayolu No:98, 34720 Kadıköy/İstanbul, Turkey
[e] Poznan University of Economics and Business, Institute of Finance, Department of Investment and Financial Markets, Al. Niepodległości 10, 61-875 Poznań, Poland
[f] University of Social Sciences, Lodz, Poland

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ABSTRACT

The COVID-19 pandemic has exerted a noteworthy impact on stock market volatility around the world. Can vaccination programs revert these adverse effects? To answer this question, we scrutinize daily data from 66 countries from January 1, 2020 to April 30, 2021. We provide convincing evidence that COVID-19 vaccination assists in stabilizing the global equity markets. The drop in volatility is robust to many considerations and does not result solely from either the pandemic itself or the government policy responses—the negative correlation remains significant after controlling for these factors. The impact of vaccinations is relatively stronger within developed markets than in emerging ones.

1. Introduction

The global-scale spread of COVID-19 has exerted an unprecedented impact on financial markets (Al-Awadhi, Alsaifi, Al-Awadhi, & Alhammadi, 2020; Albulescu, 2021; Baek, Mohanty, & Glambosky, 2020; Zaremba, Kizys, Aharon, & Demir, 2020). The effect was further exacerbated by devastating containment and closure policies (Heyden & Heyden, 2021; Zaremba et al., 2020). The arrival of the first coronavirus vaccines in early 2021 brought with it promises of both a return to normality and stability within the financial market. However, have they succeeded? Do mass vaccinations help play a role in stabilizing financial markets? In this paper, we investigate the empirical relation between daily mass vaccinations and stock market volatility.

We focus on volatility, as it can be regarded as a barometer of macroeconomic and financial risk, stress, or uncertainty (Zaremba et al., 2020). Stock market volatility is a key input in asset pricing models (Chung, Wang, & Wu, 2019; French, Schwert, & Stambaugh, 1987). It is countercyclical and can be induced by large swings in risk premia that investors require to invest in the stock market (Mele, 2007). Volatility can be driven by the consumption growth uncertainty (Tauchen, 2011). High volatility can disrupt consumption and investment plans in the economy (Campbell, 1993; Campbell, 1996; Campbell, Giglio, Polk, & Turley, 2018). Furthermore, in the consumption-based capital asset pricing model with habit formation of Campbell & Cochrane (1999), stock market volatility can encompass external habit formation, which lies at the heart of consumers' or investors' psychology. This highlights the importance of monitoring stock market volatility by financial analysists, investors, policymakers, and regulators.

To test the effect of vaccination on stock market volatility, we use data covering 66 markets from around the world for the period of the

* Corresponding author.
E-mail addresses: w.rouatbi@montpellier-bs.com (W. Rouatbi), ender.demir@medeniyet.edu.tr (E. Demir), r.kizys@soton.ac.uk (R. Kizys), adam.zaremba@ue.poznan.pl, a.zaremba@montpellier-bs.com (A. Zaremba).

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global COVID-19 pandemic, which ranges from 2020 to 2021. We employ novel international vaccination data that, to our knowledge, has not been employed in any finance studies so far. Using panel regressions, we examine the relationship between various measures of vaccinations and daily stock market volatility.

We find that mass vaccinations significantly decrease the stock market volatility. The decline is independent of the impact of the pandemic's dynamics or the related government policy responses. Furthermore, the phenomenon is robust to many considerations. Moreover, the effect of vaccinations on stock market volatility is relatively more robust in developed than in emerging markets.

Our study contributes to two principal strains of the finance literature. First, we add to the research on the impact of the COVID-19 pandemic on the volatility in international financial markets. Earlier studies primarily concentrated on the role of the pandemic itself—including infections and casualties—or the related government policy responses (Albulescu, 2021; Baek et al., 2020; Bai, Wei, Wei, Li, & Zhang, 2021; Engelhardt, Krause, Neukirchen, & Posch, 2021; Zaremba, Kizys, Tzouvanas, Aharon, & Demir, 2021). We are the first to explore the role of mass COVID-19 vaccination programs on stock market volatility. Second, we extend the discussion on how financial markets react to news on vaccines. Only a few articles have scrutinized this issue. Chan, Chen, Wen, & Xu (2021) document that equity markets react positively when consecutive phases of clinical trials begin. On the other hand, Acharya, Johnson, Sundaresan, & Zheng (2020) explore how successful vaccination programs may affect global wealth. To the best of our knowledge, the vaccines' role within global market volatility remains unchartered territory.

The remainder of the article proceeds as follows. Section 2 surveys the related literature. Section 3 summarizes our data and methodology. Section 4 presents the empirical findings. Finally, Section 5 concludes the study.

2. Literature review

The outbreak of COVID-19 in December 2019 and its worldwide effects have attracted researchers' attention, and the number of studies exploring the impact of the pandemic on financial markets has increased exponentially. Early studies focused on the pandemic's impact on financial markets. In this vein, Al-Awadhi et al. (2020), Topcu & Gulal (2020), and Ashraf (2020a) document that the growth-rate of confirmed COVID-19 cases and deaths negatively influence the stock prices. The effect of the pandemic is found to be heterogeneous across industries (Baek et al., 2020; Goodell & Huynh, 2020; Li, Zhou, Chen, & Liu, 2021). A further extension is performed on the effects of the pandemic on liquidity (Haroon & Rizvi, 2020; Zaremba, Kizys, et al., 2021) and volatility (Albulescu, 2021; Baek et al., 2020; Bai et al., 2021; Engelhardt et al., 2021; Onali, 2020; Zaremba et al., 2020). In addition to equities, ample studies explore the influence on other asset classes such as oil prices (Sharif, Aloui, & Yarovaya, 2020; Wu, Wang, Wang, & Zeng, 2021), gold (Gharib, Mefteh-Wali, & Jabeur, 2021; Mensi, Sensoy, Vo, & Kang, 2020), cryptocurrencies (Conlon & McGee, 2020; Demir, Bilgin, Karabulut, & Doker, 2020), exchange rates (Njindan Iyke, 2020), real estate (Ling, Wang, & Zhou, 2020; Milcheva, 2021), and bonds (Falato, Goldstein, & Hortaçsu, 2020). In addition to the impact of COVID-19-related deaths and cases, the government restrictions imposed to flatten the curve are explored (Ashraf, 2020b; Heyden & Heyden, 2021; Kizys, Tzouvanas, & Donadelli, 2021).

A number of studies investigate which firm-specific factors can mitigate the impact of the pandemic. Ding, Levine, Lin, & Xie (2021), Ramelli & Wagner (2020), and Fahlenbrach, Rageth, & Stulz (2021) emphasize the role of pre-pandemic financial conditions such as low debt, high profitability, and higher financial flexibility to cope with COVID-19. Broadstock, Chan, Cheng, & Wang (2021), Albuquerque, Koskinen, Yang, & Zhang (2020), and Ding et al. (2021) show that stock prices of firms with high environmental ratings and ESG scores are more resilient to the pandemic, while Bae, El Ghoul, Gong, & Guedhami (2021), as well as Takahashi & Yamada (2021) argue that ESG scores cannot provide such an immunity. Exposure to international trade (Ramelli & Wagner, 2020), market power (Hyun, Kim, & Shin, 2020), corporate culture (Li, Liu, Mai, & Zhang, 2020), work from home feasibility (Bai, Brynjolfsson, Jin, Steffen, & Wan, 2020), and family ownership (Ding et al., 2021) are among the factors that can influence the firm performance during the pandemic period. In addition to firm-level factors, the same research questions are also explored at the country level. Prior studies show that the market-level immunity is affected by national culture (Ashraf, 2021; Fernandez-Perez, Gilbert, Indriawan, & Nguyen, 2021; Kaczmarek, Perez, Demir, & Zaremba, 2021), the level of economic freedom (Erdem, 2020), government responses to the pandemic (Narayan, Phan, & Liu, 2021), and pre-pandemic economic conditions (Zaremba, Aharon, Demir, Kizys, & Zawadka, 2021).

