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FX markets' reactions to COVID-19: Are they different?☆

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ABSTRACT

In this paper, we empirically investigate the impact of the COVID-19 pandemic on FX markets. We find important differences between COVID-19 and previous high-risk episodes: the Global Financial Crisis, the Swiss National Bank's removal of the Swiss franc/euro floor, and Brexit. Contrary to these episodes, the USD did not show any safe haven characteristics during the pandemic. Furthermore, the estimated volatility and non-parametric value-at-risk of three currency portfolios indicate that COVID-19 was not as risky as previous stressful events. We provide evidence that investors could minimize COVID-19 risk by investing in the Canadian dollar and the Japanese yen, and by reducing their exposure to European currencies.

1. Introduction

COVID-19 is the most adverse peacetime shock to the global economy in a century (World Bank, 2020, p. 136). Not only are its effects on market volatility the largest in the history of pandemics (Baker et al., 2020; Costa Junior et al., 2021), but several uncertainty indicators have reached their highest values on record (Altig et al., 2020; Baker et al., 2020; Sharif et al., 2020). Fig. 1 shows that the VIX index peaked during the pandemic outbreak in March 2020 at a value higher than the maximum reached during the Global Financial Crisis in October 2008.

Such a large jump in uncertainty may have profound adverse effects on resource allocation (Bloom, 2014) and financial stability (Bekaert and Hoerova, 2014). Thus, the shock has immediately boosted academic debate on the effects of the global pandemic on financial markets (see, *inter alia*, Goodell, 2020). A growing body of financial literature has studied how local and global news on the evolution of COVID-19 has affected the volatility of stock markets (Albulescu, 2020; Ashraf, 2020; Onali, 2020; Baek et al., 2020; Salisu and Vinh Vo, 2020). This literature examines the increase in global risk due to the pandemic with a focus on both developed (Bai et al., 2020; Narayan et al., 2020; Zaremba et al., 2020; Zhang et al., 2020) and emerging markets (Topcu and Gulal, 2020; Corbet et al., 2020a, 2021; Pandey and Kumari, 2021). Further, it investigates the responses of European investment funds (Mirza et al., 2020) and banking sectors around the globe (Rizwan et al., 2020). Other studies have examined the influence of the pandemic on the prices of cryptocurrencies (Goodell and Goutte, 2020; Mnif et al., 2020; Iqbal et al., 2021), gold (Corbet et al., 2020b), oil and energy (Mensi et al., 2020; Salisu et al., 2020b; Yoshino et al., 2020), and other commodities (Salisu et al., 2020a; Ji et al., 2020).

While the global foreign exchange market is the largest in the world, foreign exchange (FX) has received little attention in the

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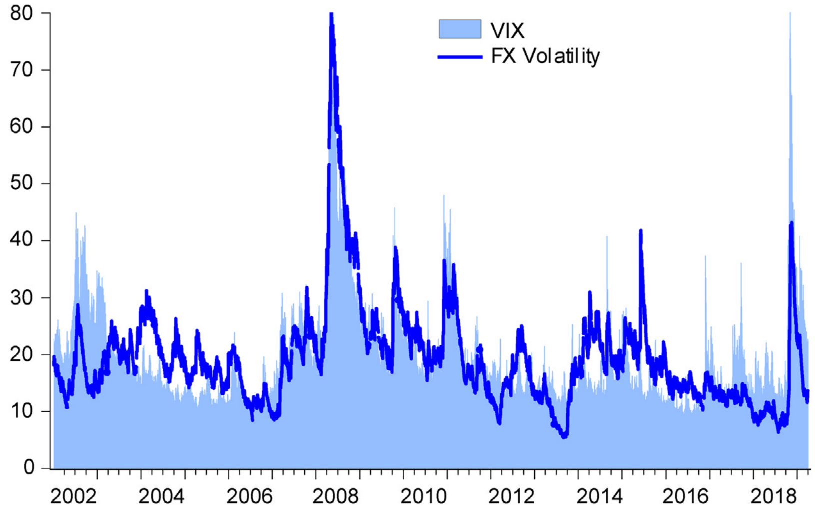


Notes: The FX volatility index is the average of the six conditional standard deviations of the excess returns relative to the US dollar (i.e., the the entries of vector $\boldsymbol{\sigma}_t$ as defined in section 2.2) that were rescaled to match the mean and standard deviation of the CBOE Volatility Index (VIX).

Fig. 1. VIX and FX volatility.

literature. The only exception, to the best of our knowledge, is the work of Aslam et al. (2020) who report a decline in the efficiency of FX markets during the pandemic.

