Stabilizing Global Foreign Exchange Markets in the Time of COVID-19: The Role of Vaccinations

Son Duy Pham[a1], Thao Thac Thanh Nguyen[b], Xiao-Ming Li[b]

[a] *University of Aberdeen Business School, Dunbar Street, Aberdeen, United Kingdom*

[b] *School of Economics and Finance, Massey University, New Zealand*

This version: December 1st 2023

[1]Corresponding author: University of Aberdeen Business School, Dunbar Street, Aberdeen, AB24 3QY, United Kingdom. Phone: +44 776791 6070.
Email addresses: son.pham@abdn.ac.uk (Son Pham), T.T.T.Nguyen1@massey.ac.nz (Thao Nguyen), X.N.Li@massey.ac.nz (Xiao-Ming Li).

Declarations of interest: None

Acknowledgements: We are grateful to the managing editor, Professor Ali M. Fatemi, and two anonymous referees for valuable comments and suggestions. All remaining errors are our own.

Stabilizing Global Foreign Exchange Markets in the Time of COVID-19: The Role of Vaccinations

Highlights:

- Covid-19 vaccination program significantly reduces the realized volatility of global foreign exchange markets.
- The stabilizing effect of vaccinations survives various robustness checks.
- The stabilizing effect is asymmetric across the quantile levels of FX volatility distribution.
- Vaccinations reduce FX volatility more in emerging markets, in countries with high economic policy uncertainty, and in nations with greater vaccine confidence.

Stabilizing Global Foreign Exchange Markets in the Time of COVID-19: The Role of Vaccinations

---

Abstract

By restoring economic openness, mitigating economic policy uncertainty, and regaining macroeconomic stability, the mass deployment of COVID-19 vaccinations should stabilize foreign exchange (FX) markets. This paper empirically examines the impact of COVID-19 vaccinations on the realized volatility of exchange rates in 30 countries/regions from January 1, 2020, to September 29, 2021. Using the heterogeneous autoregressive model with measurement errors, we find that the COVID-19 vaccine rollout stabilizes global FX markets; this result holds through a series of robustness checks. The stabilizing effect is asymmetric across the quantile levels of FX volatility distribution. Furthermore, the stabilizing effect is more pronounced in emerging markets, countries with high economic policy uncertainty, and nations with greater vaccine confidence.

JEL Classification Codes: G01; G12; G15, H12; H15; I18

Keywords: COVID-19 vaccinations; Exchange rate volatility; Realized volatility; Heterogeneous Autoregressive model; Measurement errors

---

1. Introduction

The global outbreak of the coronavirus disease (COVID-19) has caused enormous damage to global economic activities and financial markets. World Economic Outlook Report April 2021 indicates that the global economy contracted sharply by 3.5% in 2020. Given the unprecedentedness of the pandemic, a significant strand of literature has investigated the disastrous effects of COVID-19 on global financial markets, including stock markets (Ashraf, 2020; Liu et al., 2020; Salisu et al., 2020; Topcu & Gulal, 2020; Zaremba et al., 2021), energy markets (Devpura & Narayan, 2020; Gil-Alana & Monge, 2020; Prabheesh et al., 2020), and foreign exchange (FX) markets (Aslam et al., 2020; Bazán-Palomino & Winkelried, 2021; Fasanya et al., 2020; Feng et al., 2021; Narayan et al., 2020; Narayan, 2020; Njindan Iyke, 2020).

COVID-19 vaccination programs were deployed worldwide at the end of 2020 to mitigate the severe negative impacts of the pandemic, following various vaccine rollout plans that differed by country. These programs were deemed essential for a return to normalcy in our social and economic lives and aimed to stabilize global financial markets. To investigate the expected outcomes of the programs, researchers have recently started to pay attention to the effects of COVID-19 vaccinations on financial markets (Acharya et al., 2020; Chan et al., 2022; Li et al., 2023; Pham et al., 2023; Rouatbi et al., 2021; To et al., 2023; Yu & Xiao, 2023). Our study contributes to this literature by examining the relationship between vaccinations and FX market volatility, filling an apparent gap in the extant literature.

There are two key motivations behind our study. First, the COVID-19 pandemic, as a global public health disaster, offers a unique opportunity to assess the impact of a worldwide vaccination program on financial markets (Hasan et al., 2023). Although the World Health Organization (WHO) declared an end to COVID-19 a public health emergency in May 2023, the world still faces the risk of another variant emerging with even deadlier potential.[2] Consequently, investigating the impacts of such disastrous public health events on financial markets could provide important policy implications for global and national authorities when the next pandemic arises. Second, we focus on the impact of vaccinations on the FX market, as FX volatility is pivotal in affecting economic stability, international trade and capital flows, inflation, and interest rates. As the world's largest financial market,[3] FX volatility heavily influences exports and imports by changing relative production and transaction costs for international trade (Baum & Caglayan, 2010; Qian & Varangis, 1994; Rahman et al., 2020).

Furthermore, increased exchange rate volatility leads to higher corporate profits and investment uncertainty, slowing productivity and gross domestic product (GDP) growth (Aghion et al., 2009; Braun & Larrain, 2005). Moreover, a rise in exchange rate volatility also induces inflation uncertainty, leading to higher interest rates and dampening consumer and investor sentiment (Grier & Grier, 2006). Finally, it has become a consensus that maintaining a constant exchange rate, hence making its volatility nonexistent, can eliminate exchange rate risk and facilitate cross-border capital flows; the advent of the Euro and the creation of other fixed exchange rate regimes, such as that in Hong Kong, represent this goal. Thus, stabilizing FX volatility also has important implications for cross-border capital flows. Given these reasons, studies on how FX volatility may be affected by COVID-19 vaccinations should interest FX traders, investors, and policymakers.

[2] During the announcement of the end of COVID-19 as a global public health emergency, WHO chief Tedros Adhanom Ghebreyesus said, "The end of COVID-19 as a global health emergency is not the end of COVID-19 as a global health threat. The threat of another variant emerging that causes new surges of disease and death remains, and the threat of another pagothen emerging with even deadlier potential remains." Source: https://news.un.org/en/story/2023/05/1136912

[3] The daily turnover of the global FX market was about 6.6 trillion USD in 2019; see the Triennial Survey of Turnover in OTC FX markets, Bank for International Settlements (BIS), April 2019.

Following Wang and Yang (2009) and Bubák et al. (2011), we employ the realized volatility (RV) calculated from intraday data to proxy the volatility in foreign exchange markets. Andersen et al. (2003) suggest that RV is a more informative measure of volatility. Consequently, various studies, such as Albulescu (2021) and Li et al. (2020), have used RV as a volatility proxy to assess the impacts of COVID-19 on global financial markets; however, these studies did not consider the heteroscedasticity in measurement errors that cause bias in computing RV, a critical issue raised by Bollerslev et al. (2016). To overcome this problem, we apply the heterogeneous autoregressive quarticity (HARQ) model proposed by Bollerslev et al. (2016) to model the RV in FX markets, which distinguish our study from the above-cited studies. This approach is necessary and novel in terms of methodological contribution to investigate the linkage between COVID-19 and financial market volatility. Furthermore, our sample data cover 30 free-floating exchange rates from January 1, 2020, to September 29, 2021. We also utilize a comprehensive, publicly available, and reliable global vaccination database named Our World in Data.

Our empirical works center around testing four hypotheses derived from economic theories and empirical evidence. These hypotheses involve determining whether an attenuating effect of COVID-19 vaccinations on FX volatility exists and whether it is affected by the country-specific economic-development stage (emerging versus developed economies), the economic policy uncertainty (EPU), and the country-level vaccine confidence. Our study indicates that massive vaccinations can significantly reduce the exchange rate volatility after controlling for the effects of the long-memory characteristic, the varying measurement errors in RV, and the pandemic's dynamics. Furthermore, we find that the variations in the administered number of daily first vaccine doses reduce FX volatility. In contrast, the changes in the number of daily second (or third) doses are insignificant in explaining the fluctuations of FX volatility.

Several additional interesting results are worth noting. First, the effect of COVID-19 vaccinations on FX volatility is more severe in emerging than in developed markets. Second, this stabilizing effect is more pronounced in countries with higher EPU during the pandemic. Third, COVID-19 vaccinations significantly reduce the volatility of FX markets in a country whose people have higher vaccine confidence.

Our main finding of the stabilizing effect of vaccinations on FX volatility holds after a series of robustness checks. These robustness checks include (1) allowing for alternative measures of vaccinations, (2) controlling additional exogenous variables relevant to FX volatility, (3) using different sampling periods, (4) employing various HARQ-type models to account for the investor fear gauge or the signed semivariances in estimating FX-RV, (5) considering estimations at different conditional distributions of FX volatility, and (6) accounting for the time difference bias.

Our paper makes several contributions to the relevant literature. The existing finance literature regarding the COVID-19 pandemic focused on the role of the pandemic itself—including infections and casualties—or the related government policy responses (Albulescu, 2021; Baek et al., 2020; Topcu & Gulal, 2020; Zaremba et al., 2021). We diverge from this routine and contribute to the growing literature that examines the effects of the COVID-19 vaccine rollout on global financial markets (Acharya et al., 2020; Chan et al., 2022; Li et al., 2023; Pham et al., 2023; Rouatbi et al., 2021; To et al., 2023; Yu & Xiao, 2023).

Furthermore, our paper distinguishes itself from the aforementioned studies in several ways. First, various papers (Acharya et al., 2020; Li et al., 2023; Pham et al., 2023; Rouatbi et al., 2021; To et al., 2023; Yu & Xiao, 2023) focus on the role of vaccinations on stock markets, we are the first to examine the effect of mass vaccination program on FX markets. Second, Rouatbi et al. (2021) and To et al. (2023) employ volatility measures from latent volatility models[4] to examine the impact of vaccinations on the volatility of stock markets. However, as McAleer and Medeiros (2008) indicated, latent volatility models fail to satisfactorily describe several stylized facts observed in financial time series. Our paper overcomes this shortcoming by using intraday trading data to calculate the RV of FX rates. According to Andersen et al. (2003), RV is considered a consistent and more effective estimate of unobservable integrated variance of assets.

In addition to the above contribution, we provide more insights into the socioeconomic impacts of vaccinations by investigating the effect of vaccinations on global FX markets (Bhargava et al., 2001; Bloom et al., 2010; Well, 2007). Rouatbi et al. (2021) and To et al. (2023) examined the heterogeneity of the vaccination effects based on economic development (i.e., developed and emerging markets). We augment our analysis by considering other country-specific factors, such as EPU and societal trust. Moreover, documenting that vaccinations stabilize FX fluctuations during the pandemic, we enrich the literature on the determinants of FX volatility (Chen et al., 2020; Eichler & Littke, 2018; Gelman et al., 2015; Mueller et al., 2017).

Finally, while the COVID-19 pandemic has been shown to destabilize global financial markets, our research provides credible evidence that mass vaccinations have been a “game changer” in restoring financial stability. Our findings have important implications for public health and macrofinance policies if COVID-19, its potential variants, or similar events occur in the future.

The remainder of this article proceeds as follows. Section 2 develops hypotheses for empirical tests, Section 3 describes the methodology used, and Section 4 presents our data

[4] Rouatbi et al. (2021) used two proxies for stock volatility. The first is the natural logarithm of absolute daily returns. The second is the natural logarithm of absolute residual returns from the CAPM model. To et al. (2023) employed the volatility estimated from the GJR-GARCH (1,1) model.

and conducts preliminary analyses. Section 5 reports and discusses the results of hypothesis tests and robustness checks, while Section 6 concludes.

2. Literature review and hypothesis development

2.1. The nexus between vaccinations and FX volatility

Exchange rate fluctuations are driven by FX market participants' forward-looking expectations formed on the news regarding the current macroeconomic fundamentals (Evans & Lyons, 2002; 2005; 2008; Rime et al., 2010). The COVID-19 pandemic and the rollout of COVID-19 vaccines have shaped the global economy via their contrasting effects on human health, productivity, cross-country border controls, and, eventually, international capital and trade flows worldwide. Based on the expectations, which incorporate the information from all these aspects, FX market participants will act accordingly concerning currency trading. Thus, which of the two opposite effects dominates is a crucial determinant of the direction in which FX volatility changes.

This subsection contemplates three mechanisms through which COVID-19 vaccinations help change expectations and reduce FX volatility. The first mechanism involves economic openness; according to the World Trade Organization, economic openness has been affected negatively by COVID-19. Hau (2002) theoretically demonstrated a negative link between the degree of economic openness and FX volatility; subsequent empirical findings supported this prediction (Bleaney, 2008; Calderón & Kubota, 2018; Calderón, 2004; Stancik, 2007). In contrast, Okonjo-Iweala (2021) predicted that the increasing rate of inoculation, which reverses the detrimental effects of COVID-19, will help the world return to the normalcy of international trade and economic openness. That is, the deployment of mass vaccinations would help attenuate global FX volatility by restoring economic openness.

The second mechanism is how COVID-19 vaccinations mitigate the effect of country-specific EPU on FX volatility. As exchange rate movements are driven by expectations of economic fundamentals, including macroeconomic policies, a high level of EPU will widen expectation dispersions, leading to greater exchange rate volatility (Banerjee, 2011). Following this conjecture, Krol (2014) determined that EPU in the United States (US) and the home country directly increases exchange rate volatility. Subsequent studies by Balcilar et al. (2016), Beckmann and Czudaj (2017), and Mueller et al. (2017) also suggested that EPU helps predict FX return and (or) volatility. Intuitively, as EPU increases during the pandemic (Albulescu, 2020; Baker et al., 2020; Caggiano et al., 2020; Sharif et al., 2020), its FX-volatility effect rises; therefore, the rollout of COVID-19 vaccines should alleviate the FX-volatility effect of EPU.

Finally, the extant literature also suggests that population health—a crucial aspect of human capital and productivity—is critical to economic development and stability (Bhargava et al., 2001; Bloom et al., 2010; Well, 2007). As vaccination is the first level of a healthcare system,[5] Schoenbaum (1987), Ryan et al. (2006), Bloom et al. (2008), and Smith et al. (2009), among others, have documented the positive impacts of vaccination programs on the economy. These impacts arise from increased labor productivity related to healthcare effects (i.e., longer life expectancy, fewer lost working days, and improved physical capacity and mental health). Vaccinations also help reduce mortality and morbidity, increasing consumption, tourism, and investment (Bärnighausen et al., 2014; Quilici et al., 2015; Rémy et al., 2015). This positive macroeconomic news could be incorporated into FX market participants' forward-looking expectations, which affect their currency-trading activities and FX volatility.

[5] See Loeppke et al. (2008).

The mass deployment of COVID-19 vaccinations can help stabilize FX markets by restoring economic openness, mitigating the FX-volatility effect of EPU, and regaining macroeconomic stability to influence FX market participants' expectations and currency-trading behavior. Therefore, we conjecture our principal hypothesis as follows:

H1: *The rollout of COVID-19 vaccinations reduces exchange rate volatility.*

2.2. The roles of country-specific factors

Extant literature suggests that the COVID-19 pandemic exerted a heterogeneous effect on global financial markets, depending on several country-specific factors such as economic strength (Harjoto et al., 2021; Uddin et al., 2021), national culture (Fernandez-Perez et al., 2021), and societal trust (Engelhardt et al., 2021). Based on the above literature, this subsection develops three hypotheses to examine whether the impact of COVID-19 vaccinations is contingent on country-specific factors, including the level of economic development, EPU, and the degree of vaccination confidence.

The first factor considers the heterogeneity of the COVID-19 vaccination on FX volatility across developed and emerging markets. Emerging economies have relatively weak public health systems, poor and financially stressful populations, and inadequate social safety nets; thus, they are generally more vulnerable to abrupt shocks than developed economies. For instance, Fisera et al. (2023) found that large-scale natural disasters increase government debt financing costs in middle- and low-income countries; however, these effects do not exist in developed economies. Concerning the impact of the pandemic, Harjoto et al. (2021) revealed that during the COVID-19 outbreak, emerging stock markets tend to react more to pandemic news (e.g., new cases and new deaths) than developed stock markets. Furthermore, emerging countries have comparatively limited monetary and fiscal capacity, which constrains their ability to provide economic stimulus programs to fight against the catastrophic effects of the COVID-19 pandemic. Consequently, we expect that the COVID-19 vaccine rollout would impose a more substantial impact on restoring economic normalcy and stabilizing financial markets in emerging countries than in developed ones. Therefore, we formulate our second hypothesis as follows:

H2: *The rollout of COVID-19 vaccines reduces FX volatility more for emerging economies than developed economies.*

Economic policy uncertainty is the second country-specific factor that could affect the vaccination-FX-volatility linkage. Krol (2014) provided empirical evidence that FX volatility increases significantly with the rise in domestic EPU or foreign EPU (or both), especially during economic instability. This finding implies that the magnitude of EPU impact on FX volatility depends on economic conditions or (and) macroeconomic fundamentals and tends to be more severe in times of market turbulence. Similarly, we infer that during the COVID-19 crisis, which created economic turbulence, high EPU will manifest its *enlarged* impact on FX volatility. Any improvement in economic conditions, such as an increase in COVID-19 vaccine rollout, would send favorable signals to FX market participants to incorporate into their information sets. Based on the above discussion, we conjecture the third hypothesis:

H3: *The rollout of COVID-19 vaccines reduces the FX-volatility impact of a given high level of EPU.*

Finally, we expect the level of vaccine confidence to be a critical country-specific factor that could influence the impact of COVID-19 vaccinations on FX volatility. Our expectation is motivated by Engelhardt et al. (2021), who found that societal trust and government trust affect the nexus between the COVID-19 pandemic and stock market volatility. Specifically, the authors documented that stock market volatility is significantly lower in high-trust countries in response to COVID-19 case announcements. This finding can also be explained by the importance of credibility when assessing the effectiveness of macroeconomic policies. Extant literature suggests that economic agents use credible information to form expectations, especially when such information involves government announcements (Calderón et al., 2004; Taylor, 1982). If the credibility of government announcements is high, economic agents will be more likely to include the announcements in their information sets, which will significantly affect their expectations and decisions. Given the above discussion, we expect that when FX markets perceive the high credibility of announced vaccine efficacy and effectiveness, increases in the vaccination rate could improve confidence in the economic recovery to the preCOVID-19 path due to the perceived reduction in uncertainty. Along this line, we propose the fourth hypothesis as follows:

H4: *The stabilizing impact of COVID-19 vaccination programs on FX volatility in high vaccine-confidence countries will be stronger than in low vaccine-confidence ones*.