An exciting, yet unexplored, field is the impact of vaccines' development and the beginning of mass vaccinations on financial markets. The finance literature explores the impact of clinical trial success of drug development (Hwang, 2013; Rothenstein, Tomlinson, Tannock, & Detsky, 2011), new drug approvals (Chen, Feng, Li, & Huang, 2020), and even news about the potential development of new cancer-curing drugs (Huberman & Regev, 2001) on the stock returns of pharmaceutical companies. However, to our knowledge, research about the vaccine development impact on stock markets is absent until the recent COVID-19 pandemic. The world has not experienced a widespread health crisis such as this one; furthermore, asymptomatic transmission of COVID-19 during the incubation period makes vaccination the only solution to achieve herd immunity. In this regard, pharmaceutical companies in Germany, the United Kingdom, the United States, and China have developed COVID-19 vaccines, which have obtained emergency use authorization from regulatory bodies. Countries have started mass vaccination programs. Only a few articles have scrutinized this issue, and we mainly contribute to this scarce, yet essential, field.

Acharya et al. (2020) develop an asset-pricing perspective to estimate the value of a cure by constructing a novel "vaccine progress indicator." They estimate that a decrease in the expected vaccine deployment time by a year leads to an increase in the stock market return (around 4% to 8% on a daily basis). Moreover, they calculate the exposure levels within each industry and explore the impact of vaccine progress in the cross-section of industries. Industries that are exposed to the pandemic experience a higher positive impact as the vaccine is deployed sooner. Chan et al. (2021) analyze the stock market reactions to the start of human clinical trials for COVID-19 vaccine candidates. They find that the average abnormal return in 49 countries rises by 15.2 basis points (bps) on the first day of clinical trials after controlling for the growth in COVID-19 cases and deaths, as well as investor sentiment. Moreover, the abnormal return increases by 30.0 bps and 51.7 bps on the first day of phase 2 and phase 3 of the human clinical trials of vaccine candidates, respectively. This implies that stock market reactions are even more substantial as vaccine development progresses to later phases.

It is also documented that there is a heterogeneous reaction towards vaccines developed in the United States, China, and other countries. Finally, Hong, Wang, & Yang (2021) construct a model of pandemic risk management and firm valuation. They find that a higher vaccine arrival timing risk will trigger the magnitude of the pandemic shock. Asset valuations are highly sensitive to vaccine arrival rates. The arrival of the vaccine would shift the stock prices to pre-pandemic levels.

Furthermore, the extant finance literature offers convincing evidence linking the spread of the pandemic with the heightened volatility (Albulescu, 2021; Baek et al., 2020; Bai et al., 2021; Engelhardt et al., 2021; Zaremba et al., 2020). Such volatility can occur due to rising economic uncertainty during the pandemic period (Altig et al., 2020; Baker et al., 2020; Sharif et al., 2020), unexpected government interventions to flatten the curve, negative demand- and supply-side

Table 1
Countries covered by the study.

Developed markets				Emerging markets											
1.	Australia	12.	Japan	1.	Argentina	12.	Greece	23.	Morocco	34.	Slovakia
2.	Austria	13.	Netherlands	2.	Bahrain	13.	Hungary	24.	Nigeria	35.	Slovenia
3.	Belgium	14.	New Zealand	3.	Brazil	14.	India	25.	Oman	36.	South Africa
4.	Canada	15.	Norway	4.	Bulgaria	15.	Indonesia	26.	Pakistan	37.	South Korea
5.	Denmark	16.	Portugal	5.	Chile	16.	Jordan	27.	Peru	38.	Sri Lanka
6.	Finland	17.	Singapore	6.	Colombia	17.	Kuwait	28.	Philippines	39.	Taiwan
7.	France	18.	Spain	7.	Croatia	18.	Lithuania	29.	Poland	40.	Thailand
8.	Germany	19.	Sweden	8.	Cyprus	19.	Luxembourg	30.	Qatar	41.	Turkey
9.	Ireland	20.	Switzerland	9.	Czechia	20.	Malaysia	31.	Romania	42.	UAE
10.	Israel	21.	United Kingdom	10.	Egypt	21.	Malta	32.	Russia	43.	Venezuela
11.	Italy	22.	United States	11.	Estonia	22.	Mexico	33.	Saudi Arabia	44.	Vietnam

This table lists the countries covered by our study.

shocks, the constant flow of policy-related news,[1] and divergence of opinions that affects trading activity (Banerjee, 2011; Harris & Raviv, 1993).[2] All these mechanisms may be partly alleviated or reverted by the introduction of vaccines. Heading towards a herd immunity, achieved thanks to vaccinations, lowers the risks of unexpected and uncontrolled growth of the pandemic. It also decreases the potential fatalities. The results should provide less economic uncertainty, lower likelihood of unexpected policies, and—in the end—greater price stability. However, vaccines can also have the opposite effect. Broad and successful vaccination campaigns may result in an overall improvement in the economy-wide sentiment, which correlates closely with the broad stock market sentiment (Jansen & Nahuis, 2003; Otoo, 1999). This positive sentiment can drive volatility up, facilitating more trading and attracting retail investors (Brown, 1999; Kumari & Mahakud, 2015; Wang, Keswani, & Taylor, 2006). In consequence, the overall effect of the vaccines on volatility may be unsure. It is, therefore, an empirical issue as to whether mass vaccinations are associated with more or less stock return volatility.

3. Data and methods

To investigate the effect of COVID-19 vaccinations on stock return volatility, we use daily stock market and pandemic–related data for 66 countries (covered by Datastream Global Equity Indices) from January 1, 2020 to April 30, 2021. Our study period starts on the first trading day after December 31, 2019 when the World Health Organization (WHO) was informed of pneumonia cases of unknown cause being detected in Wuhan City, China (WHO, 2020).[3] We gather vaccination statistics from a novel dataset from the COVID-19 Data Hub website, funded by the Institute for Data Valorization (IVADO, Canada).[4] To the best of our knowledge, this data has, so far, never been used in finance studies. We exclude China from our analysis because of the unavailability of daily vaccination data for this country.[5] Table 1 visualizes the list of markets covered by our data set.

In our principal empirical analysis, we estimate different specifications of the following model:

$$VOLATILITY_{i,t} = \alpha + \beta \bullet VACCINATION_{i,t-1} + \Gamma^{'} \bullet CONTROLS_{i,t-1} + \Lambda^{'} \bullet WEEKDAY_{i,t} + \varepsilon_{i,t} \quad (1)$$

where $VOLATILITY_{i,t}$ is one of two variables, Log $|R|_{i,t}$ and Log $|RR_{CAPM}|_{i,t}$ for country i on day t. The dependent variable Log $|R|$ is the natural logarithm of absolute daily returns. The use of absolute returns to measure volatility is informed by Antonakakis & Kizys (2015). To ensure the robustness of our findings, we consider an alternative measure of stock return volatility; namely, the natural logarithm of absolute residual returns from the CAPM model, Log $|RR_{CAPM}|$, similarly as in Schwert (1989). Following Zaremba et al. (2020), the logarithmic transformation a) warrants that daily volatility in levels is positive definite, and b) allows to account for the presence of non-linearities in the relation between the level of volatility and its covariates. The residual is estimated using rolling regressions based on five years of daily data. The market return in the model is proxied by the value-weighted portfolio of all the markets in the sample. The risk-free return is sourced from Kenneth R. French's website.[6]

Our primary focus is on the coefficient of *VACCINATION*. To assure the robustness of our findings, we use four different vaccination-related variables. Namely, i) Log (Daily Vaccinations), defined as the natural logarithm of the daily number of COVID-19 vaccinations. ii) Daily Vaccinations Per 100,000, computed as the daily number of COVID-19 vaccinations divided by the country population and then multiplied by 100,000. We use daily vaccinations by 100,000 instead of daily vaccinations per million to improve the readability of our tables by scaling up the coefficients of this variable (using only four decimals). iii) Vaccination Period, which is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Finally, iv) Δ Daily Vaccinations Dummy, which is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Negative coefficients of these four variables would suggest that stock market volatility decreases with the daily number of vaccinated individuals and when the countries get access to COVID-19 vaccines.

CONTROLS is a vector of control variables, which are shown in prior studies to affect stock return volatility (Bae et al., 2021; Zaremba et al., 2020). This vector includes i) Stringency Index, a score between 0 and 100 that reflects the stringency of a government policy response to the COVID-19 pandemic. The index, obtained from Hale et al. (2021), aggregates a range of different containment and closure measures (Zaremba et al., 2020). ii) BM, which is the book-to-market ratio based on accounting data lagged by four months to avoid look-ahead bias. iii) Log (TV), computed as the natural logarithm of daily trading volume in U.S. dollars. iv) Δ Infections to Cases, defined as the daily change in the number of COVID-19 infections to the cumulative number of cases. v) Δ Deaths to Cases, which is the daily change in the number of COVID-19 deaths to the cumulative number of cases. Finally, vi) US Elections, which is a dummy variable that takes the value 1 for the period that starts at November 3, 2020 (election date) and ends on January 7, 2021

[1] "News implied volatility and disaster concerns," (Manela & Moreira, 2017).