We aim to help bridge this gap by identifying the reaction of the FX markets to the COVID-19 outbreak, and comparing them to previous high-risk episodes.[1] For this purpose, we first compute a multivariate FX volatility index to identify periods of high volatility. Then, we study the performance of three currency portfolios, as in Baz et al. (2001), Barroso and Santa Clara (2015) and Ackermann et al. (2017). Two of these portfolios are constructed using mean-variance optimization that allows for dynamic weights that can switch between long and short positions. The other is a static equally weighted portfolio. The performance of the portfolios is assessed based on volatility, the Sharpe ratio, and diversification ratio. Third, we compare these portfolios' performances with that of the S&P500 index (a well-known benchmark). Thus, in this study we attempt to answer the question of 'how did COVID-19 affect currency returns and currency portfolios?'.

In this paper, we show that the volatility and the non-parametric value-at-risk (VaR) of the three portfolios are extremely high in periods of high volatility in the FX markets. In particular, we identify three additional high-risk episodes since 2001: the Global Financial Crisis, the Swiss National Bank (SNB) removal of the Swiss franc (CHF)/euro (EUR) floor, and Brexit.

Contrary to the other high-risk episodes, we provide evidence that the US dollar (USD) has weakened during the COVID-19 pandemic. This weakness means that investors have been rushing into currencies other than the USD. Thus, the USD has not shown safe haven characteristics during the COVID-19 pandemic.

The study of the performances of three currency portfolios during these episodes shows the COVID-19 pandemic has not created new worries for investors. The volatility and VaR of the portfolios during the pandemic are relatively lower than in previous high-risk episodes. In addition, both risk metrics returned to their pre-pandemic levels much faster than in previous high-risk episodes.

One of the contributions of this paper is the calculation of the global minimum variance (GMV) and the maximally diversified (MD) currency portfolios, since the literature has mainly focused on carry-trade portfolios (see Engel (2014) for further details). In this sense, our paper is closely related to Clarke et al. (2013) and Ackermann et al. (2017). We show that if we estimate means, variances, and covariances, then the mean-variance approach can give new insights into currency portfolios. For instance, the MD portfolio generates a positive Sharpe ratio, while the GMV produces a negative one during the COVID-19 pandemic. Furthermore, we show that to minimize risk during the pandemic, investors should allocate more money to the Japanese yen (JPY) and the Canadian dollar (CAD), and less money to European currencies.

The rest of the paper is organized as follows: Section 2 presents the performance measures of the currency portfolios. In section 3, we describe the data and report our main results. Section 4 provides concluding remarks and some avenues for future research.

[1] The COVID-19 pandemic was still outgoing at the time of submitting this paper, so it is worth clarifying that the episode we study is the development of the so-called first wave of contagion after the announcement of the pandemic. Curiously, although the second and even third waves were significantly more severe from an epidemiological point of view (i.e., in terms of confirmed COVID-19 cases or recorded deaths), the financial markets, especially the FX markets, were not nearly as volatile as in the outburst of the pandemic. Thus, in the sample of study the volatility related to the COVID-19 crisis may be overestimated, that makes it comparable to the other episodes of stress in the FX markets, and provides upper bounds for our measures of risk. In subsection 3.2 we discuss this selection further.

2. Currency returns and portfolios

In order to answer the question of how the COVID-19 pandemic has affected currency returns and therefore currency portfolios, a review of the concept of ex-ante excess returns on foreign deposits (or bonds) and the construction techniques for portfolios is important.

2.1. Currency returns

The profits in the FX markets are motivated by the failure of the condition of uncovered interest rate parity (UIP). The UIP stipulates that interest rate differential moves one-to-one with the expected change in the exchange rate; thus, high-interest-rate currencies tend to depreciate against low-interest-rate currencies. In his seminal paper, Fama (1984) provides conclusive evidence that rejects the validity of the UIP condition. A vast amount of subsequent empirical research has supported Fama's conclusions, such as Lewis (1995), Engel (1996), Menkhoff et al. (2012), and Engel (2014).

At time t, the UIP links the domestic interest rate (i_t); the foreign interest rate (i_t^*); the nominal spot exchange rate (Z_t), which is the price of domestic currency per unit of foreign currency; and the expected nominal exchange rate ($\mathrm{E}_t(Z_{t+1})$) as follows:

$$\frac{\mathrm{E}_t(Z_{t+1})}{Z_t}(1+i_t^*) = (1+i_t). \tag{1}$$

The left-hand side of equation (1) is the expected return from lending money in the foreign money market that is measured in domestic currency per unit of foreign currency. The right-hand side of equation (1) is the expected return of lending domestic currency in the domestic money market. For the purpose of this paper, we consider the US as the domestic economy and any other country in the sample (Australia, Canada, Germany, Japan, Switzerland or the UK) as the foreign economy.