3. Methodologies

Our paper follows Wang and Yang (2009) and Bubák et al. (2011), employing RV as a proxy of volatility in the foreign exchange markets.[6] Section 4 presents our baseline model to investigate the impact of COVID-19 vaccinations on FX volatility based on the HARQ model. The HARQ model, advanced by Bollerslev et al. (2016) from the original heterogeneous autoregressive (HAR) model (Corsi, 2009),[7] inherits the advantage of the HAR model by effectively capturing the long-memory behavior of RV. Furthermore, it accounts for the variation in measurement errors in RV estimation. Using the HARQ model is expected to model the volatility in foreign exchange markets better than the original HAR model.

3.1. The RV estimator

[6] We do not use implied volatility as a proxy because Neely (2009) demonstrates that implied volatility is a biased forecast of foreign exchange variance and is not informationally efficient.

[7] The HAR model has been widely used to estimate realized volatility in the FX market (Bubák et al., 2011; Busch et al., 2011; Lyócsa et al., 2021; Wang & Yang, 2009) due to its capability to account for the long-memory property of realized volatility.

We apply the notion of realized variance (RV) introduced by Andersen and Bollerslev (1998) in estimating the daily volatility of an exchange rate; the RV measure is constructed using the high-frequency intraday data of financial returns. First, define the ith Δ-period intraday return within day t as,

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

where P is the mid-quote of the exchange rate, and r is the intraday return.

Then, compute the RV from the sum of squared intraday return:

$$RV_t = \sum_{i=1}^{M} r_{i,t}^2$$

where $M \equiv 1/\Delta$ is the number of observations within a trading day, and Δ is the sampling frequency. Following Andersen et al. (2001), we employed a sampling frequency of five minutes. As $\Delta \to 0$ or $M \to \infty$, RV_t is an effective and consistent estimator for unobservable integrated variance (Andersen et al., 2003).

3.2. The HARQ model and our baseline model

With the availability of high-frequency intraday data, the recent literature focused on modeling time-varying return volatility using RV. Among these models, the HAR model proposed by Corsi (2009) has gained popularity due to its simplicity and consistent application forecasting performance. HAR can parsimoniously capture the high persistence of the volatility process through a hierarchical structure of three volatility components over short-, medium-, and long-term intervals. The original HAR model hinges on a linear function of past daily, weekly, and monthly RV components as follows:

$$RV_{t+1} = \beta_0 + \beta_d RV_t + \beta_w RV_t^w + \beta_m RV_t^m + \varepsilon_{t+1}$$

where β_0, β_d, β_w, and β_m are the autoregressive parameters to be estimated. RV_{t+1} is the realized variance of day $t + 1$. RV_t, $RV_t^w = \frac{1}{5}\sum_{j=0}^{4} RV_{t-j}$, and $RV_t^m = \frac{1}{22}\sum_{j=0}^{21} RV_{t-j}$

denote daily, weekly, and monthly lagged realized variances, respectively. Finally, ε_{t+1} is the error term.

With any nonzero sampling frequency, the estimate of RV contains measurement errors, which induce a bias of RV from the actual integrated volatility (Bollerslev et al., 2016).[8] The HAR model does not address this problem of measurement errors; however, the HARQ model shown below, advanced by Bollerslev et al. (2016), remedies the problem:

$$RV_{t+1} = \beta_0 + \left(\underbrace{\beta_d + \beta_Q RQ_t^{\frac{1}{2}}}_{\beta_{d,t}}\right) RV_t + \beta_w RV_t^w + \beta_m RV_t^m + \varepsilon_{t+1} \tag{1}$$

where RQ denotes the realized quarticity and is estimated by $(\frac{M}{3})\sum_{i=1}^{M} r_{i,t}^4$. $RQ^{1/2}$ is known as the asymptotic standard deviations of return time series, and β_Q is an additional autoregressive parameter to be estimated. According to Bollerslev et al. (2016), RQ is a consistent estimator of integrated quarticity (IQ) in case of no jumps. $\beta_Q RQ_t^{\frac{1}{2}}$ makes $\beta_{d,t}$ time-varying to capture the attenuation effects of measurement errors in the RV estimator while accounting for the strong persistence of volatility via $\beta_{d,t}$. We expect β_Q to be negative and significant.[9] The higher the measurement error captured by RQ (i.e., the higher the value of RQ), the less the weight assigned to the historical component RV_t should be (i.e., the lower the value of $\beta_{d,t}$).

To investigate the impact of COVID-19 vaccinations on volatility, we include the COVID-19 vaccination-related variables and add exogenous variables to Equation (1) to control for the pandemic dynamics. Our principal empirical analysis used a panel data regression in the following baseline model:

[8] The measurement error in RV leads to the attenuation effects in estimated autoregressive parameters for the RV process and, hence, the inconsistency in the RV estimator.
[9] The incremental information of the heteroskedasticity in measurement errors characterized by RQ_t proves to be effective in modeling the realized volatility of many assets, such as stocks (Bollerslev et al., 2016), energy markets (Bissoondoyal-Bheenick et al., 2020), and cryptocurrencies (Qiu et al., 2021).

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^{w} + \beta_m RV_{i,t}^{m} + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \varepsilon_{i,t+1} \quad (2)$$

where $Covid_{i,t}$ is a list of three variables as proxies for the pandemic intensity of country i. These include the natural logarithm of the reproduction rate (R), the natural logarithm of the new cases per one million people (New_cases), and the natural logarithm of the new deaths per one million people (New_deaths). While early studies tended to use the newly confirmed cases and (or) new deaths as the proxies of the COVID-19 pandemic, recent studies have shifted attention to the *R* number as a totemic figure of the pandemic (Díaz et al., 2022; Sarkodie et al., 2022). *R* is the average number of people infected by an infectious person and helps evaluate the coronavirus's ability to spread; when R is greater than one, the pandemic is highly contagious as the number of infected people is expected to increase. In contrast, R less than one indicates that the spread of the disease is slowing and will gradually stop.

Following Rouatbi et al. (2021), we employ three vaccination-related variables to represent the key regressor, $Vax_{i,t}$, in Equation (2). These variables measure the intensity of the COVID-19 vaccine rollout and include (1) New_vax, defined as the natural logarithm of the number of daily new COVID-19 vaccine doses per one million people. Furthermore, (2) $Vax\_Increase$ is a dummy variable that equals one if the daily change in New_vax is strictly positive, and zero otherwise. Finally, (3) Vax_Period is a dummy variable that equals one for the period starting the country's first COVID-19 vaccine administration onward and zero otherwise.

3.3. Other HARQ-type models used for robustness checks

We also use three extensions of the HARQ model to check the robustness of our main empirical results from Equation (2). The first incorporates the investor fear gauge (IFG) to create the HARQ-IFG model[10]:

$$RV_{t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_t^{\frac{1}{2}}\right) RV_t + \beta_w RV_t^w + \beta_m RV_t^m + \beta_{IFG} IFG_t + \varepsilon_{t+1} \quad (3)$$

where IFG_t is a proxy of IFG measured by the Chicago Board Options Exchange volatility index of the S&P 500 index (Sarwar, 2012). Other variables in the HARQ-IFG model are the same as before.

Following Patton and Sheppard (2015), we consider signed realized semivariances (RS) to capture their distinctive effects. The resultant HARQ-RS model decomposes daily RV in the standard HAR model into two signed semivariances, RS^+ and RS^-:

$$RV_{t+1} = \beta_0 + \left(\beta_d^+ + \beta_Q^+ RQ_t^{\frac{1}{2}}\right) RS_t^+ + \left(\beta_d^- + \beta_Q^- RQ_t^{\frac{1}{2}}\right) RS_t^- + \beta_w RV_t^w + \beta_m RV_t^m + \varepsilon_{t+1} \quad (4)$$

where $RS_t^+ = \sum_{i=1}^{M} r_{i,t}^2 I[r_{i,t} > 0]$ and $RS_t^- = \sum_{i=1}^{M} r_{i,t}^2 I[r_{i,t} < 0]$ are, respectively, positive and negative RS. $I[.]$ is the indicative function taking the value one if the argument is true.

Third, implied volatility (IV) is a biased forecast of foreign exchange variance and is not informationally efficient (Jorion, 1995; Neely, 2009). Nonetheless, Plíhal and Lyócsa (2021) show that the inclusion of IV as a predictor could enhance the forecast accuracy of HAR-type models in modeling foreign exchange volatility. As a result, following Plíhal and Lyócsa (2021), we add implied volatility of foreign exchanges to Equation (1) to create the so-called IV-HARQ as follows,[11]

[10] Gong and Lin (2018) include a measure of investor fear gauge in the HARQ model for crude oil futures' realized volatility. They find that the HARQ-IFG model outperforms the HARQ model.
[11] This is equivalent to the IV-HAR model in Plíhal and Lyócsa (2021) presented by Equation (5).

$$RV_{t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_t^{\frac{1}{2}}\right) RV_t + \beta_w RV_t^w + \beta_m RV_t^m + \beta_{IV}^d IV_t^d + \beta_{IV}^w IV_t^w + \beta_{IV}^m IV_t^m + \varepsilon_{t+1} \quad (5)$$

where IV_t^d, IV_t^w, and IV_t^m are, respectively, daily, weekly, and monthly implied volatilities of foreign exchanges at day t. Daily implied volatility is calculated from one-month foreign exchange options. Weekly and monthly implied volatilities are computed as the average daily implied volatility over 5 and 22 trading days, respectively. Other variables in Equation (5) are defined the same as in Equation (2).

We add pandemic-related variables ($Covid_{i,t}$) and vaccination variables ($Vax_{i,t}$) to the HARQ-type extension models to robustly check the effect of COVID-19 vaccinations, as described in Equations (6), (7), and (8). These additions lead to the following equations:

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^w + \beta_m RV_{i,t}^m + \beta_{IFG} IFG_t + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \varepsilon_{i,t+1} \quad (6)$$

$$RV_{i,t+1} = \beta_0 + \left(\beta_d^+ + \beta_Q^+ RQ_{i,t}^{\frac{1}{2}}\right) RS_{i,t}^+ + \left(\beta_d^- + \beta_Q^- RQ_{i,t}^{\frac{1}{2}}\right) RS_{i,t}^- + \beta_w RV_{i,t}^w + \beta_m RV_{i,t}^m + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \varepsilon_{i,t+1} \quad (7)$$

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^w + \beta_m RV_{i,t}^m + \beta_{IV}^d IV_{i,t}^d + \beta_{IV}^w IV_{i,t}^w + \beta_{IV}^m IV_{i,t}^m + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \varepsilon_{i,t+1}. \quad (8)$$

4. Data

4.1. Data sources

Our study uses the high-frequency bid/ask quotes of exchange rates and the data on the pandemic dynamics and COVID-19 vaccine rollout. Consistent with most prior literature on

FX volatility using the high-frequency measure of volatility,[12] we restrict our sample to only significant free-floating exchange rates. The sample includes 30 free-floating FX markets whose exchange rates against the US dollar (USD) account for a larger proportion of 65% of the global FX turnover.[13] Therefore, the results of our empirical analysis can demonstrate vaccination effects from a global perspective. The high-frequency bid and ask quotes of these exchange rates are extracted from the Thomson Reuters Tick History database from January 1, 2020, to September 29, 2021, which we use to compute the mid-quotes. The starting date of our research period coincides with the early COVID-19 outbreak in Wuhan, China. Following Andersen et al. (2001), we choose the sampling frequency of five minutes to balance the costs of measurement errors and market microstructure noise in calculating RV. Furthermore, following Andersen et al. (2003), we exclude weekends and major holidays to avoid the weekend/holiday effects on volatility.

The data on the dynamics of the pandemic and COVID-19 vaccine rollout come from Our World in Data.14 Our World in Data is a global public dataset that tracks the scale and rate of the COVID-19 pandemic across countries worldwide. The dataset is widely used in recent papers regarding the impacts of COVID-19 vaccinations (Benati & Coccia, 2022; Mathieu et al., 2021; Wang et al., 2023). The data on COVID-19 vaccinations started on December 18, 2020, based on the first day of vaccination data recorded for Norway in the dataset.

Data on other macroeconomic variables used in the empirical analysis, such as FX bid-ask spread and FX implied volatility, are sourced from Global Financial Databases and Thomson Reuters DataStream.

4.2. Summary statistics and preliminary analyses

[12] See Busch et al. (2011), Bubák et al. (2011). *Wang and Yang (2009), and Bazán-Palomino and Winkelried (2021), among others*.

[13] See the Triennial Central Bank Survey, Bank for International Settlements (BIS), April 2019.

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

Panel A of Table 1 reports the descriptive statistics of the variables in the baseline regression model. We winsorize all variables at the 1st and the 99th percentiles to mitigate the impact of outliers. The pandemic and vaccination-related variables are not presented in natural logarithms to facilitate interpretation. We find that the average RV for the whole sample is the highest at the daily frequency (RV = 0.60) and decreases for weekly (RV^w = 0.55) and monthly frequencies (RV^m = 0.54). These figures imply a decreasing trend of realized variance over decreasing data frequency. Furthermore, the RV and the quarticity exhibit skewness, and their kurtosis indicate that they do not follow a normal distribution.

Regarding the pandemic dynamics, the average reproduction rate (R) is 0.99, indicating that during the research period, about one person became infected in the selected countries. The vaccination data are also noteworthy; the average daily new vaccine doses per one million people (New_vax) is relatively low at 1,719.53. The average proportion of days with an increase in vaccination rate is measured by the average of $Vax\_Increase$, which equals 0.23. The dummy variable for the vaccination period (Vax_Period) has an average value of 0.37, which is relatively low because the vaccination period for each country represents a part of our sample

Table 1, Panel B shows the mean values of all variables for each country (or region) in the sample. The variables for the European Union (EU), except Vax_Period, are calculated as the average of all countries in the EU that use the Euro as their currency.15 Vax_Period for Europe is a dummy variable that equals 1 for the period starting the union's first day of COVID-19 vaccination data onward and zero otherwise.[16] We find that Russia's currency has the highest RV (1.60), followed by Brazil (1.47) and Mexico (1.37). Conversely, India has

[15] These countries are Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia, and Spain.
[16] The vaccination data for EU countries started on December 28, 2020, which was also the first day for France, Germany, and Italy.

the most stable currency during the pandemic, illustrated by its lowest average RV (0.11), followed by Thailand (0.17) and Indonesia (0.18).[17] Concerning the contagion of the pandemic, New Zealand has the lowest transmission rate, represented by a low average reproduction rate (R = 0.90), while the highest reproduction rates belong to Peru (1.09), Europe (1.08), and Brazil (1.08). Among the 30 selected countries/regions, the average daily vaccine doses administered per one million people is highest in Uruguay (3,176.83), followed by Israel (2,917.46), Chile (2,840.47), and Denmark (2,595.49). From the bottom, Egypt and South Africa have the lowest average daily new vaccinations per one million people, at 269.26 and 493.67, respectively.

According to the Morgan Stanley Capital International Annual Market Classification Review in 202, we divide the sample into emerging and developed countries.18 Panel C of Table 1 displays the descriptive statistics of the two subsamples. Regarding the average RV, emerging markets' currencies fluctuate more than developed countries' exchange rates, as shown by their mean realized variances of 0.69 and 0.44, respectively. The average number of new cases and new deaths per one million people and the reproduction rate indicate that the COVID-19 pandemic is more severe in emerging than in developed countries; however, the figures for three vaccination-related measures indicate that the COVID-19 vaccine rollout in emerging countries is far behind developed ones. For instance, the average daily new vaccinations per one million people in developed markets are significantly higher than those in emerging countries, as evidenced by the mean of New_vax(2,178.48 vs. 1,477.54).

Figures 1 and 2 depict the over-time evolution of the cross-sectional mean of four variables: realized variance (RV), reproduction rate (R), new COVID-19 cases (New_cases), and new

[17] In addition to average daily realized volatility, we report annualized realized volatility by country in Appendix A1.

[18] Developed countries in the sample include Canada, Denmark, Israel, Norway, the United Kingdom, Australia, Japan, and New Zealand. Europe, with major constituent countries in the developed category, is ranked as a developed area (see https://www.msci.com/our-solutions/indexes/market-classification).

vaccinations (New_vax). Figure 1 shows that the average RV and reproduction rate were the highest in March 2020, during the early stage of the pandemic. After this period, the RV decreased significantly before spiking again in October 2020 due to the uncertainty of the US presidential election, the increase in COVID-19 cases in many countries, and the reimposition of national lockdown measures, which raised concerns among investors.[19] While the reproduction rate dropped considerably from March 2020, its average value remained over one after that, implying that the pandemic was still developing. Figure 2 depicts newly confirmed COVID cases versus newly administered vaccine doses, indicating that as daily new vaccinations increased rapidly in early 2021 (which reflects the increasing global accessibility to the COVID-19 vaccine), newly confirmed COVID cases tended to decline.