[2] Hasan, Politsidis, & Sharma (2021) indicate that the COVID-19 pandemic adversely affected the costs of financing.

[3] Our results are robust to starting the period at different later dates, such as March 11, 2020, the date at which the WHO announced the COVID–19 outbreak a pandemic.

[4] Https://covid19datahub.io.

[5] In an unreported analysis, we experimented with including Chinese statistics based on interpolated newspaper estimates. Our findings remained unaffected.

[6] *Https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.*

Table 2
Descriptive statistics.

	Log $\lvert R\rvert$	Log $\lvert RR_{CAPM}\rvert$	Log (Daily Vaccinations)	Daily Vaccinations Per 100,000	Vaccination Period	Δ Daily Vaccinations Dummy	Stringency Index	BM	Log (TV)	Log (MV)	Δ Infections to Cases	Δ Deaths to Cases	US Elections
Panel A: Descriptive statistics: Full sample													
Mean	−5.277	−5.375	1.860	70.501	0.207	0.102	55.101	0.719	11.450	11.781	0.005	0	0.138
St. deviation	1.395	1.265	4.082	219.282	0.405	0.302	25.622	0.424	3.499	2.084	0.059	0.001	0.345
First quartile	−5.947	−6.036	0	0	0	0	42.130	0.521	9.087	10.170	−0.002	0	0
Median	−5.053	−5.183	0	0	0	0	60.190	0.705	11.963	11.885	0	0	0
Third quartile	−4.326	−4.500	0	0	0	0	74.540	0.925	14.066	13.267	0.003	0	0
Panel B: Descriptive statistics: Developed markets													
Mean	−5.119	−5.393	2.232	92.857	0.237	0.128	53.697	0.647	13.992	13.416	0.005	0	0.138
St. deviation	1.306	1.215	4.459	251.692	0.426	0.334	24.331	0.241	2.019	1.496	0.058	0.001	0.345
First quartile	−5.733	−6.015	0	0	0	0	40.740	0.472	12.542	12.385	−0.001	0	0
Median	−4.910	−5.174	0	0	0	0	60.190	0.610	13.976	13.311	0	0	0
Third quartile	−4.246	−4.549	0	0	0	0	71.300	0.778	15.237	14.465	0.003	0	0
Panel C: Descriptive statistics: Emerging markets													
Mean	−5.356	−5.366	1.667	58.876	0.192	0.089	55.803	0.756	10.151	10.963	0.004	0	0.138
St. deviation	1.431	1.289	3.857	199.39	0.394	0.284	26.217	0.487	3.380	1.841	0.059	0.001	0.345
First quartile	−6.055	−6.050	0	0	0	0	43.060	0.572	7.666	9.786	−0.002	0	0
Median	−5.134	−5.187	0	0	0	0	61.110	0.786	10.453	10.822	0	0	0
Third quartile	−4.376	−4.477	0	0	0	0	75.930	0.969	12.762	12.473	0.003	0	0

This table presents descriptive statistics on the different variables used in our primary analysis. Log $\lvert R\rvert$ (Log $\lvert RR_{CAPM}\rvert$) is the logarithm of absolute daily returns (the logarithm of residual returns from the CAPM model). Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccination Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Stringency Index is a score between 0 and 100 that reflects the daily government response to COVID-19 and is computed using different government nonpharmaceutical interventions. BM is the book-to-market ratio. Log (TV) is the natural logarithm of daily trading volume in U.S. dollars. Log (MV) is the natural logarithm of market capitalization in U.S. dollars. Δ Infections to Cases is the daily change in the number of COVID-19 infections to the total number of confirmed COVID-19 cases (in percentage). Δ Deaths to Cases is the daily change in the number of COVID-19 deaths to the total number of confirmed COVID-19 cases (in percentage). US Elections is a dummy variable that takes the value of 1 for the period that starts at November 3, 2020 and ends at January 7, 2021, and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 3
Pairwise correlation coefficients between major variables.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Log $\lvert R \rvert$	1.000												
2. Log $\lvert RR_{CAPM} \rvert$	0.611***	1.000											
3. Log (Daily Vaccinations)	−0.055***	−0.054***	1.000										
4. Daily Vaccinations Per 100,000	−0.053***	−0.054***	0.743***	1.000									
5. Vaccination Period	−0.073***	−0.068***	0.878***	0.619***	1.000								
6. Δ Daily Vaccinations Dummy	−0.039***	−0.041***	0.729***	0.597***	0.649***	1.000							
7. Stringency Index	0.052***	0.070***	0.209***	0.160***	0.219***	0.148***	1.000						
8. BM	0.024***	0.027***	−0.110***	−0.053***	−0.092***	−0.076***	0.098***	1.000					
9. Log (TV)	0.134***	0.078***	0.068***	0.025***	0.022***	0.038***	−0.008	−0.141***	1.000				
10. Log (MV)	0.081***	0.023***	0.094***	0.047***	0.048***	0.054***	−0.033***	−0.236***	0.917***	1.000			
11. Δ Infections to Cases	0.055***	0.041***	−0.034***	−0.020***	−0.039***	−0.015**	−0.065***	0.004	0.018**	0.008	1.000		
12. Δ Deaths to Cases	0.022***	0.015**	−0.018***	−0.009	−0.021***	−0.004	0.016**	0.011*	0.016**	0.008	0.335***	1.000	
13. US Elections	−0.051***	−0.032***	−0.117***	−0.109***	−0.098***	−0.063***	0.110***	−0.029***	0.013*	0.011*	−0.033***	−0.017***	1.000

This table displays correlation coefficients between the different variables used in our primary analysis. Log |R| (Log $\lvert RR_{CAPM} \rvert$) is the logarithm of absolute daily returns (the logarithm of residual returns from the CAPM model). Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccinations Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Stringency Index is a score between 0 and 100 that reflects the daily government response to COVID-19 and is computed using different government nonpharmaceutical interventions. BM is the book-to-market ratio. Log (TV) is the natural logarithm of daily trading volume in U.S. dollars. Log (MV) is the natural logarithm of market capitalization in U.S. dollars. Δ Infections to Cases is the daily change in the number of COVID-19 infections to the total number of confirmed COVID-19 cases (in percentage). Δ Deaths to Cases is the daily change in the number of COVID-19 deaths to the total number of confirmed COVID-19 cases (in percentage). US Elections is a dummy variable that takes the value of 1 for the period that starts at November 3, 2020 and ends at January 7, 2021, and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. The asterisks *** and ** denote statistical significance at the 1% and 5% levels, respectively.

(when the Congress confirmed Joe Biden as the winner), and zero otherwise. *Weekday dummies (WEEKDAY)* is a vector of indicator variables to control for the potential day of the week effect on market return volatility (Kiymaz & Berument, 2003). Furthermore, to extend Eq. (1) to a dynamic panel framework, we add the lagged dependent variable to the list of control variables.

Panel A of Table 2 reports descriptive statistics of the variables used in our primary analysis. All continuous variables are winsorized at the 1st and the 99th percentiles to mitigate the effect of outliers. Statistics of the two dependent variables are in line with those of Zaremba et al. (2020) with a mean Log |R| and mean Log $\lvert RR_{CAPM} \rvert$ of −5.277 and −5.375, respectively. Table 2 also shows that the average number of daily vaccinations per 100,000 is relatively low (less than 71); this is because most of the country-day observations are not in the vaccination period (mean Vaccination Period of 0.207). Panels B and C of Table 2 display descriptive statistics for the subsamples of developed and emerging markets, respectively. Not surprisingly, the vaccination-related variables are, on average, higher in developed countries compared to emerging ones.

Table 3 shows the pairwise correlation coefficients between all the variables used in our principal analysis and indicates that Log |R| and Log $\lvert RR_{CAPM} \rvert$ are both significantly and negatively correlated with each of the four vaccination-related variables, thus providing preliminary evidence that COVID-19 vaccination programs play an important role in stabilizing the global equity markets. Moreover, the correlation coefficients between the four vaccination variables are highly positive (more than 0.597). Interestingly, the correlations among the regressors are generally low, except those between Log (TV) and Log (MV). Thus, we run our regressions after using only one of these two variables as a regressor.