We can then define the expected currency return between period t and $t+1$ as:

$$r_t = \frac{\mathrm{E}_t(Z_{t+1})}{Z_t}(1+i_t^*) - (1+i_t). \tag{2}$$

2.2. Currency portfolios

Next, we present two construction techniques for a risk-based portfolio that follow a minimum-variance and maximum-diversification objective functions, and a passive investment strategy.

The first is the global minimum variance (GMV) portfolio that minimizes the portfolio volatility, thus it lies on the left-most tip of the ex-ante efficient frontier. The second is the maximally diversified (MD) portfolio that maximizes the ratio of weighted average volatilities in currency returns to portfolio volatility, the so-called diversification ratio. Choueifaty and Coignard (2008) show that the MD resembles a traditional mean-variance portfolio under the assumption that expected returns are proportional to their volatility; and perform well during episodes of turbulence where such proportionality is more likely to hold. Further, the passive investment strategy is an equally weighted (EW) portfolio that gives the same weight to each currency return in a portfolio regardless of the correlation structure and individual risk. Ackermann et al. (2017) discuss how, despite its simplicity, the EW can perform well, especially during calm periods.

Consider $n+1$ currencies that include the USD as the benchmark ("currency 0"). Let $\boldsymbol{r}_t$ be the $n \times 1$ vector of returns from the currencies with respect to the USD, and let $\boldsymbol{\Sigma}_t$ be the $n \times n$ covariance matrix of $\boldsymbol{r}_t$ that is conditional on information up to time t. We also define $\boldsymbol{\sigma}_t$ as the vector of volatilities, so its k-th entry is the conditional standard deviation of the k-th return: $(\boldsymbol{\sigma}_t)_k = \sqrt{(\boldsymbol{\Sigma}_t)_{kk}}$.

Let $\boldsymbol{w}_t$ be the vector of currency shares in a given portfolio. We use the following performance measures:

$$V(\boldsymbol{w}_t) = \sqrt{\boldsymbol{w}_t'\boldsymbol{\Sigma}_t\boldsymbol{w}_t}, \qquad S(\boldsymbol{w}_t) = \frac{\boldsymbol{r}_t'\boldsymbol{w}_t}{V(\boldsymbol{w}_t)}, \qquad D(\boldsymbol{w}_t) = \frac{\boldsymbol{\sigma}_t'\boldsymbol{w}_t}{V(\boldsymbol{w}_t)}, \tag{3}$$

where $V(\boldsymbol{w}_t)$ is the portfolio volatility that equals the conditional standard deviation of the portfolio return $\boldsymbol{r}_t'\boldsymbol{w}_t$. The $S(\boldsymbol{w}_t)$ is the Sharpe ratio, that is, the risk-adjusted return. And $D(\boldsymbol{w}_t)$ is the diversification ratio proposed in Choueifaty and Coignard (2008) that equals the ratio of the weighted average of volatilities divided by the portfolio volatility. A higher ratio means better diversification (e.g., due to lower correlations).

The fourth performance measure is the VaR that captures tail risk, and is computed non-parametrically as the fifth percentile of the distribution of the historical portfolio returns.

All portfolios satisfy the sum up constraint $\boldsymbol{w}_t'\boldsymbol{1}_n = 1$ in which $\boldsymbol{1}_n$ is the sum vector of dimension $n \times 1$ (i.e., all entries of $\boldsymbol{w}_t$ sum to one). On the one hand, the GMV portfolio minimizes $V(\boldsymbol{w}_t)$ subject to $\boldsymbol{w}_t'\boldsymbol{1}_n = 1$. The solution is:

$$\widetilde{\boldsymbol{w}}_t = \frac{\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n}{\boldsymbol{1}_n'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n},$$

such that:

$$V(\widetilde{\boldsymbol{w}}_t) = \frac{1}{\sqrt{\boldsymbol{1}_n'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n}}, \quad S(\widetilde{\boldsymbol{w}}_t) = \frac{\boldsymbol{r}_t'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n}{\sqrt{\boldsymbol{1}_n'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n}} \quad \text{and} \quad D(\widetilde{\boldsymbol{w}}_t) = \frac{\boldsymbol{\sigma}_t'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n}{\sqrt{\boldsymbol{1}_n'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n}}.$$

On the other hand, the MD portfolio maximizes $D(\boldsymbol{w}_t)$ subject to $\boldsymbol{w}_t'\boldsymbol{1}_n = 1$. The solution is:

$$\hat{\boldsymbol{w}}_t = \frac{\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\sigma}_t}{\boldsymbol{1}_n'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\sigma}_t},$$

such that:

$$V(\hat{\boldsymbol{w}}_t) = \frac{\sqrt{\boldsymbol{\sigma}_t'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\sigma}_t}}{\boldsymbol{\sigma}_t'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{1}_n}, \quad S(\hat{\boldsymbol{w}}_t) = \frac{\boldsymbol{r}_t'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\sigma}_t}{\sqrt{\boldsymbol{\sigma}_t'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\sigma}_t}} \quad \text{and} \quad D(\hat{\boldsymbol{w}}_t) = \sqrt{\boldsymbol{\sigma}_t'\boldsymbol{\Sigma}_t^{-1}\boldsymbol{\sigma}_t}.$$

Finally, EW portfolio uses $\boldsymbol{w}_t = (1/n)\boldsymbol{1}_n$.