We further examine the pairwise correlation coefficients between all the variables used in the baseline model, primarily to determine the presence of the multicollinearity problem. Table 2 presents the results of the correlation matrix, showing two main findings. First, the daily RV of global exchange rates significantly and negatively correlates with each of the three COVID-19 vaccination proxies, providing preliminary evidence that the vaccine rollout may reduce FX volatility. Second, strong positive relationships exist between the three vaccination-related variables. The highest correlation coefficient (0.86) is between the new vaccinations per one million people (New_vax) and the dummy variable for the vaccination period (Vax_Period). High correlation coefficients indicate the presence of multicollinearity if two or more vaccination-related variables are included in the baseline regression model. To circumvent the multicollinearity problem, we regress the FX-RV on each vaccination-related variable separately.

We further employ two unit-root tests for panel data to check the stationarity of the variables. These are the Im–Pesaran–Shin (IPS) test proposed by Im et al. (2003) and the panel unit-root

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

test suggested by Maddala and Wu (1999), i.e., the MW test. The null hypothesis of both tests is the presence of a unit root in the time series. We present the test statistics[20] and their *p*-values in Table 3. The test results strongly reject the null hypothesis, indicating that the selected variables are stationary.

5. Empirical results

5.1. Relationship between COVID-19 vaccinations and foreign exchange volatility

5.1.1. Main vaccination-related variables

This subsection presents the results of testing hypothesis H1 using Equation (2), developed in subsection 3.2.[21] Following Hasan et al. (2023), we account for the country-fixed effect and estimate Equation (2) using ordinary least squares, with robust standard errors clustered at the country level. Columns 1, 2, and 3 of Table 4 present the estimation results of three regressions in each of which the key explanatory variable for vaccination is, in turn, New_vax, $Vax\_Increase$, and Vax_Period.

The results in Column (1) reveal that daily new vaccine doses administered per one million people (New_vax) have a negative relationship with FX volatility. This effect is highly statistically significant at the 1% level. Regarding economic significance, the estimated parameter of New_vax (–0.002) indicates that a 10% increase in New_vax (in log) would decrease FX volatility by 0.02 units (Panel C).

In line with Column 1, Column (2) shows that an increase in daily vaccination rate ($Vax\_Increase$) exerts a negative and significant effect on the RV of exchange rates. Specifically, following the day with an increase in the average vaccination rate, the FX volatility decreases by 0.0029 units; thus, the more vaccines administered, the greater the

[20] Both tests are conducted with an intercept in the time series model.

[21] None of the explanatory variables in Equation (2) exhibits evidence of multicollinearity, as shown by the unreported variance inflation factors, which are all below 3. The variance factors are available upon request.

decline in FX volatility. Furthermore, regression results in Column (3) suggest that FX volatility would decline markedly by 0.0815 units during the vaccination period compared to the preceding period. This result corroborates our conclusion in Columns 1 and 2 that vaccinations reduce FX volatility.

Furthermore, the coefficient estimates of other control variables in Equation (2) are worth discussing. First, the past short-term (daily), medium-term (weekly), and long-term (monthly) components of RV are highly significant in explaining its current variations, as illustrated by the estimates of β_d, β_w, and β_m, respectively. Second, all the coefficient estimates of β_Q for the effect of measurement errors are consistently negative and statistically significant. This result conforms to the above-discussed intuition of the HARQ model that the greater the measurement error variance, the less contribution the past RV would make to explaining the present RV. Third, we find intriguing findings regarding the impact of the three pandemic proxies. Specifically, while the coefficient estimates of New_cases and New_deaths are insignificant, the estimated parameter of the reproduction rate (R) is positive and statistically significant across three model specifications. R is a forward-looking metric that helps evaluate the potential spread of the pandemic in the future (Díaz et al., 2022); thus, our results suggest that investors in FX markets consider the future state of the pandemic (i.e., R) more than information about the current situation (i.e., New_cases and New_deaths) in their decision-making process.

In addition to using the country-fixed-effect model, we employ pooled OLS and random effect methods to estimate Equation (2). Appendix A2 presents the regression results of these approaches, which are mostly consistent with Table 4. Specifically, the coefficient estimates of all vaccination proxies are negative and statistically significant, supporting our previous finding about the attenuating effect of vaccinations on FX volatility.

Furthermore, the effect of vaccinations on FX volatility may follow a U-shaped pattern. To explicitly test this possibility, we include the squared of variable New_vax in Equation (2), i.e., Equation (A3). The regression results of Equation (A3) in Appendix A3 contradict this possibility and support a linear relationship between vaccinations and FX volatility.

In summary, the Equation (2) results support hypothesis H1: COVID-19 vaccine rollouts help stabilize FX markets by reducing FX volatility. As the first FX market evidence, this finding contributes to the literature on the stabilizing effect of vaccinations on financial markets.

5.1.2. New first doses versus new second (third) doses

In the primary analysis, our vaccination-related variable, New_vax, encompasses the information on administering the first and second (or third) vaccine doses. We conjecture that the reducing effects of innovations in the new first and second doses on FX volatility may vary in magnitude and significance. Specifically, since people who take the first vaccine dose are likely to receive the second, the data on new first doses could be more informative for investors to assess a country's vaccination coverage. As such, we explore whether the stabilizing effects of new first and new second doses on FX volatility are different by employing two variables of new vaccination. The first variable is $First\_Dose$, measured by the change in the daily total number of people who received the first vaccine dose per 100 people in the total population. The second is $Second\_Dose$, calculated as the change in the daily total number of people who received all other doses prescribed by the vaccination protocol per 100 people in the total population.[22]

We re-estimate Equation (2) with the two new vaccination variables, and Table 5 presents the regression results using country-fixed effects estimations. Our empirical results show that the estimated coefficient of $First\_Dose$ is negative and statistically significant in Column (1), while the estimated parameter of $Second\_Dose$ is negative but insignificant, as evidenced in

[22] The data used to calculate $First\_Dose$ and $Second\_Dose$ are collected from Our World in Data.

Column (2).[23] This result indicates that new first-dose deployment innovations have significant implications for FX market participants. Conversely, the dynamics of the number of people fully vaccinated are less informative.

5.2. Robustness checks

5.2.1. Different HARQ-type models

This subsection presents the results of robustness checks using different HARQ-type models as described by Equations (6), (7), and (8). Table 6, Panel A, presents the results of Equation (6) when employing the HARQ-IFG model, showing that the estimated β_{IFG} coefficient is positive and statistically significant across model specifications. This result indicates that FX volatility positively relates to the IFG, which is consistent with Gong and Lin (2018). Moreover, the results show that using the HARQ-IFG to model FX volatility does not alter our principal results. The negative coefficient estimates of New_vax, $Vax\_Increase$, and Vax_Period show that the attenuation effect of COVID-19 vaccination programs on the realized volatility (RV) holds across the three model specifications.

Table 6 Panel B reports the results of Equation (7) when applying the HARQ-RS model to model FX volatility, showing that the estimated parameters of the three vaccination proxies are all negative and statistically significant. These results confirm the stabilizing impact of the COVID-19 vaccine rollout on FX volatility after controlling for signed semirealized variance.

Finally, Table 6 Panel C reports the results of Equation (8) when we include the implied volatility of exchange rates in the HARQ model (IV-HARQ). The estimated coefficients of daily, weekly, and monthly implied volatility are statistically significant, indicating that the expected volatility in FX options markets explains FX-RV. More importantly, the estimated

[23] We regress FX volatility on the variable of $First\_Dose$ and $Second\_Dose$ separately to avoid the multicollinearity problem in the model.

parameters of New_vax, $Vax\_Increase$, and Vax_Period stay significantly negative, corroborating the decreasing effect of the COVID-19 vaccine rollout on FX volatility.

In summation, Table 6 indicates that the negative relationship between COVID-19 vaccinations and FX volatility documented in our study is not sensitive to the choice of different HAR-type models to estimate RV. Again, our overarching hypothesis H1 holds.

5.2.2. Alternative measures of integrated quarticity

This paper employs realized quarticity (RQ) to estimate integrated quarticity (IQ) in the baseline model represented in Equation (2). RQ is a consistent estimator of IQ in the case of no jumps. We followed Bollerslev et al. (2016) to examine the sensitivity of our key empirical results to different quarticity estimators, replacing RQ in Equation (2) with several alternative estimators of integrated quarticity. The first alternative estimator is the tri-power quarticity (TPQ), developed by Barndorff-Nielsen and Shaphard (2006). The calculation of TPQ is as follows:

$$TPQ_t = M\mu_{4/3}^{-3} \sum_{i=1}^{M-2} |r_{t,i}|^{4/3} |r_{t,i+1}|^{4/3} |r_{t,i+2}|^{4/3} \quad (9)$$

where $\mu_{4/3} \equiv 2^{\frac{2}{3}}\Gamma(\frac{7}{6})/\Gamma(\frac{1}{2}) = \mathbb{E}(|Z|^{\frac{4}{3}})$. Barndorff-Nielsen and Shaphard (2006) stated that TPQ is a consistent estimator of integrated quarticity in the presence of jumps in the return series.

The second alternative measure of IQ is the jump-robust $MedRQ$ estimator suggested by Andersen et al. (2012). $MedRQ$ is computed using as follows:

$$MedRQ_t \equiv \frac{3\pi}{9\pi + 72 - 52\sqrt{3}} \frac{M^2}{M-2} \sum_{i=1}^{M-2} median(|r_{t,i}|, |r_{t,i+1}|, |r_{t,i+2}|)^4. \quad (10)$$

Lastly, we employ the truncated RQ estimator ($TrRQ$) developed by Mancini (2009). This estimator is estimated as follows:

$$TrRQ_t = M \sum_{i=1}^{M} |r_{t,i}^4| \mathbb{I}_{\{r_{t,i} \leq \alpha_i M^{\varpi}\}} \quad (11)$$

where α_i and ϖ are turning parameters, estimated as in Bollerslev et al. (2013).

Based on alternative estimators of IQ, we re-estimate Equation (2) by replacing RQ with each new estimator. The regression results of Equation (2) using alternative measures of IQ are reported in Table 7. Panels A, B, and C of Table 7 present the regression results of Equation (2) using $TPQ, MedRQ,$ and $TrRQ$, respectively. The sign and statistical significance of three vaccination-related variables in Table 7 are highly consistent with our baseline results in Table 4. In all panels, the parameter estimate of any of the three vaccination-related variables is negatively and statistically significant. These results reaffirm our key finding about the stabilizing effect of the COVID-19 vaccine rollout on the FX volatility. Furthermore, they indicate that this finding is independent of the choice of integrated quarticity estimator in the baseline model.

5.2.3. More control variables

One potential concern is that omitted variables related to RV may bias the estimation of the COVID-19 vaccination effects. To address this concern, we augment Equation (2) with additional control variables used in the literature to explain FX volatility. The factors influencing the supply and demand for foreign exchanges can indirectly affect exchange rate volatility. These variables include, but are not limited to, GDP growth, inflation, money supply growth, interest rates, capital flows, trade flows, industrial production growth, EPU, and liquidity (Chen et al., 2020; Eichler & Littke, 2018; Mueller et al., 2017; Gelman et al., 2015; Giannellis & Papadopoulos, 2011; Krol, 2014; Morana, 2009; Bollerslev & Melvin, 1994; and among others); however, most of these variables have no daily data available. Therefore, our regression first includes the following additional control variables: the volatility of the US interest rates (US_yield_vol), the volatility of the home country's interest rates ($Home\_yield\_vol$), and the volatility of the FX bid-ask spread ($Spread\_vol$). The volatility of interest rates (US_yield_vol or $Home\_yield\_vol$) is measured by the five-day standard deviation of yields on one-year treasury notes of a country. The volatility of exchange rate spreads is computed as the five-day standard deviation of the closing bid-ask spreads of an exchange rate. Daily data on the rates of country-specific one-year treasury notes are collected from Global Financial Databases, and daily data on the closing bid-ask spreads of an exchange rate is from Thomson DataStream.

In addition to these macroeconomic variables, Equation (2) includes that variable US_new_vax, measured as the natural logarithm of the number of daily new COVID-19 vaccine doses per one million people in the US. As the exchange rates in the paper are quoted against the USD, the intensity of vaccinations in the US might be another factor driving the FX volatility. Finally, several studies documented that governments' policies can affect the stability of financial markets during the pandemic (Bakry et al., 2022; Zaremba et al., 2020). Consequently, Equation (2) includes the variable $Stringency$, measured by the change in overall government stringency index for country i between time t and time $t-1$. The stringency index is a composite measure of nine response[24] metrics, indicating the overall stringency of the government's response to the pandemic. The index ranges between 0 and 100, and a higher score implies a stricter response. Given the discussion above, we specify the augmented model as follows:

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^{w} + \beta_m RV_{i,t}^{m} + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \beta_x X_{i,t} + \varepsilon_{i,t+1} \quad (12)$$

where $X_{i,t}$ denotes the 5×1 vector of the five additional exogenous variables mentioned above, and β_x is the 1×5 vector of coefficients.

[24] The nine metrics used to calculate the stringency index are school closures, workplace closures, cancellation of public events, restrictions on public gatherings, public transport closures, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls. The data on the stringency index are sourced from OurWorld in Data's website.

Table 8 reports the regression results of Equation (12). Among the additional control variables, the volatility of the US interest rates is positively and significantly correlated with exchange rate volatility across different model specifications, as evidenced by the coefficients of US_yield_vol. Furthermore, a positive and significant relationship exists between the spread volatility and the realized volatility of exchange rates, in line with Bollerslev and Melvin (1994); however, $Home\_yield\_vol$ is insignificant in explaining the RV of exchange rates when added to the HARQ model. Interestingly, weak evidence indicates that the intensity of the COVID-19 vaccine rollout in the US reduces FX volatility, as shown by the coefficient estimate of US_new_vax in Column (1). Furthermore, the coefficient estimates of $Stringency$ are positive and statistically significant across different model specifications, indicating that the index positively affects FX volatility. These results align with Rouatbi et al. (2021) and Bakry et al. (2022), who found that the strict containment measures by the government contribute to amplifying stock market volatility. Most importantly, the coefficients of all three vaccination-related variables remain highly significant and negative when estimated by the augmented HARQ model in Equation (12). This result lends further support to hypothesis H1.

5.2.4. Different sampling periods

As another robustness check of our results, we re-estimate the baseline model using three sampling periods with different starting dates of the global COVID-19 outbreak. Following Rouatbi et al. (2021), we choose three starting dates; March 11, 2020, when the WHO declared COVID-19 a pandemic (Panel A); June 6, 2020, considered to be the end of the initial postcrisis rebound period (Bae & Ghoul, 2021) (Panel B); and August 11, 2020, when Russia officially approved the world’s first COVID-19 vaccine (Panel C). Table 9 shows that the coefficients of different proxies of COVID-19 vaccinations remain negative and statistically significant across the three sample periods; thus, our affirmative test result of H1 holds, irrespective of the sample period.

5.2.5. Does the effect of vaccinations differ across various quantiles of FX volatility?

This subsection exceeds the mean regression presented in the primary analysis to explore the possibility that the effect of vaccinations on FX volatility is heterogeneous under different conditional distributions (i.e., quantiles). This additional analysis is motivated by the prior finding that the relationship between the FX market and other financial markets or macroeconomic indicators varies depending on FX market conditions (Chen et al., 2020; Huang et al., 2011; Nusair & Olson, 2019; Tsai, 2012; Viola et al., 2019).

We employ a fixed-effect panel quantile regression model[25] proposed by Koenker (2004) to estimate the effects of COVID-19 vaccinations on FX volatility under different quantiles of FX volatility. This model has the advantage of accounting for the country-specific unobserved heterogeneity. The quantile function of $RV_{i,t+1}$ in Equation (2) can be written as follows:

$$Q_\tau\left(RV_{i,t+1}\middle|\tau\right) = \alpha_{0,\tau} + \alpha_{1,\tau}RV_{i,t} + \alpha_{2,\tau}RQ_{i,t}^{1/2}RV_{i,t} + \alpha_{3,\tau}RV_{i,t}^{w} + \alpha_{4,\tau}RV_{i,t}^{m} + \alpha_{5,\tau}Covid_{i,t} + \alpha_{6,\tau}Vax_{i,t} + \varepsilon_{i,t} \quad (13)$$

where $Q_\tau(RV_{i,t+1}\,|\,\tau)$ is the τ-th quantile regression function, $\alpha_{j,\tau}$ (j = 0,..,6) is the estimated parameters of the intercept and regressors at τ-th quantile, and $\varepsilon_{i,t}$ is the standard error. Equation (10) is estimated using a penalized quantile regression estimator (Koenker, 2004). We employ nineteen quantiles from the 5th to the 95th percentile with an increment of 5 percentiles for the analysis.

For brevity, Table 10 only presents the estimated parameters of the vaccination variables at different quantile levels. Two remarkable findings stand out. First, the estimated parameters

[25] See Koenker (2004) for a full reference of the estimation method.

of New_vax and Vax_Period are consistently negative and statistically significant across all selected quantiles. The estimated coefficient for $Vax\_Increase$ is negative and statistically significant for 14 out of 19 percentiles. The three vaccination-related variables in the panel quantile regression have broad adverse and significant effects, implying that the sign of the COVID-19 vaccination effect on FX volatility holds regardless of the quantile levels. Second, the vaccine rollout on FX volatility exhibits a strong asymmetric effect, depending on the quantile level of volatility distribution. Figure 3 presents the plots of the estimated parameter of three vaccination-related variables through different quantile levels, consistently showing that the stabilizing effect is most pronounced when FX volatility is high (i.e., at the 95th quantile).