The baseline regression, outlined in Eq. (1), is estimated using three different methods: pooled ordinary least squares (OLS), fixed effects, and random effects estimator. First, the use of pooled OLS is motivated by other studies that examined the effects of COVID-19 on financial markets (see, e.g., Kizys et al., 2021; Papadamou, Fassas, Kenourgios, & Dimitriou, 2021). Following Wooldridge (2002, p. 150), the pooled OLS estimator is consistent insofar as it meets two conditions: i) the orthogonality conditions $E(X_{i,\,t}{}'\varepsilon_{i,\,t}) = 0$, where $X_{i,\,t}{}'$ is the row vector of the explanatory variables (*VACCINATION*, *CONTROLS*, and *WEEKDAY*); and ii) the mild rank condition $E(\sum_{t=1}^{T} X_{i,\,t}{}'X_{i,\,t}) = K$, where K is the number of explanatory variables in the model. Second, the fixed effects estimator additionally allows to account for any observed heterogeneity in stock market volatility across countries. An advantage of the fixed effects estimator is that it allows for arbitrary correlation between the unobserved country fixed effect and the observed explanatory variables, $X_{i,\,t}$. Third, juxtaposed with the pooled OLS and fixed effects estimators, the random effects estimator carries several advantages and may be preferred under specific scenarios. First, when the sample is relatively small and is relative to the entire population (Gelman, 2005; Green & Tukey, 1960). Second, the random effects estimator is preferred if the focus is on the entire population from which the sample is drawn, rather than in unobserved country-specific characteristics, per se (Gelman, 2005; Searle, George Casella, & McCulloch, 2009, p. 15–16). Third, the fixed effects estimation method requires estimating country-specific intercepts, which can come at the cost of a significant reduction in the number of degrees of freedom. Fourth, the random effects estimator allows to control for time-invariant predictors of stock market volatility. Notably, our conclusions do not depend on this methodological choice. Therefore, the results remain qualitatively unchanged (see Section 4.2 for details).

4. Results

We begin our discussion of results with an overview of the general findings. Subsequently, we turn to further robustness checks and additional analyses.

Table 4
Main regressions.

	Dependent variable: Log $\vert R \vert$				Dependent variable: Log $\vert RR_{CAPM} \vert$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Daily Vaccinations) $_{t-1}$	−0.0245***				−0.0193***			
	(−10.62)				(−9.11)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0004***				−0.0003***		
		(−9.23)				(−8.76)		
Vaccination Period			−0.2824***				−0.2271***	
			(−12.35)				(−10.69)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.2041***				−0.2008***
				(−6.78)				(−7.12)
Log $\vert R \vert$ $_{t-1}$	0.1490***	0.1507***	0.1475***	0.1532***				
	(19.66)	(19.89)	(19.74)	(20.19)				
Log $\vert RR_{CAPM} \vert$ $_{t-1}$					0.1615***	0.1621***	0.1598***	0.1648***
					(22.45)	(22.50)	(22.48)	(22.88)
Stringency Index $_{t-1}$	0.0026***	0.0023***	0.0026***	0.0021***	0.0029***	0.0027***	0.0029***	0.0026***
	(7.09)	(6.20)	(7.17)	(5.70)	(8.38)	(7.82)	(8.54)	(7.52)
BM $_{t-1}$	0.1077***	0.1238***	0.1026***	0.1235***	0.0903***	0.1020***	0.0841***	0.0999***
	(5.22)	(6.00)	(5.03)	(5.96)	(4.57)	(5.18)	(4.31)	(5.05)
Log (TV) $_{t-1}$	0.0578***	0.0567***	0.0575***	0.0566***	0.0375***	0.0367***	0.0372***	0.0368***
	(21.36)	(20.95)	(21.45)	(20.85)	(15.03)	(14.72)	(15.02)	(14.72)
Δ Infections to Cases $_{t-1}$	1.1661***	1.1636***	1.1887***	1.1605***	1.1197***	1.1158***	1.1303***	1.1104***
	(6.64)	(6.60)	(6.85)	(6.58)	(6.79)	(6.76)	(6.92)	(6.72)
Δ Deaths to Cases $_{t-1}$	11.4441	11.1499	12.8158	11.1452	21.6755**	21.2725**	22.0595**	21.1077**
	(1.05)	(1.02)	(1.20)	(1.01)	(2.21)	(2.16)	(2.29)	(2.14)
US Elections	−0.2449***	−0.2308***	−0.2397***	−0.2156***	−0.1574***	−0.1491***	−0.1555***	−0.1383***
	(−8.79)	(−8.33)	(−8.73)	(−7.81)	(−6.49)	(−6.19)	(−6.50)	(−5.77)
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756
R^2	0.0693	0.0680	0.0709	0.0663	0.0575	0.0570	0.0583	0.0564
F–value	125.75***	122.81***	131.95***	119.45***	104.18***	103.55***	108.07***	100.88***

This table presents pooled OLS estimates of the relationship between COVID-19 vaccinations and stock return volatility. The dependent variables are the logarithm of absolute daily returns (Log $|R|$, Columns 1–4) and the logarithm of absolute residual returns from the CAPM model (Log $|RR_{CAPM}|$, Columns 5–8). Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations Per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccinations Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Stringency Index is a score between 0 and 100 that reflects the daily government response to COVID-19 and is computed using different government nonpharmaceutical interventions. BM is the book-to-market ratio. Log (TV) is the natural logarithm of daily trading volume in U.S. dollars. Log (MV) is the natural logarithm of market capitalization in U.S. dollars. Δ Infections to Cases is the daily change in the number of COVID-19 infections to the total number of confirmed COVID-19 cases (in percentage). Δ Deaths to Cases is the daily change in the number of COVID-19 deaths to the total number of confirmed COVID-19 cases (in percentage). US Elections is a dummy variable that takes the value of 1 for the period that starts at November 3, 2020 and ends at January 7, 2021, and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. All specifications include weekday dummies. Heteroskedasticity-robust *t*-statistics are in parentheses beneath the regressions' coefficients. The asterisks *** and ** denote statistical significance at the 1% and 5% levels, respectively. *Obs.* and R^2 denote the number of observations and the coefficient of determination, respectively.

4.1. Baseline empirical findings

Our baseline empirical findings are summarized in Table 4. In the estimated regression models, as summarized in Columns 1–4, the stock return volatility is constructed as the natural logarithm of absolute daily returns, which can be regarded as a total (i.e., systematic and unsystematic) risk of investment. By contrast, in Columns 5–8, the volatility measured as the natural logarithm of absolute daily residual returns, obtained from the CAPM, can be interpreted as an unsystematic risk of investment. In Columns 1 and 5 (2 and 6, 3 and 7, 4 and 8), the key explanatory variable is the log of daily vaccinations (Daily Vaccinations Per 100,000, Vaccination Period, and Δ Daily Vaccinations Dummy, respectively).

We begin by scrutinizing the coefficient estimates summarized in Columns 1 and 5. The results show that the log of daily vaccinations exerts a negative and significant effect (at the 1% significance level) on stock return volatility. This effect has a similar size for the two volatility measures. Therefore, both the systematic and unsystematic risks of investment diminish in response to mass vaccinations. Specifically, when daily vaccinations increase by 10%, stock return volatility decreases by 0.245% if the volatility is measured as the log of absolute returns; on the other hand, it decreases by 0.193% if the volatility is measured as the log of absolute residual returns.

In agreement with the results displayed in Columns 1 and 5, the coefficient estimates reported in Columns 2 and 6 indicate that the number of vaccinations per 100,000 has a negative and significant effect on the two measures of stock market volatility. Thus, the larger the share of a population is immunized, the larger the volatility decline is in international stock markets. Specifically, if 1000 individuals per 100,000 are immunized on a given day, the stock market volatility declines by 0.4% and 0.3% if the volatility is measured as the log of absolute returns and the log of absolute residual returns, respectively.

Qualitatively similar results are echoed in Columns 3 and 7, which indicate that stock market volatility declined markedly after mass vaccinations were rolled out irrespective of the vaccination scale. Concretely, the stock market volatility is 0.2824% (0.2271%) lower after the rollout of vaccines than before the rollout if the logarithm of absolute returns (residual returns) is used as the dependent variable.