2.3. Measuring covariances

We follow Ackermann et al. (2017) to improve the measurement of the covariance matrix of currency returns. These authors emphasize the importance of distinguishing the random component of returns from the observed part at the time when investment decisions are made.

Let Z_{kt} be the exchange rate measured as USD per the k-th currency (foreign currency) for $k = 1, 2, \dots, n$. When trading currencies, the total return of a speculative position opened at time t and closed at $t+1$ depends on three different factors: the k-th currency interest rate (i_{kt}), the US interest rate (i_{0t}), and the appreciation of the k-th currency ($z_{k,t+1} = Z_{k,t+1}/Z_{k,t} - 1$). Thus, the k-th currency return of a spot position is:

$$r_{k,t+1} = (1 + z_{k,t+1})(1 + i_{kt}) - (1 + i_{0t}). \tag{4}$$

Given the information set at time t, $r_{k,t+1}$ is random because $z_{k,t+1}$ is random, but i_{kt} and i_{0t} are known. Thus, the covariance between currency returns factorizes as follows:

$$\mathrm{Cov}_t(r_{k,t+1}, r_{k',t+1}) = \mathrm{Cov}_t(z_{k,t+1}, z_{k',t+1})(1 + i_{kt})(1 + i_{k't}). \tag{5}$$

Let $\boldsymbol{\Omega}_t$ be the covariance matrix of appreciation rates such that $[\boldsymbol{\Omega}_t]_{kk'} = \mathrm{Cov}_t(z_{k,t+1}, z_{k',t+1})$, and let $\boldsymbol{G}_t$ be a diagonal matrix such that $[\boldsymbol{G}_t]_{kk} = (1 + i_{kt})$. Then, the covariance matrix of the vector of currency returns that features in the aforementioned portfolio problems is $\boldsymbol{\Sigma}_t$, such that $[\boldsymbol{\Sigma}_t]_{kk'} = \mathrm{Cov}_t(r_{k,t+1}, r_{k',t+1})$, and that satisfies $\boldsymbol{\Sigma}_t = \boldsymbol{G}_t\boldsymbol{\Omega}_t\boldsymbol{G}_t$. The time-varying nature of $\boldsymbol{\Omega}_t$ is modelled as a dynamic conditional correlation GARCH process.

2.4. Dynamic conditional correlation (DCC) GARCH

The DCC-GARCH model advanced in Engle (2002) facilitates the parsimonious estimation of a relatively large time-varying covariance matrix. The approach provides an adequate compromise between simplicity and flexibility, and has proven to be convenient in empirical applications.

Let $\boldsymbol{r}_t$ be the six-dimensional currency return series that can be decomposed as $\boldsymbol{r}_t = \boldsymbol{\mu}_t + \boldsymbol{a}_t$, where $\boldsymbol{\mu}_t = \mathrm{E}_{t-1}(\boldsymbol{r}_t)$ is the conditional mean of $\boldsymbol{r}_t$ given the available information at time $t-1$, and $\boldsymbol{a}_t$ is a vector of innovations. The conditional covariance matrix is $\boldsymbol{\Omega}_t = \mathrm{Cov}_{t-1}(\boldsymbol{a}_t)$, so that $\boldsymbol{a}_t = \boldsymbol{\Omega}_t^{1/2}\boldsymbol{\varepsilon}_t$, where $\boldsymbol{\varepsilon}_t$ is an *iid* random vector with $\mathrm{E}(\boldsymbol{\varepsilon}_t) = \boldsymbol{0}$ and $\mathrm{Cov}(\boldsymbol{\varepsilon}_t) = \boldsymbol{I}_k$.