5.2.6. Addressing time difference bias

This study employs daily data, an approach consistent with most research on the impacts of the COVID-19 pandemic and vaccinations on global financial markets (Apergis et al., 2022; Rouatbi et al., 2021; Topcu & Gulal, 2020; Zaremba et al., 2021). However, using daily data may be subject to the time difference bias as the information about the severity of the pandemic and the deployment of vaccinations at day t might not be publicly available promptly at day $t + 1$. To address this concern, we follow Augustin et al. (2022) and Hasan et al. (2023), using weekly data on the COVID-19 pandemic and vaccine rollout to conduct a further robustness check for our key empirical results. We assume that k represents weekly data, $k = 1,2,3, \ldots$, and estimate the following equation:

$$RV_{i,k+1}^{w} = \beta_0 + \beta_w RV_{i,k}^{w} + \beta_m RV_{i,k}^{m} + \beta_c Covid_{i,k} + \beta_v Vax_{i,k} + \varepsilon_{i,k+1} \tag{14}$$

where $RV_{i,k}^{w}$ and $RV_{i,k}^{m} = \frac{1}{4}\sum_{j=0}^{3} RV_{i,k-j}$ denote the weekly and monthly realized FX volatility of country i in week k. $Covid_{i,k}$ and $Vax_{i,k}$ are defined the same as in Equation (8), except they are weekly.

Table 11 presents the regression results of Equation (14), showing that the coefficient estimates of vaccination variables are negative and statistically significant across different model specifications. These results indicate that our key empirical finding about the stabilizing effect of vaccinations holds after controlling for the time difference bias.

5.3. Additional analyses

This section conducts additional analyses by testing hypotheses H2, H3, and H4 developed in subsection 2.2. The test results are presented below.

5.3.1. Heterogeneous impacts in developed versus emerging markets

We first examine subhypothesis H2 concerning the role of economic development in shaping the effect of vaccinations on FX volatility. To differentiate the effects of the COVID-19 vaccine rollout on FX volatility between emerging and developed markets, we estimate the model as follows:

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^{w} + \beta_m RV_{i,t}^{m} + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \beta_{veme} Vax_{Eme,i,t} + \varepsilon_{i,t+1} \quad (15)$$

where $Vax_{Eme,i,t} = Vax_{i,t} \times EME_i$; the dummy variable, EME_i, is 1 if market i is emerging and 0 otherwise.

Table 12 reports the regression results of Equation (15), showing that the estimates of β_{veme} on $New\_vax \times EME$, $Vax\_Increase \times EME$, or $Vax\_Period \times EME$ are all statistically significant and negative. $\beta_v + \beta_{veme}$ is more negative than β_v, suggesting that the stabilizing impact of the COVID-19 vaccine rollout on exchange rates is more pronounced in emerging markets than in developed markets. Therefore, H2 is supported.

5.3.2. The role of COVID-19 vaccinations in affecting EPU's volatility effects

This subsection examines subhypothesis H3. To test the hypothesis, we collect the data on the EPU index for the selected countries in our sample. The data is downloadable from the website https://www.policyuncertainty.com/index.html and is published monthly. Among the 30 countries/regions in our sample, 10 countries have available EPU index data. We calculate the average EPU index for each country during the COVID-19 pandemic from January 2020 to May 2021. We then divide the selected countries into two subsamples: high and low EPU. A country is in the high EPU group if its average EPU index is higher than 219 during the pandemic (the median value); otherwise, it is in the low EPU group. Figure 4 displays the average EPU index of each country, showing Russia had the highest EPU during the pandemic while India exhibited the lowest EPU.

To examine hypothesis H3, we estimate the following equation:

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^{w} + \beta_m RV_{i,t}^{m} + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \beta_{epu} Vax_{Epu,i,t} + \varepsilon_{i,t+1} \quad (16)$$

where $Vax_{Epu,i,t} = Vax_{i,t} \times Epu_i$. The Epu_i dummy variable equals 1 if country i is in the subsample of high EPU and 0 otherwise. We expect the estimate of β_{epu} to be negative, implying that the stabilizing effect of $Vax_{i,t}$ will be stronger when the country has a high EPU.

Table 13 reports the regression results of Equation (16), showing that the estimates of β_{epu} associated with New_vax_EPU, $Vax\_Increase\_EPU$, or Vax_Period_EPU are all negative with a higher statistical significance. This result indicates that FX markets perceived increases in the COVID-19 vaccine rollout as conducive to improving economic conditions. Furthermore, $\beta_v + \beta_{epu}$ is more negative than β_v. Therefore, we can also conclude that the stabilizing effect of the COVID-19 vaccine rollout on FX volatility is more significant in countries with high EPU during the pandemic. This finding is consistent with our expectations stated in H3.

5.3.3. The role of vaccine confidence

We next examine subhypothesis H4. We use data from the Wellcome Foundation Global Monitor26 2018 survey about global attitudes to science and health from over 140,000 people in more than 140 countries to proxy for vaccine confidence. Following Sturgis et al. (2021) and Feleszko et al. (2021), we focus on confidence in vaccines using the response to Question 26: "Do you strongly or somewhat agree, strongly and somewhat disagree, or neither agree nor disagree with the following statement? Vaccines are effective." We rely on the proportion of respondents who answered "Strongly agree" as a score for confidence in vaccination in a country.

Figure 5 plots the vaccine-confidence score of selected countries in the sample. Among 29 countries,[27] people in Japan, South Korea, and Russia are among the least confident in the effectiveness of vaccination. In contrast, people in Egypt, India, and Mexico strongly believe in the efficacy of vaccination. Based on the vaccine-confidence score, we define a country as high-confidence if its score is larger than the median; otherwise, it is considered a low-confidence country. We re-estimate the following equation to investigate the role of vaccine confidence in affecting the effect of COVID-19 vaccinations on FX volatility:

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^{w} + \beta_m RV_{i,t}^{m} + \beta_c Covid_{i,t} + \beta_v Vax_{i,t} + \beta_{trust} Vax_{Trust,i,t} + \varepsilon_{i,t+1} \quad (17)$$

where $Vax_{Trust,i,t} \equiv Vax_{i,t} Trust_i$. The $Trust_i$ dummy variable equals 1 if country i is in the subsample of high vaccine confidence and 0 otherwise.

Table 14 reports the regression results of Equation (17), showing a negative and statistically significant estimate of β_{trust} across all model specifications. Thus, $\beta_v + \beta_{trust} < \beta_v < 0$,

[26] https://wellcome.org/reports/wellcome-global-monitor/2018#downloads-4d1c
[27] We exclude Europe as the survey data because some countries in the group are missing.

which supports H4 and indicates that the reducing effect of the vaccine rollout on FX volatility is more pronounced in countries with high vaccine confidence.

5.3.4. Robustness checks of additional analyses

As a robustness check of the test results for H2, H3, and H4, we regress FX-RV on all the interaction-type control variables, including $Vax_{Eme,i,t}$, $Vax_{Epu,i,t}$, and $Vax_{Trust,i,t}$. The limitation of data on the EPU index restricts our regression to a sample of 10 countries. Appendix A4 shows that the estimates of coefficients on $Vax_{Eme,i,t}$, $Vax_{Epu,i,t}$, and $Vax_{Trust,i,t}$ are all statistically significant and negative, regardless of which vaccination measure was applied. These results corroborate our above conclusion that the stabilizing effect of vaccinations on FX volatility is more pronounced in emerging markets, countries with high EPU, and nations with greater vaccine confidence. We also re-estimate the model for the sample of 29 countries with two control variables, including $Vax_{Eme,i,t}$ and $Vax_{Trust,i,t}$; the EPU interaction term was excluded. Appendix A5 shows that the negative coefficient estimates further affirm the increased stabilizing effect of the vaccinations on FX volatility in emerging markets and countries with higher vaccine confidence. Thus, our test results in support of H2, H3, and H4 are robust.

6. Concluding remarks

This study investigates comprehensively how the vaccine rollout affects FX volatility, contributing to a relatively new strand of literature related to the impact of COVID-19 vaccinations on global financial markets. We developed four testable hypotheses based on economic theories, influential studies of exchange rate movements, and extensive relevant empirical evidence. The test results show that the vaccine rollouts worldwide contribute to stabilizing global FX markets by attenuating FX volatility. This stabilizing effect is significant after controlling for the pandemic's dynamics, and it remained robust to alternative proxies of vaccinations and different approaches for panel regression. The effect also survives additional robustness checks with an alternative estimator of integrated quarticity applied, more control variables, different sampling periods, various HARQ-type regression models, numerous quantile level regressions, and time difference bias.

Our findings have significant practical implications for practitioners and policymakers. The pronounced stabilizing effect of COVID-19 vaccinations on FX volatility indicates that FX market participants should monitor vaccine deployment and development information—especially the innovations in first-dose-vaccination-related news—if their business decisions depend on volatility. Furthermore, the FX market stability is crucial to import–export activities, investment, consumption, and ultimately, economic stabilization; therefore, policymakers worldwide should encourage the deployment and support the development of vaccination programs. This approach is essential for emerging economies, high vaccine-confidence nations, and high EPU countries, where the role of vaccine rollout in stabilizing the FX market is more pronounced than in other countries.

References

Acharya, V. V., Johnson, T., Sundaresan, S., & Zheng, S. (2020). *The value of a cure: An asset pricing perspective (no. w28127)*. National Bureau of Economic Research.

Aghion, P., Bacchetta, P., Rancière, R., & Rogoff, K. (2009). Exchange rate volatility and productivity growth: The role of financial development. *Journal of Monetary Economics*, *56*(4), 494–513. https://doi.org/10.1016/j.jmoneco.2009.03.015

Albulescu, C. (2020). *Do COVID-19 and crude oil prices drive the US economic policy uncertainty? arXiv preprint arXiv:2003.07591*.

Albulescu, C. T. (2021). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, *38*, 101699. https://doi.org/10.1016/j.frl.2020.101699, PubMed: 32837380

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, *39*(4), 885–901. https://doi.org/10.2307/2527343

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001). The distribution of realized exchange rate volatility. *Journal of the American Statistical Association*, *96*(453), 42–55. https://doi.org/10.1198/016214501750332965

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, *71*(2), 579–625. https://doi.org/10.1111/1468-0262.00418

Andersen, T. G., Dobrev, D., & Schaumburg, E. (2012). Jump-robust volatility estimation using nearest neighbor truncation. *Journal of Econometrics*, *169*(1), 75–93. https://doi.org/10.1016/j.jeconom.2012.01.011

Apergis, N., Danuletiu, D., & Xu, B. (2022). CDS spreads and COVID-19 pandemic. *Journal of International Financial Markets, Institutions and Money*, *76*, 101433. https://doi.org/10.1016/j.intfin.2021.101433

Areal, N. M. P. C., & Taylor, S. J. (2002). The realized volatility of FTSE-100 futures prices. *Journal of Futures Markets*, *22*(7), 627–648. https://doi.org/10.1002/fut.10018

Ashraf, B. N. (2020). Stock markets' reaction to COVID-19: Cases or fatalities? *Research in International Business and Finance*, *54*, 101249. https://doi.org/10.1016/j.ribaf.2020.101249, PubMed: 34170989

Aslam, F., Aziz, S., Nguyen, D. K., Mughal, K. S., & Khan, M. (2020). On the efficiency of foreign exchange markets in times of the COVID-19 pandemic. *Technological Forecasting and Social Change*, *161*, 120261. https://doi.org/10.1016/j.techfore.2020.120261, PubMed: 32836478

Augustin, P., Sokolovski, V., Subrahmanyam, M. G., & Tomio, D. (2022). In sickness and in debt: The COVID-19 impact on sovereign credit risk. *Journal of Financial Economics*, *143*(3), 1251–1274. https://doi.org/10.1016/j.jfineco.2021.05.009, PubMed: 36268533

Bae, K. H., & Ghoul, S.EI., *Gong*, Z.J., & Guedhami, O. (2021). Does CSR matter in times of crisis? Evidence from the COVID-19 pandemic. *Journal of Corporate Finance, 67*, 101876.

Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters*, *37*, 101748. https://doi.org/10.1016/j.frl.2020.101748, PubMed: 32895607

Baker, S. R., Nicholas, B., Steven, J. D., & Stephen, J. T. (2020). *Covid-induced economic uncertainty*. No. w26983. National Bureau of Economic Research.

Bakry, W., Kavalmthara, P. J., Saverimuttu, V., Liu, Y., & Cyril, S. (2022). Response of stock market volatility to COVID-19 announcements and stringency measures: A comparison of developed and emerging markets. *Finance Research Letters*, *46*, 102350. https://doi.org/10.1016/j.frl.2021.102350, PubMed: 35431683

Balcilar, M., Gupta, R., Kyei, C., & Wohar, M. E. (2016). Does economic policy uncertainty predict exchange rate returns and volatility? Evidence from a nonparametric causality-in-quantiles test. *Open Economies Review*, *27*(2), 229–250. https://doi.org/10.1007/s11079-016-9388-x

Banerjee, S. (2011). Learning from prices and the dispersion in beliefs. *Review of Financial Studies*, *24*(9), 3025–3068. https://doi.org/10.1093/rfs/hhr050

Barndorff-Nielsen, O. E., & Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics*, *4*(1), 1–30. https://doi.org/10.1093/jjfinec/nbi022

Bärnighausen, T., Bloom, D. E., Cafiero-Fonseca, E. T., & O'Brien, J. C. (2014). Valuing vaccination. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(34), 12313–12319. https://doi.org/10.1073/pnas.1400475111, PubMed: 25136129

Baum, C. F., & Caglayan, M. (2010). On the sensitivity of the volume and volatility of bilateral trade flows to exchange rate uncertainty. *Journal of International Money and Finance*, *29*(1), 79–93. https://doi.org/10.1016/j.jimonfin.2008.12.003

Bazán-Palomino, W., & Winkelried, D. (2021). FX markets' reactions to COVID-19: Are they different? *International Economics*, *167*, 50–58. https://doi.org/10.1016/j.inteco.2021.05.006

Beckmann, J., & Czudaj, R. (2017). Exchange rate expectations and economic policy uncertainty. *European Journal of Political Economy*, *47*, 148–162. https://doi.org/10.1016/j.ejpoleco.2016.06.003

Benati, I., & Coccia, M. (2022). Global analysis of timely COVID-19 vaccinations: Improving governance to reinforce response policies for pandemic crises. *International Journal of Health Governance* [Ahead-of-print], *27*(3), 240–253. https://doi.org/10.1108/IJHG-07-2021-0072

Bhargava, A., Jamison, D. T., Lau, L. J., & Murray, C. J. (2001). Modeling the effects of health on economic growth. *Journal of Health Economics*, *20*(3), 423–440. https://doi.org/10.1016/s0167-6296(01)00073-x, PubMed: 11373839

Bissoondoyal-Bheenick, E., Brooks, R., Do, H. X., & Smyth, R. (2020). Exploiting the heteroskedasticity in measurement error to improve volatility predictions in oil and biofuel feedstock markets. *Energy Economics*, *86*, 104689. https://doi.org/10.1016/j.eneco.2020.104689

Bleaney, M. (2008). Openness and real exchange rate volatility: In search of an explanation. *Open Economies Review* [Review], *19*(2), 135–146. https://doi.org/10.1007/s11079-007-9054-4

Bloom, D. E., Canning, D., Hu, L., Liu, Y., Mahal, A., & Yip, W. (2010). The contribution of population health and demographic change to economic growth in China and India. *Journal of Comparative Economics*, *38*(1), 17–33. https://doi.org/10.1016/j.jce.2009.11.002, PubMed: 20419074

Bloom, D. E., Canning, D., & Weston. (2008). *Fighting the diseases of poverty* (1st ed). Routledge.

Bollerslev, T., & Melvin, M. (1994). Bid—Ask spreads and volatility in the foreign exchange market. *Journal of International Economics*, *36*(3–4), 355–372. https://doi.org/10.1016/0022-1996(94)90008-6

Bollerslev, T., Patton, A. J., & Quaedvlieg, R. (2016). Exploiting the errors: A simple approach for improved volatility forecasting. *Journal of Econometrics*, *192*(1), 1–18. https://doi.org/10.1016/j.jeconom.2015.10.007

Bollerslev, T., Todorov, V., & Li, S. Z. (2013). Jump tails, extreme dependencies, and the distribution of stock returns. *Journal of Econometrics*, *172*(2), 307–324. https://doi.org/10.1016/j.jeconom.2012.08.014

Braun, M., & Larrain, B. (2005). Finance and the Business Cycle: International, Inter-Industry Evidence. *Journal of Finance*, *60*(3), 1097–1128. https://doi.org/10.1111/j.1540-6261.2005.00757.x

Bubák, V., Kočenda, E., & Žikeš, F. (2011). Volatility transmission in emerging European foreign exchange markets. *Journal of Banking and Finance*, *35*(11), 2829–2841. https://doi.org/10.1016/j.jbankfin.2011.03.012

Busch, T., Christensen, B. J., & Nielsen, M. Ø. (2011). The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets. *Journal of Econometrics*, *160*(1), 48–57. https://doi.org/10.1016/j.jeconom.2010.03.014

Caggiano, G., Castelnuovo, E., & Kima, R. (2020). The global effects of Covid-19-induced uncertainty. *Economics Letters*, *194*, 109392. https://doi.org/10.1016/j.econlet.2020.109392, PubMed: 32834236

Calderón, C. (2004). *Trade openness and real exchange rate volatility: Panel data evidence. Central Bank of Chile*. Working Paper 294.