Next, we also scrutinize if an increase in daily vaccinations manifests in volatility declines. In this regard, the results summarized in Columns 4 and 8 show that positive changes in the number of persons immunized during vaccination campaigns trigger adverse effects on volatility. Notably, in countries where the number of daily vaccinations on average increased during the vaccination period, the volatility decreased by 0.2041% and 0.2008% for absolute returns and absolute residual returns, respectively.

All in all, mass vaccinations stabilize stock market volatility through reduced uncertainty levels. This finding is consistent with Altig et al.

Table 5
Robustness tests: alternative regression frameworks and dependent variables.

Panel A: Alternative regression frameworks

	Without weekday dummies				Fixed effects regressions				Random effects regressions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (Daily Vaccinations) $_{t-1}$	−0.0250***				−0.0223***				−0.0245***			
	(−10.81)				(−2.97)				(−7.22)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0004***				−0.0003***				−0.0004***		
		(−9.56)				(−2.79)				(−5.15)		
Vaccination Period			−0.2847***				−0.2404***				−0.2824***	
			(−12.43)				(−3.14)				(−8.92)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.2211***				−0.1669**				−0.2041***
				(−7.43)				(−2.15)				(−5.01)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756
R^2	0.0638	0.0626	0.0653	0.0610	0.0474	0.0463	0.0474	0.0454	0.0363	0.0338	0.0370	0.0320
F–value (Wald chi2)	174.16***	170.14***	183.40***	164.71***	51.40***	47.10***	50.30***	46.65***	(666.80***)	(540.24***)	(712.48***)	(594.21***)

Panel B: Alternative dependent variables

	Dependent variable: Log $\lvert RR_{FF} \rvert$				Dependent variable: Log $\lvert RR_{AMP} \rvert$				Dependent variable: Log $\lvert RR_{CAR} \rvert$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (Daily Vaccinations) $_{t-1}$	−0.0179***				−0.0176***				−0.0170***			
	(−8.57)				(−8.50)				(−8.24)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0003***				−0.0003***				−0.0003***		
		(−8.99)				(−8.58)				(−8.76)		
Vaccination Period			−0.1928***				−0.2120***				−0.1883***	
			(−9.44)				(−10.19)				(−9.22)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.1829***				−0.1747***				−0.1706***
				(−6.64)				(−6.41)				(−6.28)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756
R^2	0.0531	0.0534	0.0529	0.0519	0.0522	0.0522	0.0527	0.0511	0.0518	0.0520	0.0513	0.0506
F–value	94.81***	95.11***	97.18***	92.52***	95.60***	95.71***	98.75***	92.84***	93.32***	94.22***	95.09***	90.95***

This table presents the results of different robustness tests. Panel A displays the regression results using the logarithm of absolute daily returns (Log |R|) as the dependent variable and after excluding the weekday dummies (Columns 1–4), and reports results from fixed effects (Columns 5–8) and random effects (Columns 9–12) estimations. In the regressions of Panel B, alternative dependent variables are used, namely, the logarithms of absolute residual returns from the Fama & French (1993) model (Log $\lvert RR_{FF} \rvert$, Columns 1–4), the Asness et al. (2013) model (Log $\lvert RR_{AMP} \rvert$, Columns 5–8), and the Carhart (1997) model (Log $\lvert RR_{CAR} \rvert$, Columns 9–12). Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccinations Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero, otherwise. Heteroskedasticity-robust *t*- and z-statistics are in parentheses beneath the regressions' coefficients. All continuous variables are winsorized at the 1st and 99th percentiles. The asterisks *** and ** denote statistical significance at the 1% and 5% levels, respectively. *Obs.* and R^2 denote the number of observations and the coefficient of determination, respectively.

Table 6
Robustness tests: additional control variables.

Panel A: Additional control variables: Set 1

	Log (MV) $_{t-1}$				Momentum $_{t-1}$				Crisis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (Daily Vaccinations) $_{t-1}$	−0.0235***				−0.0173***				−0.0223***			
	(−10.23)				(−5.91)				(−9.68)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0004***				−0.0002***				−0.0004***		
		(−8.91)				(−5.25)				(−8.79)		
Vaccination Period			−0.2742***				−0.2452***				−0.2556***	
			(−12.04)				(−8.23)				(−11.20)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.1984***				−0.0941***				−0.1864***
				(−6.63)				(−2.82)				(−6.20)
Additional control variable	−0.1278***	−0.1291***	−0.1250***	−0.1327***	−0.2106***	−0.2872***	−0.1033*	−0.3446***	0.8424***	0.8519***	0.8370***	0.8560***
	(−10.72)	(−10.82)	(−10.68)	(−11.08)	(−4.00)	(−6.10)	(−1.94)	(−7.48)	(22.33)	(22.58)	(22.37)	(22.65)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756
R^2	0.0750	0.0738	0.0763	0.0724	0.0701	0.0697	0.0710	0.0689	0.0908	0.0900	0.0918	0.0885
F–value	123.41***	120.76***	129.11***	118.29***	116.96***	116.03***	121.92***	114.07***	162.67***	160.82***	168.34***	158.30***

Panel B: Additional control variables: Set 2

	With month dummies				With quarter dummies			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Daily Vaccinations) $_{t-1}$	−0.0424***				−0.0373***			
	(−15.22)				(−14.17)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0006***				−0.0005***		
		(−12.66)				(−11.26)		
Vaccination Period			−0.4927***				−0.4453***	
			(−17.26)				(−16.51)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.2982***				−0.2922***
				(−8.93)				(−9.04)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756
R^2	0.0923	0.0888	0.0946	0.0854	0.0760	0.0721	0.0788	0.0703
F–value	89.78***	85.25***	94.64***	82.27***	110.22***	104.09***	117.25***	101.27***

This table presents the results of different robustness tests. Panel A shows regression results using Log |R| as the dependent variable, and after including three variables—one at a time—as additional controls to our main regressions. Log (MV) is the natural logarithm of market capitalization in U.S. dollars. Momentum is defined as the total log return in months *t*–12 to *t*–2. Crisis is a dummy variable that takes the value of 1 for the COVID-19 crisis period from February 18 to March 20, 2020 (Bae et al., 2021). In Panel B, month (Columns 1–4) and quarter (Columns 5–8) dummies are added to the regressions. Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccinations Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Heteroskedasticity-robust *t*-statistics are in parentheses beneath the regressions' coefficients. All continuous variables are winsorized at the 1st and 99th percentiles. The asterisks *** and ** denote statistical significance at the 1% and 5% levels, respectively. *Obs.* and R^2 denote the number of observations and the coefficient of determination, respectively.

Table 7
Robustness tests: alternative study periods.

Panel A: Starting from March 11, 2020 (when the WHO considered the COVID-19 as a pandemic)

	Dependent variable: Log |R|				Dependent variable: Log |RR_{CAPM}|			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Daily Vaccinations) $_{t-1}$	−0.0247***				−0.0192***			
	(−10.65)				(−9.04)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0004***				−0.0003***		
		(−9.24)				(−8.64)		
Vaccination Period			−0.2851***				−0.2274***	
			(−12.43)				(−10.67)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.2017***				−0.1990***
				(−6.67)				(−7.03)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17,852	17,852	18,376	17,827	17,852	17,852	18,376	17,827
R^2	0.0642	0.0626	0.0663	0.0606	0.0532	0.0527	0.0546	0.0517
F–value	99.16***	96.31***	105.36***	93.16***	81.58***	80.89***	85.79***	77.84***

Panel B: Starting from June 6, 2020 (end of the post-crisis recovery period, Bae et al., 2021)

	Dependent variable: Log |R|				Dependent variable: Log |RR_{CAPM}|			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Daily Vaccinations) $_{t-1}$	−0.0149***				−0.0113***			
	(−6.26)				(−5.16)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0003***				−0.0002***		
		(−6.36)				(−6.00)		
Vaccination Period			−0.1785***				−0.1428***	
			(−7.57)				(−6.49)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.1175***				−0.1273***
				(−3.85)				(−4.43)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,611	15,611	16,099	15,586	15,611	15,611	16,099	15,586
R^2	0.0414	0.0415	0.0427	0.0399	0.0340	0.0345	0.0348	0.0336
F–value	56.26***	55.95***	59.67***	53.92***	44.34***	45.10***	46.60***	43.29***