The DCC-GARCH model decomposes $\boldsymbol{\Omega}_t$ into conditional standard deviations:

$$\boldsymbol{D}_t = \mathrm{diag}(\sigma_{11t}^{1/2}, \dots, \sigma_{kkt}^{1/2}) \tag{6}$$

and a time-varying conditional correlation ($\boldsymbol{\rho}_t$):

$$\boldsymbol{\Omega}_t = \boldsymbol{D}_t\boldsymbol{\rho}_t\boldsymbol{D}_t. \tag{7}$$

First, each of the individual diagonal elements in $\boldsymbol{D}_t$ is modelled by using a separate univariate GARCH(1,1) to form the vector of predicted standardized residuals ($\boldsymbol{e}_t$). Then, the pairwise conditional correlations among them are modelled. Engle (2002) proposes the following structure which depends upon few parameters:

$$\boldsymbol{Q}_t = (1 - \theta_1 - \theta_2)\boldsymbol{Q} + \theta_1\boldsymbol{Q}_{t-1} + \theta_2\boldsymbol{e}_{t-1}\boldsymbol{e}_{t-1}', \tag{8}$$

Here $\boldsymbol{Q}_t$ is the covariance matrix of standardized residuals, $\boldsymbol{Q}$ is the unconditional covariance matrix of standardized residuals, and θ_1 and θ_2 are non-negative real numbers that satisfy $0 < \theta_1 + \theta_2 < 1$. The conditional correlation matrix is then defined as $\boldsymbol{\rho}_t = \boldsymbol{J}_t\boldsymbol{Q}_t\boldsymbol{J}_t$, where:

$$\boldsymbol{J}_t = \mathrm{diag}(q_{11t}^{-1/2}, \dots, q_{kkt}^{-1/2}) \tag{9}$$

is a normalization matrix as q_{iit} denotes the (i, i)-th element of $\boldsymbol{Q}_t$.

3. Results

3.1. Data

Our dataset consists of daily observations of quoted currencies (against the USD) and overnight LIBOR interest rates for seven markets: Australia, Canada, Switzerland, the Euro Area, Japan, the United Kingdom, and the United States. The data are from Bloomberg and cover the period from January 3, 2001, to August 24, 2020, and yields 4742 observations per country. Australia and Canada discontinued their LIBOR rates in May 2013, so from that period on we use local overnight rates: RBA Official Cash Rate for Australia and CORRA for Canada.

3.2. High-risk episodes

Fig. 1 plots the VIX index, which is a well-established measure of global uncertainty, and our FX volatility index. Our index is in the spirit of Menkhoff et al. (2012): the cross-sectional average of all estimated GARCH volatility series of currency returns (the entries of $\boldsymbol{\sigma}_t$). The index shows that uncertainty and FX volatility move together, and times of high uncertainty may be associated with high volatility episodes in the FX markets. While the Global Financial Crisis (GFC) and COVID-19 are global shocks, Brexit and the change in the SNB exchange rate policy refer to local shocks with significant effects on the global FX market. On September 6, 2011, after a sharp appreciation of the CHF relative to the EUR, the SNB introduced a minimum exchange rate of 1.20 CHF/EUR that was removed on January 15, 2015. Similarly, Brexit started to unfold on June 23, 2016.

Fig. 2 shows our portfolio measures of risk, volatility, and VaR. It shows that these measures produce local extreme values during the aforementioned episodes. The annualized average volatility series of GMV, MD, and EW during COVID-19 are similar to those of the SNB and Brexit (local shocks), but considerably lower than those of the GFC (global shock). Further, for the tail risk, the VaR values are extremely high during the GFC, moderately high during the SNB, and very similar during Brexit.

The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020, and our sample runs 109 trading days later (August 19, 2020). Given this data availability, we give the same treatment to each of the episodes of study and consider windows that begin approximately a month before the occurrence of the core event, and end 126 trading days later (six-month trading period). Thus, since the GFC started on September 15, 2008 (the collapse of Lehman Brothers), our window runs from 08 to 15–2008 to 02-23-2009. Likewise, the SNB period starts on 12-15-2014 and ends on 06-26-2015, while the Brexit window runs from 05 to 13–2016 to 11-21-2016. And, the first wave of COVID-19 begins on 02-11-2020 and ends on 08-19-2020.