Calderón, C., Duncan, R., & Schmidt-Hebbel, K. (2004). The role of credibility in the cyclical properties of macroeconomic policies in emerging economies. *Review of World Economics*, *140*(4), 613–633. https://doi.org/10.1007/BF02659617

Calderón, C., & Kubota, M. (2018). Does higher openness cause more real exchange rate volatility? *Journal of International Economics*, *110*, 176–204. https://doi.org/10.1016/j.jinteco.2017.08.002

Chan, K. F., Chen, Z., Wen, Y., & Xu, T. (2022). COVID-19 vaccines and global stock markets. *Finance Research Letters*, *47*, 102774. https://doi.org/10.1016/j.frl.2022.102774, PubMed: 35283695

Chen, L., Du, Z., & Hu, Z. (2020). Impact of economic policy uncertainty on exchange rate volatility of China. *Finance Research Letters*, *32*, 101266. https://doi.org/10.1016/j.frl.2019.08.014

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics*, *7*(2), 174–196. https://doi.org/10.1093/jjfinec/nbp001

Devpura, N., & Narayan, P. K. (2020). Hourly oil price volatility: The role of COVID-19. *Energy Research Letters*, *1*(2), 1–5. https://doi.org/10.46557/001c.13683

Díaz, F., Henríquez, P. A., & Winkelried, D. (2022). Stock market volatility and the COVID-19 reproductive number. *Research in International Business and Finance*, *59*, 101517. https://doi.org/10.1016/j.ribaf.2021.101517, PubMed: 34663999

Eichler, S., & Littke, H. C. N. (2018). Central Bank transparency and the volatility of exchange rates. *Journal of International Money and Finance*, *89*, 23–49. https://doi.org/10.1016/j.jimonfin.2018.07.006

Engelhardt, N., Krause, M., Neukirchen, D., & Posch, P. N. (2021). Trust and stock market volatility during the COVID-19 crisis. *Finance Research Letters*, *38*, 101873. https://doi.org/10.1016/j.frl.2020.101873, PubMed: 36569649

Evans, M. D. D., & Lyons, R. K. (2002). Order flow and exchange rate dynamics. *Journal of Political Economy*, *110*(1), 170–180. https://doi.org/10.1086/324391

Evans, M. D. D., & Lyons, R. K. (2005). Meese-Rogoff Redux: Micro-Based Exchange-Rate Forecasting. *American Economic Review*, *95*(2), 405–414. https://doi.org/10.1257/000282805774669934

Evans, M. D. D., & Lyons, R. K. (2008). How is macro news transmitted to exchange rates? *Journal of Financial Economics*, *88*(1), 26–50. https://doi.org/10.1016/j.jfineco.2007.06.001

Fasanya, I. O., Oyewole, O., Adekoya, O. B., & Odei-Mensah, J. (2020). Dynamic spillovers and connectedness between COVID-19 pandemic and global foreign exchange markets. *Economic Research*, *34*, 1–13[Editor1].

Feleszko, W., Lewulis, P., Czarnecki, A., & Waszkiewicz, P. (2021). Flattening the curve of COVID-19 vaccine rejection–an international overview. *Vaccines*, *9*(1). https://doi.org/10.3390/vaccines9010044, PubMed: 33451104

Feng, G. F., Yang, H. C., Gong, Q., & Chang, C. P. (2021). What is the exchange rate volatility response to COVID-19 and government interventions? *Economic Analysis and Policy*, *69*, 705–719. https://doi.org/10.1016/j.eap.2021.01.018

Fernandez-Perez, A., Gilbert, A., Indriawan, I., & Nguyen, N. H. (2021). COVID-19 pandemic and stock market response: A culture effect. *Journal of Behavioral and Experimental Finance*, *29*, 100454. https://doi.org/10.1016/j.jbef.2020.100454, PubMed: 33520663

Fisera, B., Horvath, R., & Melecky, M. (2023). Natural disasters and debt financing costs. *Climate Change Economics*, *14*(3), 2350015. https://doi.org/10.1142/S201000782350015X

Gelman, M., Jochem, A., Reitz, S., & Taylor, M. P. (2015). Real financial market exchange rates and capital flows. *Journal of International Money and Finance*, *54*, 50–69. https://doi.org/10.1016/j.jimonfin.2015.02.004

Giannellis, N., & Papadopoulos, A. P. (2011). What causes exchange rate volatility? Evidence from selected EMU members and candidates for EMU membership countries. *Journal of International Money and Finance*, *30*(1), 39–61. https://doi.org/10.1016/j.jimonfin.2010.07.002

Gil-Alana, L. A., & Monge, M. (2020). Crude oil prices and COVID-19: Persistence of the shock. *Energy Research Letters*, *1*(1), 1–4. https://doi.org/10.46557/001c.13200

Gong, X., & Lin, B. (2018). The incremental information content of investor fear gauge for volatility forecasting in the crude oil futures market. *Energy Economics*, *74*, 370–386. https://doi.org/10.1016/j.eneco.2018.06.005

Grier, R., & Grier, K. B. (2006). On the real effects of inflation and inflation uncertainty in Mexico. *Journal of Development Economics*, *80*(2), 478–500. https://doi.org/10.1016/j.jdeveco.2005.02.002

Harjoto, M. A., Rossi, F., Lee, R., & Sergi, B. S. (2021). How do equity markets react to COVID-19? Evidence from emerging and developed countries. *Journal of Economics and Business*, *115*, 105966. https://doi.org/10.1016/j.jeconbus.2020.105966, PubMed: 33518845

Hasan, I., Marra, M., To, T. Y., Wu, E., & Zhang, G. (2023). COVID-19 pandemic and global corporate CDS spreads. *Journal of Banking and Finance*, *147*, 106618. https://doi.org/10.1016/j.jbankfin.2022.106618, PubMed: 35873083

Hau, H. (2002). Real exchange rate volatility and economic openness: Theory and evidence. *Journal of Money, Credit, and Banking*, *34*(3a), 611–630. https://doi.org/10.1353/mcb.2002.0002

Huang, A. Y., Peng, S.-P., Li, F., & Ke, C.-J. (2011). Volatility forecasting of exchange rate by quantile regression. *International Review of Economics and Finance*, *20*(4), 591–606. https://doi.org/10.1016/j.iref.2011.01.005

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7

Jorion, P. (1995). Predicting volatility in the foreign exchange market. *Journal of Finance*, *50*(2), 507–528. https://doi.org/10.1111/j.1540-6261.1995.tb04793.x

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis*, *91*(1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006

Krol, R. (2014). Economic policy uncertainty and exchange rate volatility. *International Finance*, *17*(2), 241–256. https://doi.org/10.1111/infi.12049

Li, Y., Liang, C., Ma, F., & Wang, J. (2020). The role of the IDEMV in predicting European stock market volatility during the COVID-19 pandemic. *Finance Research Letters*, *36*, 101749. https://doi.org/10.1016/j.frl.2020.101749, PubMed: 32908465

Li, Y., Shi, Y., Shi, Y., Yi, S., & Zhang, W. (2023). COVID-19 vaccinations and risk spillovers: Evidence from Asia-Pacific stock markets. *Pacific-Basin Finance Journal*, *79*, 102004. https://doi.org/10.1016/j.pacfin.2023.102004

Liu, M., Choo, W.-C., & Lee, C.-C. (2020). The response of the stock market to the announcement of global pandemic. *Emerging Markets Finance and Trade*, *56*(15), 3562–3577. https://doi.org/10.1080/1540496X.2020.1850441

Loeppke, R., Nicholson, S., Taitel, M., Sweeney, M., Haufle, V., & Kessler, R. C. (2008). The impact of an integrated population health enhancement and disease management program on employee health risk, health conditions, and productivity. *Population Health Management*, *11*(6), 287–296. https://doi.org/10.1089/pop.2008.0006, PubMed: 19108644

Lyócsa, Š., Plíhal, T., & Výrost, T. (2021). FX market volatility modelling: Can we use low-frequency data? *Finance Research Letters*, *40*, 101776. https://doi.org/10.1016/j.frl.2020.101776, PubMed: 33020698

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(S1), 631–652. https://doi.org/10.1111/1468-0084.0610s1631

Mancini, C. (2009). Non-parametric threshold estimation for models with stochastic diffusion coefficient and jumps. *Scandinavian Journal of Statistics*, *36*(2), 270–296. https://doi.org/10.1111/j.1467-9469.2008.00622.x

Mathieu, E., Ritchie, H., Ortiz-Ospina, E., Roser, M., Hasell, J., Appel, C., Giattino, C., & Rodés-Guirao, L. (2021). A global database of COVID-19 vaccinations. *Nature Human Behaviour*, *5*(7), 947–953. https://doi.org/10.1038/s41562-021-01122-8, PubMed: 33972767

McAleer, M., & Medeiros, M. C. (2008). Realized volatility: A review. Econometric reviews, 27(1-3), 10-45. https://doi.org/10.1080/07474930701853509

Morana, C. (2009). On the macroeconomic causes of exchange rate volatility. *International Journal of Forecasting*, *25*(2), 328–350. https://doi.org/10.1016/j.ijforecast.2009.01.013

Mueller, P., Tahbaz-Salehi, A., & Vedolin, A. (2017). Exchange rates and monetary policy uncertainty. *Journal of Finance*, *72*(3), 1213–1252. https://doi.org/10.1111/jofi.12499

Narayan, P. K. (2020). Has COVID-19 changed exchange rate resistance to shocks? *Asian Economics Letters*, *1*(1), 1–4. https://doi.org/10.46557/001c.17389

Narayan, P. K., Devpura, N., & Wang, H. (2020). Japanese currency and stock market-What happened during the COVID-19 pandemic? *Economic Analysis and Policy*, *68*, 191–198. https://doi.org/10.1016/j.eap.2020.09.014, PubMed: 33012962

Neely, C. J. (2009). Forecasting foreign exchange volatility: Why is implied volatility biased and inefficient? And does it matter? *Journal of International Financial Markets, Institutions and Money*, *19*(1), 188–205. https://doi.org/10.1016/j.intfin.2007.11.002

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703–708. https://doi.org/10.2307/1913610

Njindan Iyke, B. (2020). The disease outbreak channel of exchange rate return predictability: Evidence from COVID-19. *Emerging Markets Finance and Trade*, *56*(10), 2277–2297. https://doi.org/10.1080/1540496X.2020.1784718

Nusair, S. A., & Olson, D. (2019). The effects of oil price shocks on Asian exchange rates: Evidence from quantile regression analysis. *Energy Economics*, *78*, 44–63. https://doi.org/10.1016/j.eneco.2018.11.009

Okonjo-Iweala, D. G. (2021). https://www.wto.org/english/news_e/spno_e/spno5_e.htm. Trade forecast press conference: Remarks.

Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, *97*(3), 683–697. https://doi.org/10.1162/REST_a_00503

Pham, S. D., Nguyen, T. T. T., Do, H. X., & Vo, X. V. (2023). Portfolio diversification during the COVID-19 pandemic: Do vaccinations matter? *Journal of Financial Stability*, *65*, 101118. https://doi.org/10.1016/j.jfs.2023.101118

Plíhal, T., & Lyócsa, Š. (2021). Modeling realized volatility of the EUR/USD exchange rate: Does implied volatility really matter? *International Review of Economics and Finance*, *71*, 811–829. https://doi.org/10.1016/j.iref.2020.10.001

Prabheesh, K. P., Padhan, R., & Garg, B. (2020). COVID-19 and the oil price – Stock market nexus: Evidence from net oil-importing countries. *Energy Research Letters*, *1*, 1–6.

Qian, Y., & Varangis, P. (1994). Does exchange rate volatility hinder export growth? *Empirical Economics*, *19*(3), 371–396. https://doi.org/10.1007/BF01205944

Qiu, Y., Wang, Z., Xie, T., & Zhang, X. (2021). Forecasting Bitcoin realized volatility by exploiting measurement error under model uncertainty. *Journal of Empirical Finance*, *62*, 179–201. https://doi.org/10.1016/j.jempfin.2021.03.003

Quilici, S., Smith, R., & Signorelli, C. (2015). Role of vaccination in economic growth. *Journal of Market Access and Health Policy*, *3*, 27044. https://doi.org/10.3402/jmahp.v3.27044, PubMed: 27123174

Rahman, H., Majumder, S. C., & Hossain, M. N. (2020). The impact of exchange rate volatility on export and import in Bangladesh. *European Online Journal of Natural and Social Sciences*, *9*.

Rémy, V., Largeron, N., Quilici, S., & Carroll, S. (2015). The economic value of vaccination: Why prevention is wealth. *Journal of Market Access and Health Policy*, *3*, 29284. https://doi.org/10.3402/jmahp.v3.29284, PubMed: 27123187

Rime, D., Sarno, L., & Sojli, E. (2010). Exchange rate forecasting, order flow and macroeconomic information. *Journal of International Economics*, *80*(1), 72–88. https://doi.org/10.1016/j.jinteco.2009.03.005

Rouatbi, W., Demir, E., Kizys, R., & Zaremba, A. (2021). Immunizing markets against the pandemic: COVID-19 vaccinations and stock volatility around the world. *International Review of Financial Analysis*, *77*, 101819. https://doi.org/10.1016/j.irfa.2021.101819, PubMed: 36530209

Ryan, J., Zoellner, Y., Gradl, B., Palache, B., & Medema, J. (2006). Establishing the health and economic impact of influenza vaccination within the European Union 25 countries. *Vaccine*, *24*(47–48), 6812–6822. https://doi.org/10.1016/j.vaccine.2006.07.042, PubMed: 17034909

Salisu, A. A., Sikiru, A. A., & Vo, X. V. (2020). Pandemics and the emerging stock markets. *Borsa Istanbul Review*, *20*, S40–S48. https://doi.org/10.1016/j.bir.2020.11.004

Sarkodie, S. A., Ahmed, M. Y., & Owusu, P. A. (2022). COVID-19 pandemic improves market signals of cryptocurrencies–evidence from Bitcoin, Bitcoin Cash, Ethereum, and Litecoin. *Finance Research Letters*, *44*, 102049. https://doi.org/10.1016/j.frl.2021.102049, PubMed: 35475023

Sarwar, G. (2012). Is VIX an investor fear gauge in BRIC equity markets? *Journal of Multinational Financial Management*, *22*(3), 55–65. https://doi.org/10.1016/j.mulfin.2012.01.003

Schoenbaum, S. C. (1987). Economic impact of influenza. The individual's perspective. *American Journal of Medicine*, *82*(6A), 26–30. https://doi.org/10.1016/0002-9343(87)90557-2, PubMed: 3109239

Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, *70*, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Smith, R. D., Keogh-Brown, M. R., Barnett, T., & Tait, J. (2009). The economy-wide impact of pandemic influenza on the UK: A computable general equilibrium modelling experiment. *BMJ*, *339*, b4571. https://doi.org/10.1136/bmj.b4571, PubMed: 19926697

Stancik, J. (2007). Determinants of exchange rate volatility: The case of the new EU members. *Czech Journal of Economics and Finance*, *57*, 56–72.

Sturgis, P., Brunton-Smith, I., & Jackson, J. (2021). Trust in science, social consensus and vaccine confidence. *Nature Human Behaviour*, *5*(11), 1528–1534. https://doi.org/10.1038/s41562-021-01115-7, PubMed: 34002053

Taylor, J. B. (1982). Establishing credibility: A rational expectations viewpoint. *American Economic Review*, *72*, 81–85.