Panel C: Starting from August 11, 2020 (Russia approved the world's first COVID-19 vaccine)

	Dependent variable: Log |R|				Dependent variable: Log |RR_{CAPM}|			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Daily Vaccinations) $_{t-1}$	−0.0059**				−0.0075***			
	(−2.18)				(−3.01)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0001***				−0.0002***		
		(−3.33)				(−4.26)		
Vaccination Period			−0.0880***				−0.1095***	
			(−3.19)				(−4.27)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.0267				−0.0790***
				(−0.82)				(−2.58)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	11,330	11,330	11,759	11,305	11,330	11,330	11,759	11,305
R^2	0.0356	0.0361	0.0365	0.0352	0.0336	0.0343	0.0343	0.0334
F–value	35.39***	35.75***	37.58***	34.81***	31.68***	32.39***	33.62***	31.20***

This table presents the results of different robustness tests. In all panels, two dependent variables are used, namely, Log |R| (Columns 1–4) and Log |RR_{CAPM}| (Columns 5–8). Panels A, B, and C display the regression results for alternative periods that start at March 11, June 6, and August 11, 2020, respectively. Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccinations Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Heteroskedasticity-robust *t*-statistics are in parentheses beneath the regressions' coefficients. All continuous variables are winsorized at the 1st and 99th percentiles. The asterisks *** and ** denote statistical significance at the 1% and 5% levels, respectively. *Obs.* and R^2 denote the number of observations and the coefficient of determination, respectively.

(2020), who underscore the time needed to develop and deploy vaccines as one of the key risk elements of the multidimensional economic uncertainty driven by the COVID-19 pandemic. This finding contrasts with the positive volatility effect of the Stringency Index, which synthesizes nonpharmaceutical government interventions. Along similar lines, Zaremba et al. (2020) document that nonpharmaceutical government responses, such as public information campaigns or cancellations of public events to reduce the reproduction rate of COVID-19, can trigger rises in stock market volatility. By contrast, we find that government health policies, which aim to achieve herd immunity within a society through mass vaccinations, are conducive to volatility declines in international stock markets. In agreement with Zaremba et al. (2020), the negative volatility effect of mass vaccinations may also signal a lower probability of stringent government responses to the COVID-19 pandemic in the future.

Moreover, vaccinations can improve public health and boost public investments (Masia, Smerling, Kapfidze, Manning, & Showalter, 2018), which leads to higher life expectancy. Higher life expectancy, in turn,

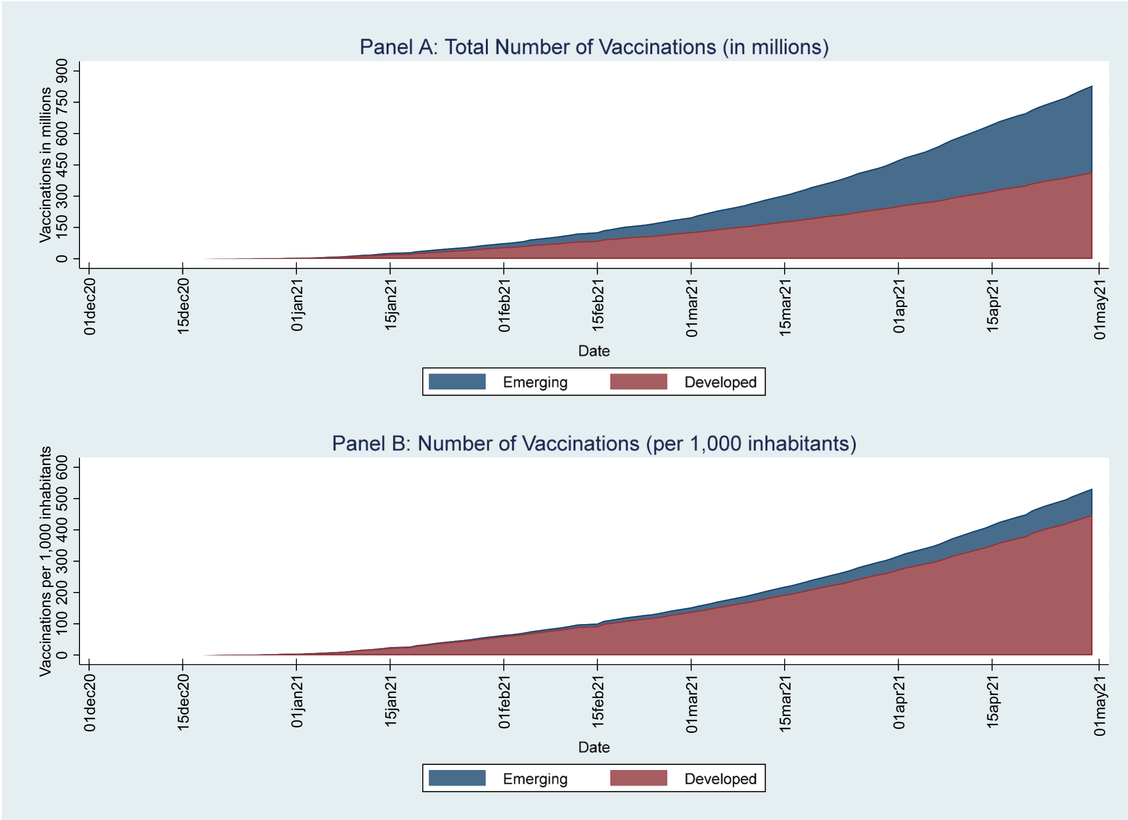

Fig. 1. Vaccination rates in developed and emerging markets.
The figure provides an overview of vaccination intensity in developed and emerging markets from when the vaccination programs officially started. Panel A presents the total number of vaccinations in millions. Panel B shows the number of shots given per 1000 inhabitants. The data for the period December 14, 2020, to April 30, 2021, is sourced from the COVID-19 Data Hub.

increases households' incentive to smooth consumption over time and save a larger share of their income (Heaton & Lucas, 1999), possibly in the form of stock market investments. Thus, when a vaccination campaign is rolled out in a country, there is a higher probability of a bull market stance, which is associated with a reduced risk of fire sales and lower stock market volatility.

4.2. Robustness checks

We undertake a number of robustness checks to ensure the validity of our results. The robustness checks are displayed in Tables 5 to 7, which, in turn, consist of a number of panels. In Table 5, Panel A, we summarize the estimation results of three different regression models: pooled OLS regressions without weekday dummies (Columns 1–4), fixed-effects regressions (Columns 5–8), and random-effects regressions (Columns 9–12). While weekday dummies are commonly used to control for the day of the week effect, we run our model without weekday dummies to explore whether our conclusions remain virtually intact. The baseline regression is estimated using pooled ordinary least squares (OLS) despite the fact that this approach is consistent under specific conditions. To overcome this possible concern, we perform fixed- and random-effects estimations. The fixed effects estimator accounts for any observed heterogeneity in stock market volatility across countries, while the random effects estimator carries several advantages and may be preferred under specific scenarios, which are discussed above.

To further verify that our findings are robust, we visualize in Table 5, Panel B, estimation results from regression models with alternative measures of the dependent variable, in line with the previous studies. In Columns 1–4, the dependent variable is the logarithm of absolute residual returns from the Fama & French (1993) model. In Columns 5–8, the results are for the logarithm of absolute residual returns from Asness, Moskowitz, & Pedersen (2013). Columns 9–12 display the results for the logarithm of absolute residual returns from the Carhart (1997) model. The details of the estimation of these residuals closely follow those of Zaremba et al. (2020).

The robustness checks in Table 6 concentrate on additional control variables that might affect the stock market volatility. In Table 6, Panel A, we include different asset pricing variables: the logarithm of market capitalization (Columns 1–4) and the momentum factor (Columns 5–8). As the early period of the pandemic (from February 18 to March 20, 2020) has a shocking and severe effect on the financial markets (Bae et al., 2021), we control for this period in the regression models with the crisis dummy (Columns 9–12).

Furthermore, it is well-known that there are seasonal effects (such as January effect, sell in May and go away, and end of the year), which might affect the stock markets. To control for such an effect, we additionally incorporate monthly (Columns 1–4) and quarterly (Columns 5–8) dummies in Table 6, Panel B.