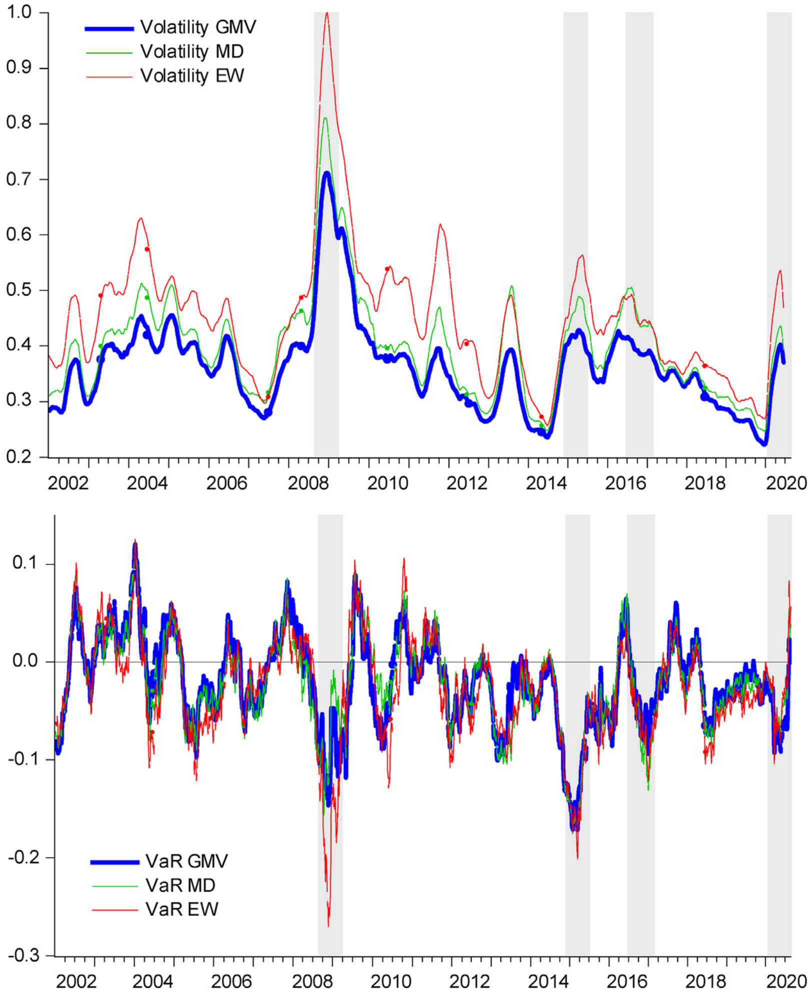
As Fig. 3 shows, all high-risk episodes have triggered a portfolio reallocation that caused swings in the FX markets of different magnitudes. During the pandemic, the depreciation of currencies relative to the USD – namely, the Australian dollar (AUD), the Canandian dollar (CAD) and the British pound (GBP) – accelerated between mid-February and late March 2020. Since the beginning of April 2020, these currencies have started to slowly recover, a rebound that may reflect the coordinated monetary policy reactions of the Federal Reserve (Fed) and the other G6 central banks (World Bank, 2020, Ch. 1). In the COVID-19 pandemic, the currencies depreciated faster than during the GFC, but such depreciations did not persist as much as in the GFC. In fact, on average, all currencies appreciated from March to August 2020 and ranged from 2% (CAD) to 18% (EUR). By contrast, except for the CHF, all other currencies depreciated against the USD during the SNB episode, while the GBP is the only currency that depreciated during the Brexit episode.

These patterns in depreciation rates during high-risk episodes highlight that the USD did not have safe haven characteristics during the COVID-19 pandemic. The main source of downward pressure on the USD is the fact that the Fed was creating massive amounts of dollars at an unprecedented rate. That is, the Fed reacted faster during the COVID-19 pandemic than in past periods of financial stress by providing up to US$ 2.3 trillion in lending to support households, firms, and state and local governments (cf. Cheng and Powell, 2021).

3.3. Currency portfolios' performance

Table 1 shows the diversification ratios and the optimal shares of the GMV and MD portfolios. The diversification ratios do not vary considerably over time, even though they tend to be higher than the sample average during global shocks such as the GFC and COVID-19, and lower than the sample average during local shocks. As for the optimal shares, a common pattern in both portfolios is the large allocation to the JPY because it typically appreciates significantly during periods of global turmoil. By contrast, both active strategies shows allocations of almost zero to the GBP during the COVID-19 pandemic. One difference between the GMV and MD worth noting is the investment in the CAD and CHF. For the CAD, the GMV indicates going short while the MD indicates going long during the COVID-19 pandemic. In particular, according to the MD strategy, risk-averse investors should increase their allocations to the CAD from about 30% in normal times to 40% during the COVID-19 pandemic. For the CHF, the GMV indicates putting 22% of investors' money in this currency, while the MD indicates only 6% during the pandemic. Conversely, during the SNB episode, the GMV suggests allocating only 7% to CHF while the MD suggests 21%, which is a considerable share of investors' wealth.