To, B. C. N., Nguyen, B. K. Q., & Nguyen, T. V. T. (2023). When the market got the first dose: Stock volatility and vaccination campaign in COVID-19 period. *Heliyon*, *9*(1), e12809. https://doi.org/10.1016/j.heliyon.2023.e12809, PubMed: 36624823

Topcu, M., & Gulal, O. S. (2020). The impact of COVID-19 on emerging stock markets. *Finance Research Letters*, *36*, 101691. https://doi.org/10.1016/j.frl.2020.101691, PubMed: 32837378

Tsai, I.-C. (2012). The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach. *Journal of International Financial Markets, Institutions and Money*, *22*(3), 609–621. https://doi.org/10.1016/j.intfin.2012.04.005

Uddin, M., Chowdhury, A., Anderson, K., & Chaudhuri, K. (2021). The effect of COVID – 19 pandemic on global stock market volatility: Can economic strength help to manage the uncertainty? *Journal of Business Research*, *128*, 31–44. https://doi.org/10.1016/j.jbusres.2021.01.061, PubMed: 36540352

Viola, A. P., Klotzle, M. C., Pinto, A. C. F., & da Silveira Barbedo, C. H. S. (2019). Foreign exchange interventions in Brazil and their impact on volatility: A quantile regression approach. *Research in International Business and Finance*, *47*, 251–263. https://doi.org/10.1016/j.ribaf.2018.08.002

Wang, H., Yu, B., Chen, X., & Yan, H. (2023). Global pattern and determinants of coronavirus disease 2019 (COVID-19) vaccine coverage and progression: A global ecological study. *Global Health Journal*, *7*(1), 18–23. https://doi.org/10.1016/j.glohj.2023.02.003, PubMed: 36785805

Wang, J., & Yang, M. (2009). Asymmetric volatility in the foreign exchange markets. *Journal of International Financial Markets, Institutions and Money*, *19*(4), 597–615. https://doi.org/10.1016/j.intfin.2008.10.001

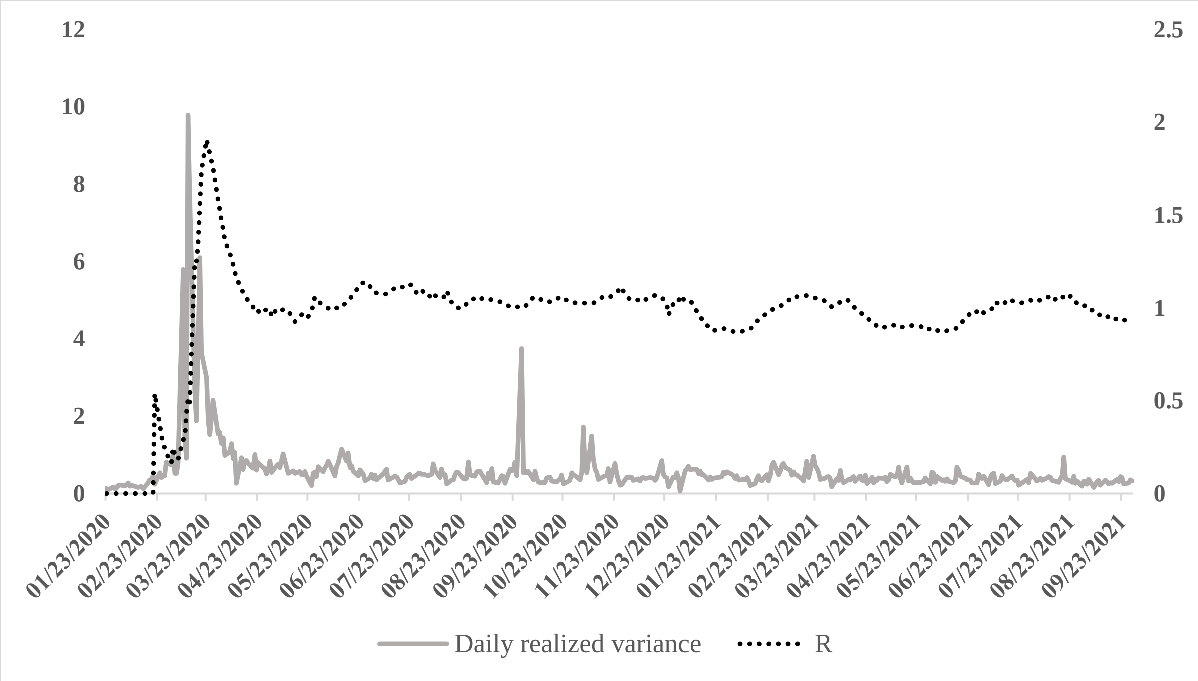
Well, D. N. (2007). Accounting for the effect of health on economic growth. *Quarterly Journal of Economics*, *122*(3), 1265–1306. https://doi.org/10.1162/qjec.122.3.1265

Yu, X., & Xiao, K. (2023). COVID-19 Government restriction policy, COVID-19 vaccination and stock markets: Evidence from a global perspective. *Finance Research Letters*, *53*, 103669. https://doi.org/10.1016/j.frl.2023.103669, PubMed: 36712284

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe. *Finance Research Letters*, *35*, 101597. https://doi.org/10.1016/j.frl.2020.101597, PubMed: 32550842

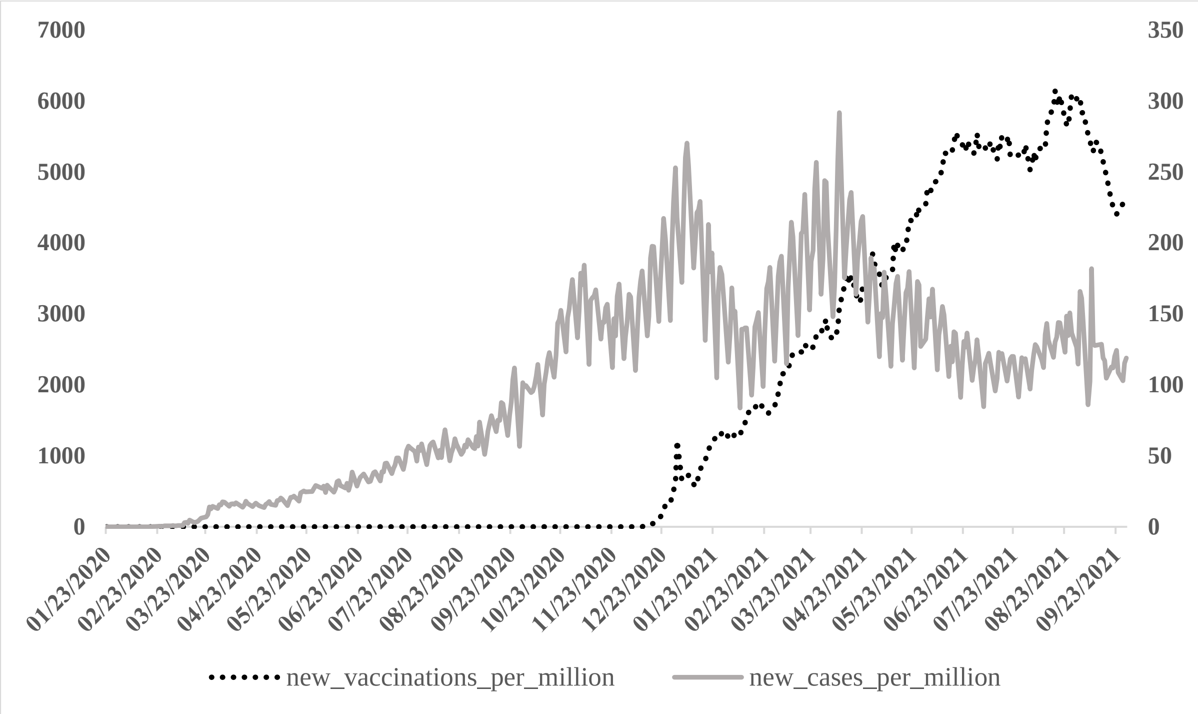
Zaremba, A., Kizys, R., Tzouvanas, P., Aharon, D. Y., & Demir, E. (2021). The quest for multidimensional financial immunity to the COVID-19 pandemic: Evidence from international stock markets. *Journal of International Financial Markets, Institutions and Money*, *71*, 101284. https://doi.org/10.1016/j.intfin.2021.101284

Figure 1. FX Volatility and COVID-19 Reproduction Rate



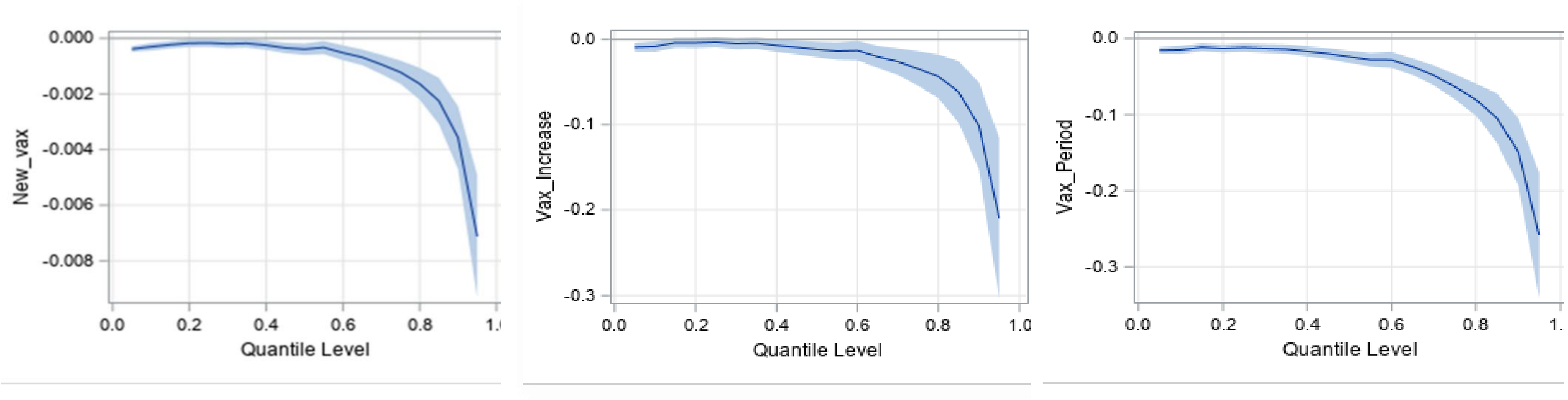
This figure displays the evolution of the average FX volatility (measured by daily realized variance (RV), left y-axis) and the average reproduction rate (R, right y-axis) over the research period from Jan 2020 to Sep 2021.

Figure 2. New COVID-19 Cases and New Vaccinations



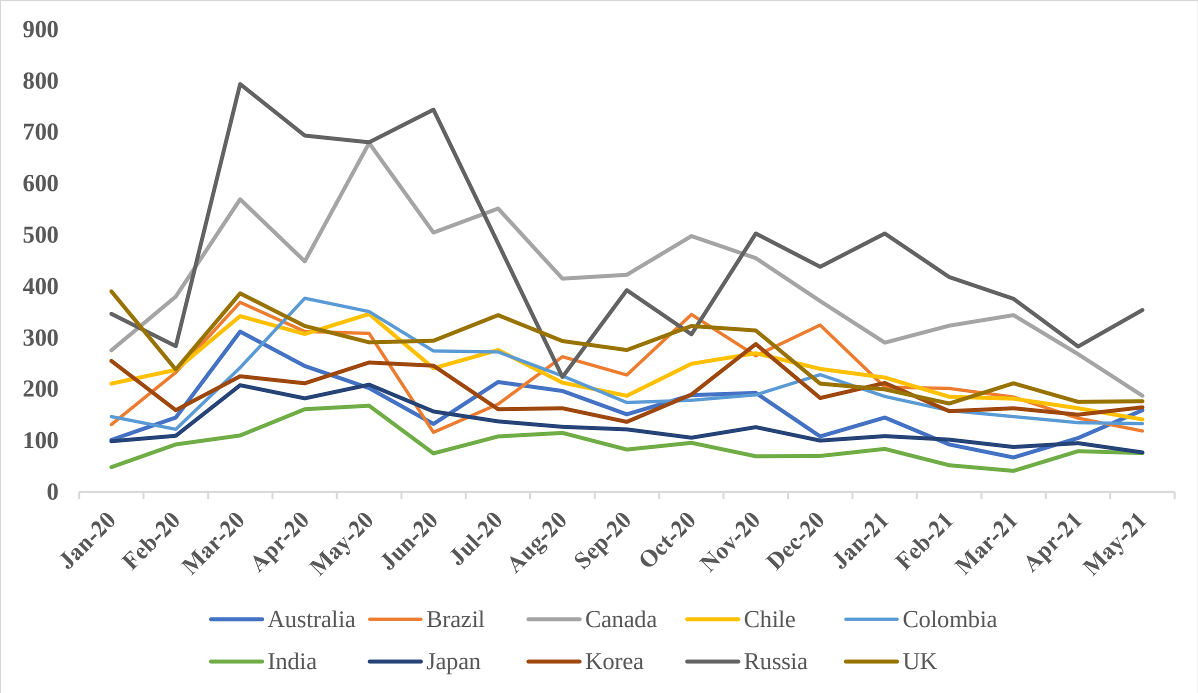
This figure displays the evolution over the research period of the average new confirmed COVID-19 cases per one million people (New_cases, right y-axis) and new vaccinations per one million people (New_vax, left y-axis) from Jan 2020 to Sep 2021.

Figure 3. Estimated Parameter of Vaccination-Related Variables by Quantile Level



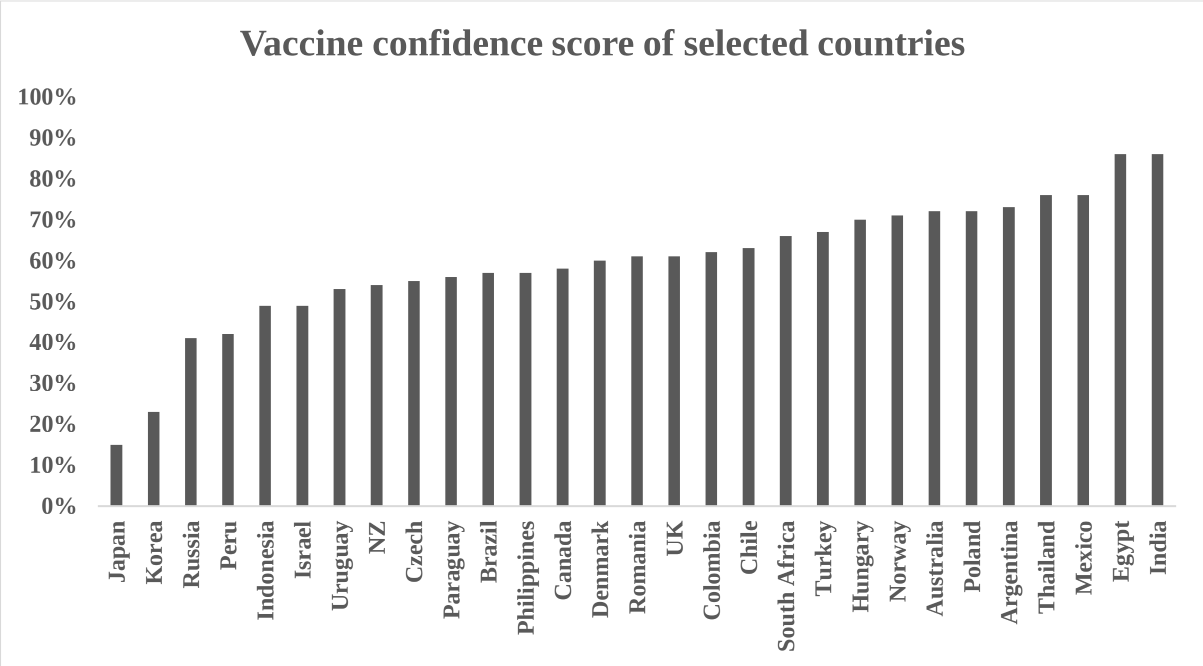
This figure plots the estimated parameter of three vaccination-related variables from the fixed-effect panel quantile regression presented in Equation (10). The blue shade reflects the 95% confidence interval.

Figure 4. Economic Policy Uncertainty Index of Selected Countries during the Pandemic



This figure displays the monthly Economic Policy Uncertainty Index of ten selected countries from January 2020 to September 2021.

Figure 5. Vaccine-Confidence Score of Selected Countries



This figure displays the vaccine-confidence score of selected countries. The score is defined as the proportion of respondents of a country answering with "Strongly agree" to Question 26 in the 2018 Wellcome Foundation Global Monitor survey: "Do you strongly or somewhat agree, strongly and somewhat disagree, or neither agree nor disagree with the following statement? Vaccines are effective."

Table 1. Summary Statistics and Correlation Matrix

Panel A. Descriptive statistics: Whole sample

	Obs.	Mean	Std. Dev	10^{th} percentile	90^{th} percentile	Kurtosis	Skewness
RV	12,429	0.60	2.35	0.07	1.24	2455.71	43.76
RV^w	12,429	0.55	1.53	0.08	1.11	694.32	22.17
RV^m	12,429	0.54	0.99	0.09	1.16	113.98	8.85
RQ	12,429	280.77	19,868.09	0.01	4.03	6145.76	78.18
R	12,429	0.99	0.42	0.57	1.39	5.68	0.19
New_cases	12,429	106.18	176.09	0.43	291.05	18.67	3.53
New_deaths	12,429	2.64	4.36	0.00	7.63	15.40	3.06
New_vax	12,429	1,719.53	30,06.97	0.00	6,384.00	4.12	2.07
$Vax\_Increase$	12,429	0.23	0.42	0.00	1.00	−0.35	1.28

Vax_Period	12,429	0.37	0.48	0.00	1.00	−1.69	0.56

Panel B. Descriptive statistics: By country

	Obs.	RV	RV^{w}	RV^{m}	RQ	R	New_cases	New_deaths	New_vax	$Vax\_Increase$	Vax_Period
Argentina	400	0.19	0.18	0.19	11.23	1.03	218.59	5.07	1,915.32	0.26	0.42
Australia	438	0.62	0.57	0.57	8.51	1.01	6.71	0.09	1,705.83	0.25	0.40
Brazil	402	1.47	1.45	1.44	43.48	1.08	183.90	5.45	1,906.41	0.27	0.35
Canada	437	0.30	0.25	0.25	0.42	1.01	74.91	1.36	2,398.88	0.28	0.47
Chile	416	0.81	0.71	0.73	27.34	1.03	137.76	3.39	2,840.47	0.21	0.45
Colombia	405	0.89	0.81	0.82	127.00	1.04	167.05	4.38	1,353.01	0.22	0.26
Czech	412	0.62	0.50	0.52	2.96	1.03	291.15	5.39	1,905.88	0.24	0.48
Denmark	415	0.22	0.19	0.19	0.33	1.03	109.69	0.83	2,595.49	0.26	0.44

Egypt	319	1.35	1.26	1.27	2.65	1.01	4.91	0.29	269.26	0.17	0.19
Europe	439	0.22	0.18	0.19	0.33	1.08	136.70	2.91	1,728.82	0.24	0.47
Hungary	411	0.52	0.43	0.45	1.81	1.04	141.24	5.64	2,174.14	0.14	0.22
India	433	0.11	0.10	0.10	0.18	1.03	39.72	0.58	1,020.07	0.25	0.39
Indonesia	382	0.18	0.18	0.18	0.46	1.05	27.01	0.94	872.43	0.27	0.35
Israel	419	0.32	0.27	0.27	1.61	1.06	266.30	1.52	2,917.46	0.22	0.48
Japan	439	0.19	0.17	0.17	0.48	1.02	21.69	0.25	2,069.15	0.23	0.30
South Korea	440	0.25	0.20	0.20	0.54	1.02	10.18	0.09	1,920.38	0.21	0.35
Mexico	414	1.37	1.13	1.17	45.16	1.06	50.35	4.10	1,321.22	0.26	0.43
New Zealand	414	0.60	0.53	0.54	4.27	0.90	1.47	0.01	1,795.87	0.25	0.38
Norway	416	1.29	1.13	1.14	81.09	1.05	66.31	0.37	2,440.07	0.29	0.49