Finally, Table 7 considers alternative holding periods. To ensure that our conclusions do not depend on our specific choice of the study period, we experiment with several alternative starting points. Table 7, Panel A, displays the results for the research period beginning on March 11, 2020, when the WHO declared the COVID-19 a pandemic. The study period in Panel B, on the other hand, starts on June 6, 2020. This date was chosen by Bae et al. (2021) as the symbolic end of the initial post-crisis rebound period. Lastly, the starting date in Panel C is August 11, 2020, when Russia approved the world's first COVID-19 vaccine.

Tables 5 to 7 show that our baseline results remain robust to the various model specifications, alternative stock market volatility measures, different control variables, and modified study periods.

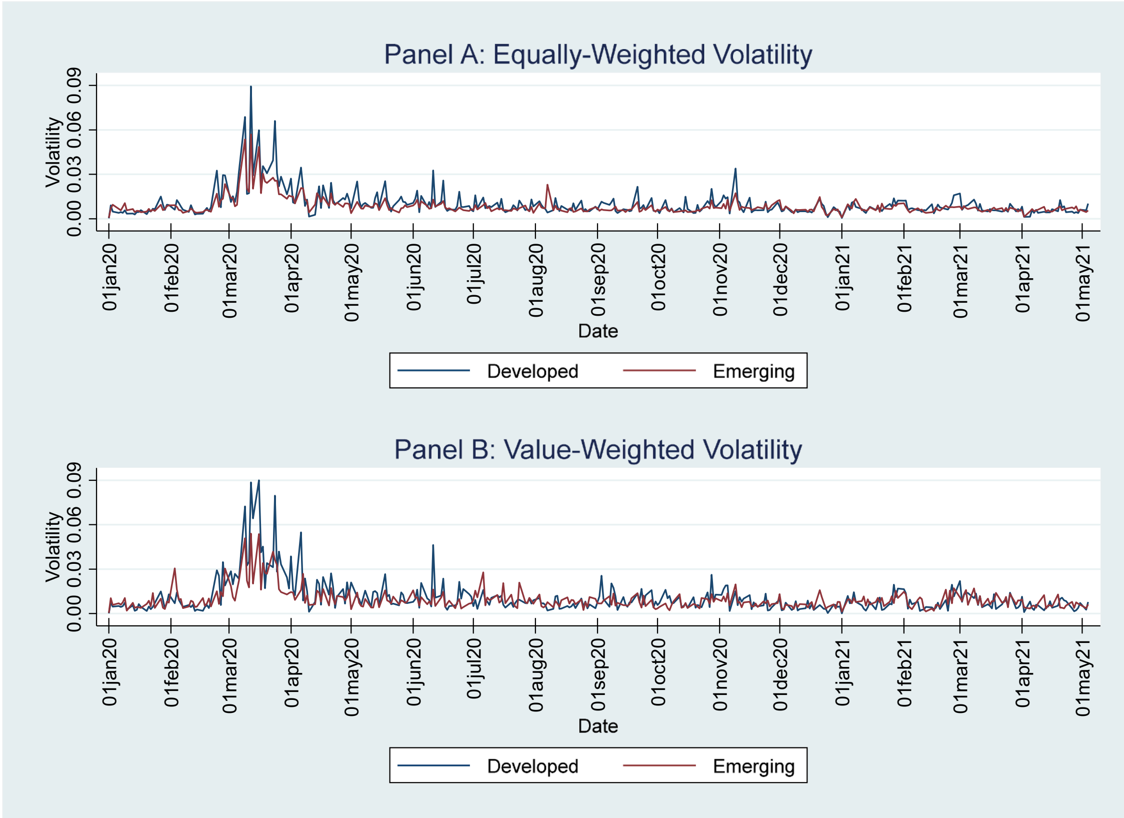

Fig. 2. Volatility in international markets during the COVID-19 pandemic.
The figure presents the average absolute returns (in %) across markets that were considered in our sample. The reported measures of volatility are for the subsamples of 22 developed and 44 emerging markets. The study period runs from January 1, 2020, to April 30, 2021. Panel A reports equal-weighted averages, while Panel B presents averages weighted according to the market capitalization.

Importantly, in all cases, the four vaccination indicators exert a negative and significant effect on the stock market volatility. Notably, the volatility effect of each vaccination measure generally features a comparable magnitude across the various model specifications. To sum up, while a vaccination campaign can improve public health in a country, our findings show that its effects extend beyond the health sector; namely, a vaccination campaign in a country is associated with a stock market volatility decline.

4.3. Vaccination effects in developed and emerging markets

So far, the global vaccination programs have revealed a striking vaccination gap between developed and emerging markets. While more than 450 million doses have already been administered worldwide, the vast majority of them have benefited the inhabitants of developed countries (Toole, 2021).[7] An investigation of commitments to buy 7.48 billion doses of COVID-19 vaccines in November 2020 revealed that more than half would go to just 14% of the global population who live in high-income countries (So & Woo, 2020). The Economics Intelligence Unit (2021) estimates that more than 85% of developing countries will not have widespread access to vaccines until 2023.

Fig. 1 presents elementary vaccination statistics through time. Over the sample period, the developed markets administered more doses than the emerging ones (Fig. 1, Panel A). The discrepancy becomes even more remarkable when considering the relative size of populations (Fig. 1, Panel B). Since there are many more people living in emerging markets than in developed markets, the difference in doses administered per 1000 inhabitants widens further. While in the developed countries in our sample, on average, 448 doses per 1000 inhabitants were administered (as of April 30, 2021), the equivalent number for the remaining markets was only 84.

Fig. 2 visualizes the variation over time in the average volatility. In Panel A, the equally weighted volatility measure is shown. In Panel B, the value-weighted volatility measure is shown, where the weights were calculated based on the market capitalization in a country on a given day. The figure indicates that volatility increased markedly in March/April 2020, when the WHO declared the COVID-19 outbreak a pandemic. Interestingly, the equally-weighted volatility is generally higher for the developed market countries relative to emerging market countries over the sample period. Nevertheless, following the rollout of vaccines, the volatility declined more in the developed countries than in the emerging market countries. One possible reason is that in the developed countries, more doses were administered to the populations and at a higher rate than in the emerging market countries.

Notably, this difference in vaccination rates may also influence investor expectations. Consequently, the traders in developed markets may see a reduced likelihood of future unexpected pandemic-linked perturbations; in emerging markets, such expectations could be less justified. Both the present situation and its future implications may exert influence at the prevailing stock price volatility level. To scrutinize this, we replicate our baseline analyses from Table 4 in developed and emerging markets separately. We closely follow the market classification by MSCI.

The results of this exercise, as reported in Table 8, uncover two essential findings. First, vaccinations help to reduce market volatility in both emerging and developed markets. In both categories, the relevant

[7] The data is from *https://www.bloomberg.com/graphics/covid-vaccine-tracker-global-distribution/* (March 23, 2021).

Table 8
The effect of vaccinations in developed and emerging markets.

	Emerging	Developed	Emerging	Developed	Emerging	Developed	Emerging	Developed
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Daily Vaccinations) $_{t-1}$	−0.0154***	−0.0420***						
	(−5.07)	(−11.65)						
Daily Vaccinations Per 100,000 $_{t-1}$			−0.0003***	−0.0006***				
			(−4.68)	(−9.02)				
Vaccination Period					−0.1993***	−0.4790***		
					(−6.88)	(−12.54)		
Δ Daily Vaccinations Dummy $_{t-1}$							−0.1121***	−0.3608***
							(−2.79)	(−7.74)
Log |R| $_{t-1}$	0.1633***	0.1017***	0.1635***	0.1105***	0.1612***	0.0997***	0.1654***	0.1134***
	(17.64)	(8.27)	(17.66)	(8.99)	(17.81)	(8.12)	(17.85)	(9.21)
Stringency Index $_{t-1}$	0.0014***	0.0060***	0.0012***	0.0048***	0.0013***	0.0064***	0.0011**	0.0045***
	(3.04)	(8.95)	(2.70)	(7.45)	(2.97)	(9.57)	(2.40)	(6.97)
BM $_{t-1}$	0.1020***	0.1141*	0.1104***	0.1869***	0.0997***	0.0669	0.1099***	0.1921***
	(4.35)	(1.81)	(4.73)	(2.99)	(4.31)	(1.05)	(4.69)	(3.05)
Log (TV) $_{t-1}$	0.0661***	0.0040	0.0650***	0.0045	0.0656***	0.0013	0.0655***	0.0044
	(18.46)	(0.54)	(18.13)	(0.61)	(18.53)	(0.18)	(18.26)	(0.59)
Δ Infections to Cases $_{t-1}$	1.0466***	1.4971***	1.0474***	1.4689***	1.0837***	1.5051***	1.0487***	1.4542***
	(4.98)	(5.48)	(4.99)	(5.36)	(5.25)	(5.52)	(4.99)	(5.29)
Δ Deaths to Cases $_{t-1}$	9.0519	15.3455	8.9469	14.4390	11.3178	16.0593	9.1166	13.9881
	(0.70)	(0.99)	(0.69)	(0.93)	(0.90)	(1.04)	(0.70)	(0.90)
US Elections	−0.1890***	−0.3733***	−0.1813***	−0.3402***	−0.1840***	−0.3803***	−0.1712***	−0.3133***
	(−5.62)	(−8.48)	(−5.42)	(−7.74)	(−5.59)	(−8.66)	(−5.14)	(−7.17)
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13,500	7337	13,500	7337	14,062	7351	13,439	7317
R^2	0.0734	0.0596	0.0731	0.0527	0.0740	0.0622	0.0724	0.0500
F–value	89.04***	38.69***	88.69***	33.94***	93.56***	40.54***	87.33***	32.01***
Cross–model comparison χ^2 for vaccination measures	32.02***		12.22***		34.38***		16.68***	