A reasonable understanding of this finding is that optimal weights adjust by shifting from one currency to another as risk conditions change. We focus on the COVID-19 pandemic, as the analysis of the other periods is similar. As described in Choueifaty and Coignard (2008), the MD portfolio equalizes each asset's risk contribution to the portfolio risk. In other words, investors should allocate 40% of their wealth to CAD and 6% to CHF to equalize the contributions of their risks to the



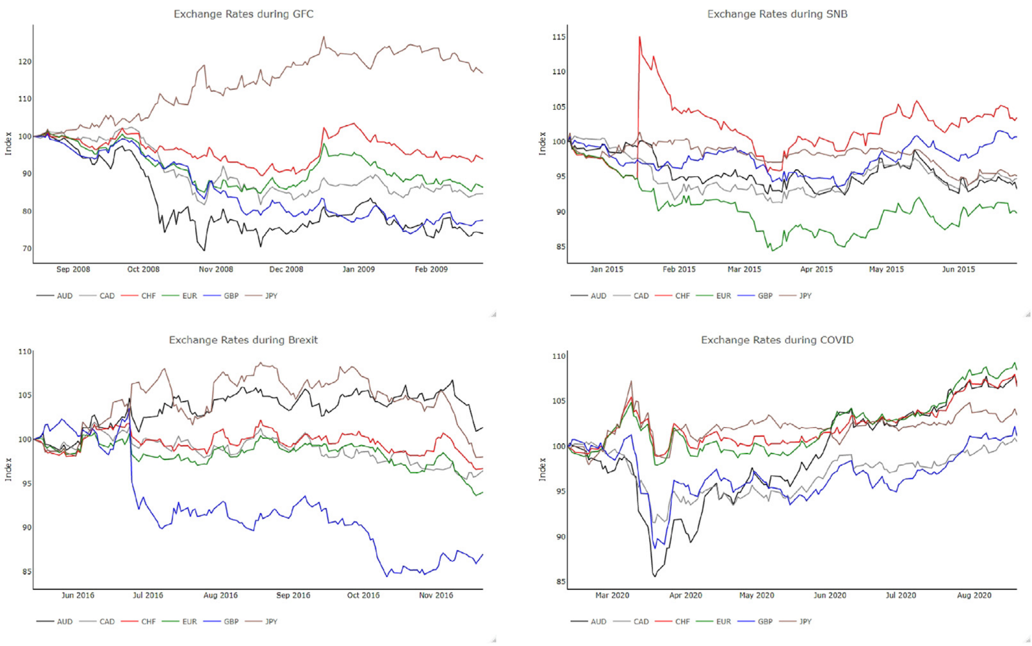
Notes: Top panel: 90-day centered moving average of $V(\boldsymbol{w}_t)$ for the global minimum variance (GMV),maximally diversified (MD) and equally weighted (EW) portfolios defined in section 2.2. Bottom panel: 90-day rolling non-parametric VaR computed as the fifth percentile of the historical distribution of portfolio returns $\boldsymbol{r}_t{}'\boldsymbol{w}_t$. Highlighted are the episodes of turbulence: Global Financial Crisis (GFC), Swiss National Bank (SNB), Brexit, and COVID-19.

Fig. 2. Portfolio risk measures: Volatility and Value-at-Risk.

portfolio. In contrast, the GMV portfolio has a minimum variance when compared to all possible portfolios. Therefore, this strategy argues for allocating −3% to CAD and 22% to CHF to minimize the portfolio's volatility during the COVID-19 period.

Table 2 shows the performance measures of the portfolios. As expected, in all cases the GMV produces the lowest volatility among portfolios, but in general this portfolio performs poorly in terms of the Sharpe ratio. On the other hand, the MD portfolio reflects an active strategy which is sensitive to market volatility and, because of its responses to shocks, can render good results in high-risk times. This is verified in our results, as the MD portfolio outperforms the other two and the S&P500 in terms of the Sharpe ratio during the GFC. However, the Sharpe ratio of the MD portfolio is lower than that of the EW during the local shocks and the pandemic. This result is not surprising because the EW may be interpreted as a passive strategy that can produce favorable results during relatively calm periods. Also, the Sharpe ratio of the S&P500 is the highest during the local shocks, pandemic, and the whole sample.

Next, Table 2 shows that the returns and risk-adjusted returns of all currency portfolios were higher during the pandemic than during the other high-risk events. Regarding risk, the GMV and MD rendered comparatively low portfolio volatilities during the COVID-19 pandemic. The portfolios' behavior indicates the COVID-19 episode was not as turbulent as previous experiences such as the GFC and local shocks. These findings may be explained by the facts that uncertainty (VIX) and FX volatility (FX volatility index) are relatively low during the local shocks, and that the high uncertainty and FX volatility during the COVID-19 pandemic was short-lived (see Fig. 1). As a result, investors were less cautious and more willing to take more risk that thus generated a higher reward-to-risk ratio.



Notes: The lengths of the windows are approximately the same among episodes: they begin one month before the occurrence of the core event and end 126 trading days later.