Paraguay	398	0.18	0.18	0.18	0.15	0.99	116.58	3.98	1,111.79	0.21	0.33
Peru	405	0.55	0.55	0.55	426.63	1.09	110.45	10.38	1,378.55	0.22	0.41
Philippines	433	0.26	0.24	0.24	2.49	1.02	36.31	0.55	655.82	0.21	0.14
Poland	411	0.50	0.41	0.42	1.57	1.04	132.57	3.77	1,710.54	0.23	0.35
Romania	415	0.26	0.23	0.24	0.44	1.05	112.27	3.65	907.10	0.23	0.46
Russia	433	1.60	1.31	1.34	7226.76	1.01	82.41	2.50	1,009.85	0.23	0.27
South Africa	410	1.29	1.12	1.16	35.35	1.05	83.44	2.94	493.67	0.23	0.23
Thailand	440	0.17	0.14	0.14	0.09	0.99	36.53	0.41	1,142.41	0.22	0.27
Turkey	404	1.09	1.27	1.24	53.98	1.07	134.57	1.34	2,262.52	0.21	0.45
UK	434	0.38	0.32	0.33	1.47	1.05	191.10	3.81	2,262.69	0.28	0.49
Uruguay	395	0.55	0.46	0.54	3.69	1.03	200.57	3.24	3,176.83	0.18	0.38

Panel C. Descriptive statistics: Emerging vs. Developed countries

	Obs.	RV	RV^{w}	RV^{m}	RQ	R	New_cases	New_deaths	New_vax	$Vax\_Increase$	Vax_Period
Emerging	8,578	0.69	0.65	0.63	423.73	1.04	115.72	3.43	1,477.54	0.22	0.34
Developed	3,851	0.44	0.38	0.38	9.66	0.91	88.07	1.13	2,178.48	0.25	0.42

Table 1 presents the descriptive statistics of the variables in the baseline regression model. *RV*, RV^w, and RV^m are the daily, weekly, and monthly realized volatility of exchange rates, respectively. *RQ* is the quarticity of RV. *R* is the reproduction rate. *New_cases* is the new confirmed cases of COVID-19 per one million people. *New_deaths* is the new deaths due to COVID-19 per one million people. *New_vax* is defined as the natural logarithm of the number of daily new COVID-19 vaccine doses per one million people. *Vax_Increase* is a dummy variable that equals 1 if the daily change in *New_vax* is strictly positive and zero otherwise. *Vax_Period* is a dummy variable that equals 1 for the period starting the country's first COVID-19 vaccine administration onward and zero otherwise. To facilitate the interpretation of variables, the COVID-19- and vaccination-related variables in Table 1 are not shown in the natural logarithm forms.

Table 2. Cross-correlation Matrix between Variables in the Baseline Model

	RV	RV^w	RV^m	RQ	R	New_cases	New_deaths	New_vax	$Vax\_Increase$	Vax_Period
RV	1.00									
RV^w	0.34***	1.00								
RV^m	0.26***	0.60***	1.00							
RQ	0.81***	0.15**	0.06**	1.00						
R	0.01*	0.08**	0.18**	−0.03*	1.00					
New_cases	0.03	0.03	0.04	−0.01	0.03*	1.00				
New_deaths	0.02	0.02	0.03	0.00	0.09*	0.26***	1.00			
New_vax	−0.06***	−0.07**	−0.11**	−0.01	−0.06*	−0.01*	−0.01*	1.00		
$Vax\_Increase$	−0.03***	−0.07***	−0.09***	−0.001	−0.02**	0.12***	0.09***	0.63***	1.00	

Vax_Period	-0.06^{***}	-0.10^{***}	-0.14^{***}	-0.01	-0.07^{***}	0.17^{***}	0.12^{***}	0.86^{***}	0.57^{***}	1.00

Table 2 shows correlation coefficients between variables used in the baseline regression model Equation (7). The correlation coefficients are averaged across countries in the sample. Variables are defined as in Table 1. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Panel Unit-Root Tests

	IPS	MW
RV	-43.31^{***}	$2{,}037^{***}$
	[<0.0001]	[<0.0001]
RV^w	-24.29^{***}	830.52^{***}
	[<0.0001]	[<0.0001]
RV^m	-19.69^{***}	740.51^{***}
	[<0.0001]	[<0.0001]
RQ	-125.93^{***}	678.61^{***}
	[<0.0001]	[<0.0001]
R	-45.12^{***}	$3{,}630.60^{***}$
	[<0.0001]	[<0.0001]
New_cases	-23.67^{***}	923.39^{***}
	[<0.0001]	[<0.0001]
New_deaths	-32.49^{***}	$1{,}358.20^{***}$
	[<0.0001]	[<0.0001]
New_vax	-9.67^{***}	267.54^{***}
	[<0.0001]	[<0.0001]
$Vax\_Increase$	-26.68^{***}	883.39^{***}
	[<0.0001]	[<0.0001]

Vax_Period	-4.47^{***}	215.19^{***}
	[<0.0001]	[<0.0001]

Table 3 shows the test statistics of two panel unit-root tests: IPS (Im et al., 2003) and MW (Maddala and Wu, 2003). The null hypothesis of the tests is that there is a unit root in the time series. The numbers in the bracket are the *p*-values of the test statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Main Regression Results

	(1)	(2)	(3)
β_d	0.310^{***}	0.311^{***}	0.298^{***}
	(5.07)	(5.08)	(4.72)
β_w	0.199^{**}	0.200^{**}	0.172^{*}
	(2.35)	(2.34)	(1.85)
β_m	0.133^{**}	0.137^{**}	0.221^{***}
	(2.32)	(2.35)	(4.01)
β_Q	-0.00085^{***}	-0.00085^{***}	-0.00081^{***}
	(−6.39)	(−6.35)	(−5.97)
R	0.0088^{**}	0.0097^{***}	0.062^{*}
	(2.51)	(2.70)	(1.85)
New_cases	0.0010	0.001	0.0019
	(0.57)	(0.24)	(0.89)
New_deaths	0.001	0.001	0.0004
	(0.64)	(0.54)	(0.21)
New_vax	-0.002^{***}		
	(−3.26)		
$Vax\_Increase$		-0.0029^{***}	
		(−3.01)	
Vax_Period			-0.0815^{**}
			(−2.61)
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2015	0.2007	0.1910

This table presents the regression results of the relationship between COVID-19 vaccine rollout and FX volatility using Equation (2) specified in subsection 3.2. We account for the country-fixed effect and estimate Equation (2) using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 5. First-Dose and Second Dose Effects

	(1)	(2)
$First\_dose$	-0.066^{**} (-1.97)	
$Second\_dose$		-0.0006 (-0.98)
Control variables	Yes	Yes
N. Obs.	12,429	12,429
Adj. R-squared	0.2541	0.1902

This table presents the regression results of the relationship between COVID-19 vaccine rollout and FX volatility using Equation (2) specified in subsection 3.2. We account for the country-fixed effect and estimate Equation (2) using ordinary least squares, with robust standard errors clustered at the country level. Two proxies for vaccinations used are $First\_dose$ and $Second\_dose$. $First\_dose$ is measured by the change in the daily total number of people who received their first vaccine dose per 100 people in the total population. $Second\_dose$ is calculated as the change in the daily total number of people who received all other doses prescribed by the vaccination protocol per 100 people in the total population. T-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 6. Regression Results Using Different HARQ-type models

Panel A. HARQ-IFG

	(1)	(2)	(3)
β_d	0.303***	0.303***	0.292***
	(4.97)	(4.98)	(4.76)
β_w	0.191***	0.189***	0.161***
	(3.82)	(3.79)	(3.11)
β_m	0.119***	0.121***	0.206***
	(3.11)	(3.12)	(3.95)
β_Q	−0.00081***	−0.00081***	−0.00076***
	(−5.10)	(−5.10)	(−4.87)
IFG	0.0035***	0.0036***	0.0029***
	(3.42)	(3.72)	(2.87)
R	0.076**	0.081***	0.052**
	(2.52)	(2.74)	(1.96)
New_cases	0.0021*	0.0019*	0.0028**
	(1.73)	(1.66)	(1.98)
New_deaths	0.0011	0.001	0.0007
	(1.31)	(1.17)	(0.51)
New_vax	−0.0019**		
	(−1.98)		
$Vax\_Increase$		−0.0018*	
		(−1.76)	
Vax_Period			−0.053**

			(−2.01)
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2038	0.2035	0.1919

Panel B. HARQ-RS

	(1)	(2)	(3)
β_d^+	0.581***	0.581***	0.119***
	(4.10)	(4.08)	(11.31)
β_Q^+	−0.002**	−0.002**	−0.001**
	(−2.43)	(−2.49)	(−2.19)
β_d^-	0.334***	0.341***	0.591***
	(3.17)	(3.24)	(4.45)
β_Q^-	0.0007	0.0007	0.0026
	(0.01)	(0.01)	(0.55)
β_w	0.141**	0.141*	0.138*
	(1.98)	(1.94)	(1.68)
β_m	0.109***	0.112***	0.209***
	(2.82)	(2.79)	(4.10)
R	0.083***	0.092***	0.063**
	(2.71)	(3.01)	(2.20)
New_cases	0.0011	0.0004	0.0015
	(0.39)	(0.01)	(0.56)
New_deaths	0.0011	0.0008	0.0002
	(1.33)	(1.11)	(0.30)
New_vax	−0.0021***		
	(−2.71)		

$Vax\_Increase$		-0.0022^{**}	
		(−1.98)	
Vax_Period			-0.074^{**}
			(−2.42)
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2101	0.2095	0.2014

Panel C. IV-HARQ

	(1)	(2)	(3)
β_d	0.212^{***}	0.212^{***}	0.213^{***}
	(4.28)	(4.27)	(4.28)
β_w	0.107^{**}	0.107^{**}	0.107^{**}
	(2.10)	(2.08)	(2.10)
β_m	0.178^{***}	0.178^{***}	0.178^{***}
	(3.35)	(3.33)	(3.35)
β_Q	-0.0006^{***}	-0.0006^{***}	-0.0006^{***}
	(−4.72)	(−4.71)	(−4.72)
IV^d	0.263^{**}	0.263^{***}	0.263^{***}
	(2.10)	(2.09)	(2.10)
IV^w	-0.142^{*}	-0.142^{*}	-0.142^{*}
	(−1.83)	(−1.82)	(−1.83)
IV^m	-0.079^{**}	-0.078^{**}	-0.079^{**}
	(−2.65)	(−2.64)	(−2.66)
R	0.016^{*}	0.022^{**}	0.017^{**}
	(1.93)	(2.01)	(1.97)

New_cases	0.002*	0.002	0.002*
	(1.71)	(1.47)	(1.65)
New_deaths	−0.001	−0.001	−0.001
	(−0.65)	(−0.82)	(−0.75)
New_vax	−0.002**		
	(−1.97)		
$Vax\_Increase$		−0.026*	
		(−1.78)	
Vax_Period			−0.051**
			(−2.37)
N. Obs.	11,986	11,986	11,986
Adj. R-squared	0.2125	0.2122	0.2124

This table presents the regression results of the relationship between COVID-19 vaccine rollout and FX volatility using different HARQ-type models as specified in Equations (6), (7), and (8) in subsection 3.3. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 7. Regression Results Using Alternative Estimators of IQ

Panel A. Using TPQ

	(1)	(2)	(3)
New_vax	-0.0018^{***}		
	(−3.06)		
$Vax\_Increase$		-0.0027^{***}	
		(−2.89)	
Vax_Period			-0.0804^{**}
			(−2.56)
Control variables	Yes	Yes	Yes
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2003	0.1997	0.1902

Panel B. Using MedRQ

	(1)	(2)	(3)
New_vax	-0.0017^{***}		
	(−3.02)		
$Vax\_Increase$		-0.0025^{***}	
		(−2.86)	
Vax_Period			-0.0791^{**}
			(−2.49)
Control variables	Yes	Yes	Yes
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2001	0.1995	0.1900

Panel C. Using TrRQ

	(1)	(2)	(3)
New_vax	-0.0022^{***}		
	(−3.34)		
$Vax\_Increase$		-0.0031^{***}	
		(−3.05)	
Vax_Period			-0.0821^{***}
			(−2.71)
Control variables	Yes	Yes	Yes
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2035	0.2029	0.1914

This table presents the regression results of Equation (2) by replacing RQ with alternative measures of integrated quarticity, including TPQ, $MedRQ$, and $TrRQ$. The formulas for these new estimators are presented in subsection 5.2.2. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. T-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 8. Additional Control Variables

	(1)	(2)	(3)
β_d	0.286***	0.288***	0.281***
	(3.94)	(4.02)	(3.79)
β_w	0.178***	0.179***	0.157**
	(3.15)	(3.08)	(2.48)
β_m	0.103***	0.104***	0.186***
	(3.71)	(3.65)	(4.07)
β_Q	−0.00075***	−0.00074***	−0.00074***
	(−4.11)	(−4.22)	(−4.55)
R	0.065**	0.069***	0.049**
	(2.59)	(2.68)	(2.02)
New_cases	0.0027**	0.0026**	0.0029**
	(2.15)	(2.23)	(2.28)
New_deaths	0.0019	0.0011	0.0006
	(1.03)	(1.01)	(0.38)
US_yield_vol	4.031***	4.104***	3.493***
	(3.03)	(3.41)	(2.74)
$Home\_yield\_vol$	−0.031	−0.030	−0.027
	(−0.65)	(−0.68)	(−0.62)
$Spread\_vol$	0.0031*	0.003*	0.003*
	(1.71)	(1.69)	(1.67)
US_new_vax	−0.0007*	−0.0006	−0.0006
	(−1.66)	(−1.63)	(−1.60)

$Stringency$	0.0021*	0.0019*	0.0019*
	(1.89)	(1.72)	(1.70)
New_vax	−0.0019**		
	(−2.56)		
$Vax\_Increase$		−0.0018**	
		(−1.98)	
Vax_Period			−0.041**
			(−1.93)
N. Obs.	11,801	11,801	11,801
Adj. R-squared	0.2061	0.2071	0.1937

This table presents the regression results of the relationship between COVID-19 vaccine rollout and FX volatility using Equation (12) with additional control variables as specified in subsection 5.2.3. We account for the country-fixed effect and estimate Equation (12) using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 9. Different Sampling Periods

Panel A. From March 11, 2020

	(1)	(2)	(3)
β_d	0.309***	0.309***	0.295***
	(3.28)	(3.27)	(3.15)
β_w	0.197***	0.197***	0.171***
	(4.23)	(4.20)	(3.55)
β_m	0.131***	0.135***	0.218***
	(4.86)	(4.80)	(5.52)
β_Q	−0.00081***	−0.00081***	−0.00076***
	(−3.65)	(−3.61)	(−3.42)
R	0.091***	0.099***	0.057**
	(3.01)	(3.34)	(2.27)
New_cases	0.0011	0.0003	0.0017
	(0.49)	(0.07)	(0.92)
New_deaths	0.001	0.0009	0.0003
	(0.96)	(0.72)	(0.05)
New_vax	−0.0023***		
	(−3.35)		
$Vax\_Increase$		−0.0027***	
		(−2.87)	
Vax_Period			−0.0798***
			(−3.08)
N. Obs.	11,824	11,824	11,824
Adj. R-squared	0.2001	0.1996	0.1889

Panel B. From June 6, 2020

	(1)	(2)	(3)
β_d	0.245^{***}	0.244^{***}	0.244^{***}
	(6.25)	(6.18)	(6.01)
β_w	0.067^{*}	0.067^{*}	0.064^{*}
	(1.73)	(1.69)	(1.69)
β_m	0.278^{***}	0.275^{***}	0.273^{***}
	(5.65)	(5.67)	(6.54)
β_Q	-0.0011^{***}	-0.0008^{***}	-0.0008^{***}
	(−5.46)	(−4.42)	(−5.36)
R	0.011	0.011	0.002
	(0.75)	(0.75)	(0.01)
New_cases	0.0013	0.0012	0.0017
	(0.78)	(0.65)	(0.86)
New_deaths	0.0017^{**}	0.0014^{**}	0.0015^{**}
	(2.27)	(2.35)	(1.98)
New_vax	-0.0018^{**}		
	(−2.21)		
$Vax\_Increase$		-0.0025^{**}	
		(−1.96)	
Vax_Period			-0.075^{***}
			(−2.75)
N. Obs.	10,125	10,125	10,125
Adj. R-squared	0.1138	0.1132	0.1131

Panel C. From August 11, 2020

	(1)	(2)	(3)
β_d	0.237^{***}	0.237^{***}	0.236^{***}
	(6.34)	(6.30)	(6.26)
β_w	0.061^{*}	0.061^{*}	0.061^{*}
	(1.68)	(1.66)	(1.67)
β_m	0.229^{***}	0.248^{***}	0.248^{***}
	(5.35)	(5.34)	(5.34)
β_Q	-0.00069^{***}	-0.00068^{***}	-0.00069^{***}
	(−5.75)	(−5.71)	(−5.67)
R	0.022^{*}	0.032^{**}	0.033^{***}
	(1.65)	(2.63)	(2.72)
New_cases	0.0019	0.0016	0.0016
	(1.15)	(0.92)	(0.89)
New_deaths	0.0017^{**}	0.0016^{**}	0.0016^{**}
	(2.21)	(2.18)	(2.18)
New_vax	-0.0017^{**}		
	(−2.35)		
$Vax\_Increase$		-0.0017^{*}	
		(−1.81)	
Vax_Period			-0.0019^{**}
			(−1.96)
N. Obs.	8,743	8,743	8,743
Adj. R-squared	0.0971	0.0965	0.0963

This table presents the regression results of the relationship between COVID-19 vaccine rollout and FX volatility using Equation (2) specified in Section 3.2 for different periods.