This table presents pooled OLS estimates of the relationship between COVID-19 vaccinations and stock return volatility using two subsamples of emerged and developed economies. The dependent variable is the logarithm of absolute daily returns, Log |R|. Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations Per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccinations Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Stringency Index is a score between 0 and 100 that reflects the daily government response to COVID-19 and computed using different government nonpharmaceutical interventions. BM is the book-to-market ratio. Log (TV) is the natural logarithm of daily trading volume in U.S. dollars. Log (MV) is the natural logarithm of market capitalization in U.S. dollars. Δ Infections to Cases is the daily change in the number of COVID-19 infections to the total number of confirmed COVID-19 cases (in percentage). Δ Deaths to Cases is the daily change in the number of COVID-19 deaths to the total number of confirmed COVID-19 cases (in percentage). US Elections is a dummy variable that takes the value of 1 for the period that starts at November 3, 2020 and ends at January 7, 2021, and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. All specifications include weekday dummies. The asterisks ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Obs.* and R^2 denote the number of observations and the coefficient of determination, respectively. The last row shows Chi-squared tests of the cross-model comparison between the vaccination coefficients using seemingly unrelated estimations.

slope coefficients are negative and significant across all the different vaccination proxies. In other words, the overall vaccination effect does not depend on the level of market development.

Second, the absolute values of the coefficients are visibly higher in developed markets than in emerging ones. Furthermore, for all of the considered vaccination variables, the difference is significant and formally confirmed by Chi-squared tests of cross-model comparisons between the vaccination coefficients using seemingly unrelated estimations.

To further verify the validity of our findings concerning the more substantial effect in developed markets, we check the robustness using an alternative methodological approach. To be specific, we replicate our baseline regressions from Table 4 after adding i) the variable Developed Dummy, which is a dummy variable that takes the value of 1 if the economy is a developed one, and zero otherwise, and ii) an interaction term between the variable Developed Dummy and each one of the four vaccination variables. The results of this test, reported in Table 9, confirm our initial observations from Table 8. The interaction terms exert negative and significant effects on stock market volatility. This finding corroborates the remarkable difference in the vaccination-volatility nexus between the developed and emerging markets.

To sum up, our findings provide support for the notion that the impact of vaccinations on market volatility has been more substantial in developed rather than in emerging markets.

5. Concluding remarks

This study documents that mass vaccinations help to stabilize the global equity markets. The beginning and development of the vaccinations decrease stock market volatility in a country after controlling for the pandemic's influence, the related containment and closure policies, and the market-specific characteristics. Our findings are robust to a battery of robustness tests such as modified regression specifications and estimation approaches, alternative volatility measures, or consideration of additional control variables.

Our conclusions have direct practical implications. Investors should closely follow the development of vaccination policies of countries. While some countries make a significant progress in terms of vaccinating the majority of their populations, others are far beyond achieving this point. There are also supply shortages of vaccines, and there can be halting periods due to delays in receiving the vaccine orders. Therefore, investors might need to alter their portfolios based on the vaccination policies. Depending on their investing strategies, they might prefer investing in countries with high or low vaccination rates. They will also bear in mind that the impact of vaccination is heterogeneous in developed and emerging markets. The decrease in volatility may be beneficial for trading conditions and long-run development. Lower volatility decreases the risk of fire sale episodes and discourages investors from moving their capital to safer asset classes. Limited volatility may also

Table 9
The effect of vaccinations in developed and emerging markets: interactions.

	Dependent variable: Log |R|				Dependent variable: Log |RR_{CAPM}|			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log (Daily Vaccinations) $_{t-1}$	−0.0213***				−0.0164***			
	(−7.11)				(−6.07)			
Daily Vaccinations Per 100,000 $_{t-1}$		−0.0004***				−0.0003***		
		(−6.87)				(−5.82)		
Vaccination Period			−0.2710***				−0.2353***	
			(−9.54)				(−8.92)	
Δ Daily Vaccinations Dummy $_{t-1}$				−0.1746***				−0.1632***
				(−4.38)				(−4.42)
Developed Dummy	0.0474*	0.0284	0.0564**	0.0259	−0.1914***	−0.2012***	−0.1973***	−0.2052***
	(1.96)	(1.22)	(2.33)	(1.10)	(−8.75)	(−9.61)	(−8.97)	(−9.71)
Log (Daily Vaccinations) $_{t-1}$ × Developed Dummy	−0.0200***				−0.0146***			
	(−4.56)				(−3.57)			
Daily Vaccinations Per 100,000 $_{t-1}$ × Developed Dummy		−0.0002**				−0.0002**		
		(−2.40)				(−2.50)		
Vaccination Period × Developed Dummy			−0.1789***				−0.0678	
			(−4.04)				(−1.63)	
Δ Daily Vaccinations Dummy $_{t-1}$ × Developed Dummy				−0.1974***				−0.1522***
				(−3.39)				(−2.73)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	20,837	20,837	21,413	20,756	20,837	20,837	21,413	20,756
R^2	0.0521	0.0496	0.0538	0.0475	0.0390	0.0377	0.0394	0.0367
F–value	87.78***	83.26***	92.96***	79.43***	66.66***	63.81***	68.52***	61.98***

This table presents pooled OLS estimates of the relationship between COVID-19 vaccinations and stock return volatility after including a dummy variable, Developed Dummy, and the interactions between this dummy variable and the different vaccination-related variables. Two dependent variables are used, namely, Log |R| (Columns 1–4) and Log |RR_{CAPM}| (Columns 5–8). Developed Dummy is a dummy variable that takes the value of 1 if the economy is a developed one, and zero otherwise. Log (Daily Vaccinations) is the natural logarithm of the daily number of COVID-19 vaccinations. Daily Vaccinations per 100,000 is the daily number of COVID-19 vaccinations divided by the country population and multiplied by 100,000. Vaccinations Period is a dummy variable that equals 1 for the period starting from the country's first vaccination day, and zero otherwise. Δ Daily Vaccinations Dummy is an indicator variable that equals 1 if the daily change in the number of COVID-19 vaccinations is strictly positive, and zero otherwise. Heteroskedasticity-robust *t*-statistics are in parentheses beneath the regressions' coefficients. All continuous variables are winsorized at the 1st and 99th percentiles. The asterisks *** and ** denote statistical significance at the 1% and 5% levels, respectively. *Obs.* and R^2 denote the number of observations and the coefficient of determination, respectively.

translate into a lower cost of capital, which facilitates economic growth. It can also improve intertemporal smoothing of consumption for households. In addition to investors, policymakers worldwide should also be aware of the meaningful impact of mass vaccinations not only on businesses, but also on financial markets.

Further studies on the topics discussed in this paper may explore the impact of vaccinations on other asset classes, such as currencies or corporate bonds. Moreover, the principal limitation of our study is the fresh and relatively short data set. Admittedly, vaccine-related news can be more directly linked with one or more channels, which predict a decrease in stock market volatility. However, exploring the vaccine-related news-volatility nexus would require a longer sample period to ensure that subsamples of no news and good news are informative. Therefore, although such an extension is interesting and important, we leave it for future research.

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