Fig. 3. Evolution of exchange rates during high-risk episodes.

Table 1
Portfolios' composition and diversification ratios during high-risk episodes.

Portfolio	Share	GFC	SNB	Brexit	COVID-19	Full Sample
GMV	AUD	−0.03	0.01	−0.05	−0.10	−0.05
	CAD	0.16	0.26	0.04	−0.03	0.23
	CHF	−0.08	0.07	0.12	0.22	−0.06
	EUR	0.14	−0.10	0.32	0.10	0.15
	GBP	0.16	0.26	0.04	−0.03	0.23
	JPY	0.46	0.45	0.15	0.32	0.32
Diversification ratio		1.63	1.22	1.34	1.49	1.40
MD	AUD	0.19	0.12	0.06	0.06	0.12
	CAD	0.25	0.23	0.30	0.40	0.31
	CHF	−0.10	0.21	0.05	0.06	0.07
	EUR	−0.07	−0.05	−0.06	0.04	−0.04
	GBP	0.16	0.20	0.28	0.02	0.19
	JPY	0.57	0.28	0.37	0.41	0.35
Diversification ratio		1.84	1.35	1.59	1.59	1.53

Notes: Currency shares $\boldsymbol{w}_t$ and diversification ratios $D(\boldsymbol{w}_t)$ during the high volatility episodes identified in Fig. 2. The portfolios are the global minimum variance (GMV) and maximally diversified (MD). The figures are sample averages of daily data from the following periods: Global Financial Crisis (GFC): August 2008–February 2009; Swiss National Bank (SNB): December 2014–June 2016; Brexit: May 2016–November 2016; COVID-19: January 2020–August 2020; Full Sample: January 2001–August 2020.

4. Conclusion

We provide evidence that, compared to other stressful events, the COVID-19 pandemic has had a relatively moderate impact on the FX markets and, consequently, on currency returns and portfolio risk metrics. This is true even though the negative effects on economic activity were expected to be even worse than during the GFC. Providing a thorough explanation of this finding is beyond the scope of this paper, but a tentative explanation is that market participants are betting on further fiscal (unemployment and tax benefits) and monetary (credit lines, asset purchase programs and negative interest rates) stimuli to mitigate the impact of COVID-19 on the real economy.

The construction techniques for the mean-variance portfolio that were applied to the currency returns shed new light on the performance of currency portfolios. Portfolio managers could exploit the fact that the MD portfolio produces a higher Sharpe ratio

Table 2
Portfolios' performance during high-risk episodes.

Portfolio	Measure	GFC	SNB	Brexit	COVID-19	Full Sample
GMV	Return	−11.57	−14.07	−8.55	−0.50	0.70
	Volatility	10.31	6.74	6.31	5.77	5.73
	Sharpe Ratio	−1.12	−2.09	−1.35	−0.09	0.12
MD	Return	−3.96	−11.98	−11.45	4.74	1.28
	Volatility	11.65	7.54	7.52	6.23	6.28
	Sharpe Ratio	−0.34	−1.59	−1.52	0.76	0.20
EW	Return	−18.55	−12.24	−8.63	10.30	1.51
	Volatility	14.12	8.42	7.43	7.54	7.17
	Sharpe Ratio	−1.31	−1.45	−1.16	1.37	0.21
S&P500	Return	−54.29	9.21	11.70	15.15	6.42
	Volatility	33.35	11.27	16.35	13.94	16.19
	Sharpe Ratio	−1.63	0.82	0.72	1.09	0.40

Notes: Annualized average return $\boldsymbol{r}_t'\boldsymbol{w}_t$, volatility $V(\boldsymbol{w}_t)$ and Sharpe ratios $S(\boldsymbol{w}_t)$ during high volatility episodes identified in Fig. 2. The portfolios are the global minimum variance (GMV), maximally diversified (MD), and equally weighted (EW). The figures are sample averages of daily data from the following periods: Global Financial Crisis (GFC): August 2008–February 2009; Swiss National Bank (SNB): December 2014–June 2016; Brexit: May 2016–November 2016; COVID-19: January 2020–August 2020; Full Sample: January 2001–August 2020.

than the GMV portfolio (active strategy), but similar to that of the EW (passive strategy), over longer horizons.

Another interesting finding is related to the heterogeneous paths followed by the exchange rates after the outbreak of the COVID-19 pandemic. Generally speaking, a safe haven currency appreciates relative to other currencies when global risk materializes. Contrary to a global shock (GFC) and two local shocks (SNB and Brexit), on average, the US dollar weakened against all sample currencies during the COVID-19 episode under study. This weakness indicates that the USD is losing its role as a safe haven currency. This discussion is part of our ongoing research agenda.

Declaration of competing interest

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

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