Panels A, B, and C display the regression results for alternative periods that start on March 11, June 6, and August 11, 2020, sequentially. We account for the country-fixed effect and estimate Equation (2) using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 10. Panel Quantile Regression Results

	New_vax (1)	$Vax\_Increase$ (2)	Vax_Period (3)
5th quantile	−0.0004***	−0.0091***	−0.0154***
	(−7.18)	(−3.51)	(−7.20)
10th quantile	−0.0003***	−0.0083***	−0.0147***
	(−4.40)	(−2.65)	(−5.53)
15th quantile	−0.0002***	−0.0040	−0.0114***
	(−3.46)	(−1.30)	(−4.30)
20th quantile	−0.0002**	−0.0040	−0.0128***
	(−2.48)	(−1.28)	(−4.73)
25th quantile	−0.0002**	−0.0032	−0.0118***
	(−2.33)	(−1.01)	(−4.21)
30th quantile	−0.0002**	−0.0050	−0.0128***
	(−2.56)	(−1.48)	(−4.32)
35th quantile	−0.0002**	−0.0044	−0.0136***
	(−2.36)	(−1.28)	(−4.40)
40th quantile	−0.0002***	−0.0072*	−0.0166***
	(−2.86)	(−1.90)	(−4.89)
45th quantile	−0.0003***	−0.0094**	−0.0197***
	(−3.69)	(−2.23)	(−5.43)

50th quantile	−0.0004***	−0.0119**	−0.0238***
	(−3.77)	(−2.55)	(−5.80)
55th quantile	−0.0003***	−0.0137***	−0.0277***
	(−2.77)	(−2.64)	(−6.05)
60th quantile	−0.0005***	−0.0131**	−0.0279***
	(−3.82)	(−2.25)	(−5.20)
65th quantile	−0.0007***	−0.204***	−0.0368***
	(−4.77)	(−3.15)	(−6.57)
70th quantile	−0.0009***	−0.0261***	−0.0482***
	(−5.32)	(−3.30)	(−7.17)
75th quantile	−0.0012***	−0.0342***	−0.0644***
	(−5.74)	(−3.30)	(−7.51)
80th quantile	−0.0015***	−0.0433***	−0.0802***
	(−5.63)	(−3.34)	(−7.48)
85th quantile	−0.0023***	−0.0617***	−0.1047***
	(−5.32)	(−3.33)	(−6.29)
90th quantile	−0.0036***	−0.1014***	−0.1491***
	(−6.22)	(−3.89)	(−6.58)
95th quantile	−0.0071***	−0.2094***	−0.2584***
	(−6.35)	(−4.37)	(−6.16)

This table presents the estimated parameters of three vaccination-related variables in the country's fixed-effect quantile regression model, Equation (13). Standard errors are in the parentheses beneath the coefficient estimates. ***, ** ,and * indicate significance the 1%, 5%, and 10% levels, respectively.

Table 11. Impact of Vaccinations Based on Weekly Data

	(1)	(2)	(3)
β_w	0.234***	0.235***	0.231***
	(3.78)	(3.80)	(3.71)
β_m	0.145**	0.149**	0.201*
	(2.55)	(2.58)	(3.85)
R	0.0091**	0.0095**	0.052**
	(2.41)	(2.54)	(1.98)
New_cases	0.001	0.001	0.002
	(0.34)	(0.34)	(0.57)
New_deaths	0.001	0.001	0.0003
	(0.54)	(0.48)	(0.16)
New_vax	−0.0015***		
	(−2.86)		
$Vax\_Increase$		−0.0018**	
		(−2.12)	
Vax_Period			−0.0713**
			(−2.31)
N. Obs.	2,248	2,248	2,248
Adj. R-squared	0.2015	0.2007	0.1910

This table presents the regression results of the relationship between COVID-19 vaccine rollout and FX volatility using weekly data as specified by Equation (14) in subsection 5.2.6. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 12. Vaccination Effects for Emerging and Developed Markets

	(1)	(2)	(3)
β_d	0.296***	0.296***	0.296***
	(4.34)	(4.33)	(4.34)
β_w	0.169***	0.169***	0.169***
	(2.23)	(2.20)	(2.23)
β_m	0.217***	0.221***	0.217***
	(4.24)	(4.26)	(4.23)
β_Q	−0.00083***	−0.00083***	−0.00083***
	(−4.88)	(−4.86)	(−4.88)
R	0.0578**	0.0669***	0.0574**
	(2.01)	(2.65)	(2.23)
New_cases	0.0017	0.0011	0.0018
	(0.85)	(0.56)	(0.91)
New_deaths	0.0003	0.0001	0.0002
	(0.11)	(0.04)	(0.08)
New_vax	−0.0023**		
	(−2.18)		
$Vax\_Increase$		−0.073**	
		(−2.19)	
Vax_Period			−0.097***
			(−2.83)
$New\_vax \times EME$	−0.0015**		
	(−2.01)		

$Vax\_Increase \times EME$		-0.042^{**}	
		(−2.35)	
$Vax\_Period \times EME$			-0.025^{*}
			(−1.78)
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.1894	0.1888	0.1895

This table presents the regression results for the impact of economic development on the relationship between COVID-19 vaccine rollout and FX volatility controlling for the emerging and developed status of countries as specified by Equation (15) in subsection 5.3.1. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 13. Vaccination Effects: The EPU impact on FX volatility

	(1)	(2)	(3)
β_d	0.297^{***}	0.299^{***}	0.296^{***}
	(6.02)	(6.04)	(5.98)
β_w	0.373^{***}	0.379^{***}	0.338^{***}
	(3.21)	(3.23)	(3.01)
β_m	0.128^{*}	0.127^{*}	0.125^{*}
	(1.69)	(1.68)	(1.65)
β_Q	-0.0041^{**}	-0.0041^{***}	-0.0042^{***}
	(−4.18)	(−4.20)	(−4.21)
R	0.051^{*}	0.043^{*}	0.041^{*}
	(1.78)	(1.66)	(1.65)
New_cases	0.0128^{**}	0.0121^{*}	0.124^{**}
	(1.98)	(1.91)	(1.95)
New_deaths	0.0003	0.0002	0.0003
	(0.15)	(0.08)	(0.16)
New_vax	-0.0014^{**}		
	(−1.96)		
$Vax\_Increase$		-0.0621^{**}	
		(−2.56)	
Vax_Period			-0.0869^{***}
			(−2.68)
$New\_vax \times EPU$	-0.0009^{**}		
	(−1.97)		

$Vax\_Increase \times EPU$		-0.0937^{**}	
		(−2.35)	
$Vax\_Period \times EPU$			-0.1056^{***}
			(−3.71)
N. Obs.	4,049	4,049	4,049
Adj. R-squared	0.4418	0.4421	0.4435

This table presents pooled OLS estimates for the impact of economic policy uncertainty on the relationship between COVID-19 vaccine rollout and FX volatility using Equation (16) discussed in Section 5.3.2. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Table 14. Vaccination Effects: The Role of Vaccine Confidence

	(1)	(2)	(3)
β_d	0.301***	0.303***	0.303***
	(5.25)	(5.28)	(5.23)
β_w	0.161***	0.161**	0.161**
	(1.97)	(1.91)	(1.93)
β_m	0.221***	0.232***	0.227***
	(3.56)	(3.69)	(3.65)
β_Q	−0.00083***	−0.00084***	−0.00084***
	(−4.98)	(−4.94)	(−4.95)
R	0.061*	0.071**	0.062*
	(1.65)	(1.78)	(1.68)
New_cases	0.0013	0.0009	0.0021
	(0.52)	(0.37)	(0.65)
New_deaths	0.0003	0.0002	0.0003
	(0.29)	(0.11)	(0.54)
New_vax	−0.0013*		
	(−1.87)		
$Vax\_Increase$		−0.073**	
		(−2.86)	
Vax_Period			−0.099***
			(−2.99)
$New\_vax \times Trust$	−0.0043***		
	(−3.11)		

$Vax\_Increase \times Trust$		-0.049^{**}	
		(−1.97)	
$Vax\_Period \times Trust$			-0.031^{*}
			(−1.71)
N. Obs.	10,335	10,335	10,335
Adj. R-squared	0.1901	0.1885	0.1890

This table presents pooled OLS estimates for the effect of vaccine confidence on the relationship between COVID-19 vaccine rollout and FX volatility using Equation (17) specified in Section 5.3.3. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Appendix A1. Annualized RV by Country

	Obs.	RV(%)	Annualized RV(%)
Argentina	400	0.19	3.01
Australia	438	0.62	9.82
Brazil	402	1.47	23.29
Canada	437	0.30	4.75
Chile	416	0.81	12.83
Colombia	405	0.89	14.10
Czech	412	0.62	9.82
Denmark	415	0.22	3.49
Egypt	319	1.35	21.39
Europe	439	0.22	3.49
Hungary	411	0.52	8.24
India	433	0.11	1.74
Indonesia	382	0.18	2.85
Israel	419	0.32	5.07
Japan	439	0.19	3.01
South Korea	440	0.25	3.96
Mexico	414	1.37	21.70

New Zealand	414	0.60	9.51
Norway	416	1.29	20.44
Paraguay	398	0.18	2.85
Peru	405	0.55	8.71
Philippines	433	0.26	4.12
Poland	411	0.50	7.92
Romania	415	0.26	4.12
Russia	433	1.60	25.35
South Africa	410	1.29	20.44
Thailand	440	0.17	2.69
Turkey	404	1.09	17.27
UK	434	0.38	6.02
Uruguay	395	0.55	8.71

This appendix shows the average daily realized volatility (RV) and the corresponding annualized realized volatility by country. Following Areal and Taylor (2002), we compute annualized realized variance by multiplying the daily realized variance by $\sqrt{251}$.

Appendix A2. Pooled Regression and Random Effects Results

Panel A. Using pooled OLS

	(1)	(2)	(3)
β_d	0.310^{***}	0.311^{***}	0.298^{***}
	(4.21)	(4.20)	(3.96)
β_w	0.199^{***}	0.200^{***}	0.172^{***}
	(3.34)	(3.31)	(2.67)
β_m	0.133^{***}	0.137^{***}	0.221^{***}
	(4.24)	(4.30)	(4.99)
β_Q	-0.001^{***}	-0.001^{***}	-0.00081^{***}
	(−4.52)	(−4.50)	(−4.29)
R	0.088^{***}	0.085^{***}	0.062^{**}
	(3.23)	(3.53)	(2.55)
New_cases	0.0013	0.00057	0.0019
	(1.02)	(0.47)	(1.54)
New_deaths	0.0011	0.00085	0.00037
	(1.42)	(1.18)	(0.47)
New_vax	-0.0024^{***}		
	(−3.95)		
$Vax\_Increase$		-0.0029^{***}	
		(−3.28)	
Vax_Period			-0.081^{***}
			(−3.57)
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2009	0.2002	0.1904

Panel B. Using random effects regressions

	(1)	(2)	(3)
β_d	0.310***	0.311***	0.298***
	(29.58)	(29.68)	(26.54)
β_w	0.199***	0.199***	0.172***
	(16.07)	(16.07)	(12.16)
β_m	0.133***	0.137***	0.221***
	(9.64)	(9.91)	(11.61)
β_Q	−0.00085***	−0.00085***	−0.00081***
	(−18.77)	(−18.85)	(−16.81)
R	0.087***	0.097***	0.062**
	(3.02)	(3.40)	(1.99)
New_cases	0.0015	0.00052	0.0019
	(0.66)	(0.26)	(0.87)
New_deaths	0.0009	0.00085	0.00037
	(0.91)	(0.79)	(0.32)
New_vax	−0.003***		
	(−4.52)		
$Vax\_Increase$		−0.0028**	
		(−2.38)	
Vax_Period			−0.0821***
			(−3.40)
N. Obs.	12,429	12,429	12,429
Adj. R-squared	0.2017	0.2007	0.1903

This table reports the regression results of Equation (2) presented in subsection 3.3 using pooled OLS and random effects. The t-statistics are computed using Newey–West (1987) heteroscedasticity and autocorrelation consistent standard errors and are in the parentheses beneath the coefficient estimates. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix A3. Regression Results of Model Testing U-shaped Pattern

	(1)
β_d	0.298^{***}
	(3.96)
β_w	0.172^{**}
	(2.67)
β_m	0.222^{**}
	(4.99)
β_Q	-0.00081^{***}
	(−4.29)
R	0.061^{**}
	(2.50)
New_cases	0.002
	(1.60)
New_deaths	0.0003
	(0.42)
New_vax	-0.0014^{***}
	(−3.00)
New_vax^2	−0.0004
	(−1.02)
N. Obs.	12,429
Adj. R-squared	0.1903

The table reports the regression results of the following equation to test the U-shaped pattern of the impact of vaccinations on FX volatility:

$$RV_{i,t+1} = \beta_0 + \left(\beta_d + \beta_Q RQ_{i,t}^{\frac{1}{2}}\right) RV_{i,t} + \beta_w RV_{i,t}^{w} + \beta_m RV_{i,t}^{m} + \beta_c Covid_{i,t} +$$

$$\beta_v New\_vax_{i,t} + \beta_u New\_vax_{i,t}^{2} + \varepsilon_{i,t+1} . \qquad \text{(A3)}$$

T-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Appendix A4. Vaccination Effects: All Interaction-type Control Variables Included

	(1)	(2)	(3)
β_d	0.463^{***}	0.445^{***}	0.461^{***}
	(5.61)	(5.44)	(5.72)
β_w	0.263^{**}	0.269^{**}	0.268^{**}
	(1.96)	(2.01)	(2.00)
β_m	0.109	0.129^{*}	0.153^{*}
	(1.32)	(1.68)	(1.89)
β_Q	-0.0094^{***}	-0.0087^{***}	-0.0093^{***}
	(−5.23)	(−4.89)	(−5.09)
R	0.0066	0.0009	−0.023
	(0.17)	(0.01)	(−0.45)
New_cases	0.0053	0.0015	0.0077
	(0.95)	(0.28)	(1.31)
New_deaths	0.0001	−0.0006	−0.0009
	(0.07)	(−0.45)	(−0.66)
New_vax	-0.0016^{**}		
	(−2.39)		

$Vax\_Increase$		-0.039^{***}	
		(-3.28)	
Vax_Period			-0.076^{**}
			(-2.11)
$New\_vax \times EME$	-0.0071^{*}		
	(-1.79)		
$Vax\_Increase \times EME$		-0.281^{***}	
		(-3.52)	
$Vax\_Period \times EME$			-0.199^{**}
			(-1.96)
$New\_vax \times EPU$	-0.0019^{*}		
	(-1.75)		
$Vax\_Increase \times EPU$		-0.019^{*}	
		(-1.67)	
$Vax\_Period \times EPU$			-0.276^{**}
			(-1.97)
$New\_vax \times Trust$	-0.0112^{***}		
	(-2.25)		
$Vax\_Increase \times Trust$		-0.470^{***}	

		(−3.75)	
$Vax\_Period \times Trust$			-0.339^{***}
			(−2.78)
N. Obs.	4,049	4,049	4,049
Adj. R-squared	0.5031	0.5051	0.5053

This table presents coefficient estimates for the effect of economic development, EPU, and vaccine confidence on the relationship between COVID-19 vaccine rollout and FX volatility with all three interaction-term control variables in one regression. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.

Appendix A5. Vaccination Effects: Economic-Development and Vaccine-Confidence Interaction Terms Included

	(1)	(2)	(3)
β_d	0.285^{***}	0.296^{***}	0.248^{***}
	(4.65)	(4.52)	(4.31)
β_w	0.158^{**}	0.150^{**}	0.131^{*}
	(2.16)	(1.97)	(1.93)
β_m	0.191^{***}	0.184^{***}	0.206^{***}
	(3.11)	(2.91)	(3.87)
β_Q	-0.00079^{***}	-0.00043^{***}	-0.00071^{***}
	(−4.63)	(−3.11)	(−4.35)
R	0.0504	0.0317	0.0406
	(0.82)	(0.49)	(0.75)
New_cases	0.0025	0.0021	0.0022
	(0.84)	(0.58)	(0.78)
New_deaths	0.0024^{*}	0.0028^{*}	0.0009^{*}
	(1.76)	(1.92)	(1.71)
New_vax	-0.011^{*}		
	(−1.78)		

$Vax\_Increase$		-0.007^{**}	
		(−2.63)	
Vax_Period			-0.774^{*}
			(−1.66)
$New\_vax \times EME$	-0.016^{*}		
	(−1.87)		
$Vax\_Increase \times EME$		-0.027^{***}	
		(−2.97)	
$Vax\_Period \times EME$			-0.849^{**}
			(−1.96)
$New\_vax \times Trust$	-0.017^{**}		
	(−2.39)		
$Vax\_Increase \times Trust$		-0.273^{*}	
		(−1.86)	
$Vax\_Period \times Trust$			-0.756^{*}
			(−1.87)
N. Obs.	10,335	10,335	10,335
Adj. R-squared	0.2183	0.2201	0.2132

This table presents coefficient estimates for the effect of economic development and vaccine confidence on the relationship between COVID-19 vaccine rollout and FX volatility. We account for the country-fixed effect and estimate the equations using ordinary least squares, with robust standard errors clustered at the country level. *T*-statistics are in the parentheses beneath the coefficient estimates. ***, **, and * indicate that the estimated parameters are statistically significant at 1%, 5%, and 10% significance levels, respectively.