Downside and upside risk spillovers between precious metals and currency markets: Evidence from before and during the COVID-19 crisis

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Abstract

This paper investigates the tail dependence dynamics and asymmetric risk spillovers between the futures of four important precious metals (gold, silver, platinum, and palladium) and seven leading currencies (EUR, GBP, JPY, CAD, AUD, CHF, and CNY) before and during the COVID-19 crisis using the time-varying-parameter copula and the conditional Value-at-Risk (CoVaR) method. The results show the symmetric dependence between currencies and precious metals before the COVID-19 crisis. In contrast, we show negative and positive tail asymmetric dependences during the pandemic crisis. The COVID-19 crisis significantly amplifies the magnitude of spillover effects among the studied markets where the AUD currency exhibits the largest transmission and reception of downside and upside spillover to/from most precious metals before and during the pandemic crisis. Currency investors and portfolio managers could use the obtained results to better hedge and manage their investment positions when markets are affected by health crises.

JEL classification: G14.

Keywords: Precious metals; Currencies, Systemic risk, COVID-19.

1. Introduction

A novel coronavirus (COVID-19) affected the city of Wuhan, Hubei, China in November 2019 and quickly spread through China's borders. The World Health Organisation (WHO) announced COVID-19 as a global pandemic March 11, 2020. This pandemic has unprecedented effects on the stability of the global economy and financial spheres downstream (Bakas and Triantafyllou, 2020; Corbet et al., 2021; Goodell, 2020). The pandemic has posed an immense risk even to developed countries, and governments worldwide have implemented restrictive measures (lockdowns, quarantines, travel restrictions, business closure, public health measures, movement restrictions, production stoppages, and social distancing, among others) to cut the number of deaths and affected cases. These measures have intensified the uncertainty and volatility of both financial and commodity markets. Foreign exchange (FX) and precious metals (PMs), two important markets for the worldwide economy, have also been influenced by the pandemic. The value of currencies has been depreciated with the evolution of the pandemic (increasing number of deaths and affected cases). The US dollar was unaffected by the pandemic in early 2020 but became subjected to pressures in 2021 following the uncontrollable outbreak of the SARS-CoV-2 variants (Delta and Omicron). The weak global oil demand significantly reduced oil prices, affecting the Canadian dollar (CAD). The Livre Sterling (GBP) has fallen by 15 percent against the US dollar since the beginning of 2020. [1] Precious metals, mainly gold, have been universally accepted as safe haven asset during crisis periods and extreme market uncertainties (Baur and Lucey, 2010; Baur and McDermott, 2010; Conlon et al., 2018; Mensi et al., 2021a). Unlike the pressure of FX markets, the PM markets have witnessed an upside pattern during the pandemic outbreak. The PM index increased by 5.4 percent in 2020Q1 due to the safe haven property of these metals during market crisis times (Ahmed and Sarkodie, 2021). Gold prices surged by 12

[1] https://www.pwc.co.uk/services/transaction-services/insights/foreign-exchange-volatility-shakes-up-valuations-as-covid-19-result.html

percent in 2020Q3 and fell by 4 percent in 2021Q1.[2] The price of silver declined by 2.3 percent in 2020Q1 but soared by 8 percent in 2021Q1. The price of platinum, in turn, rose by 24 percent in 2021Q1. This led to a 2 percent decline in the PM index in 2021Q1 due to the decline of the price of gold (World Bank, 2021). Conversely, the prices of silver, palladium, and platinum rose as a result of the metals' wider use in industry. This reflects the ongoing recovery in industrial demand and supply disruptions. These statistics clearly indicate that PM markets have experienced phases of upside and downside trends. This uncertainty in the value of PMs demonstrates the importance of studying its linkages with financial markets.

A significant interaction between Currencies and commodities have been documented in the literature (e.g., Antonakakis and Kizys, 2015; Sakemoto, 2018; Mensi et al., 2020). For example, Sari et al. (2010) found that there is a weak long-run equilibrium relationship between PMs, oil prices, and the USD/EUR currencies. More specifically, PM prices respond to shocks in the prices of other PMs (gold, silver, platinum, and palladium) and the USD/EUR exchange rate. On the other hand, Jain and Ghosh (2013) showed that there is a cointegration and the Granger causality relation among oil prices, PMs (gold, platinum, and silver), and the Indian Rupee/USD exchange rate. On the same line of thought, Antonakakis and Kizys (2015) shows that information contents of gold, silver, platinum, and the CHF/USD and GBP/USD exchange rates help to improve the forecast accuracy of both the return and volatility on palladium and crude oil returns and volatilities. Furthermore, the spillover effect from gold, silver, and platinum to the other assets was high during and after the 2008-2009 global financial crisis. Interestingly, Pierdzioch et al. (2016) demonstrate that gold and silver are strong hedges against depreciations of major exchange rates (such as AUD/USD, CAN/USD, EUR/USD, GBP/USD, and JPY/USD). However, the hedging properties of palladium and platinum are validated only for AUD/USD and CAD/USD.

[2] https://openknowledge.worldbank.org/bitstream/handle/10986/34621/CMO-October-2020.pdf

Furthermore, the authors show that PMs could comprise safe haven assets during periods of large exchange-rate movements. Sakemoto (2018) confirm the results of Pierdzioch et al. (2016) and show that gold and silver has hedge and safe haven properties for currency portfolios for all the considered strategies (carry, momentum, and value). Silver is identified as a strong hedge during extreme market conditions. Churchill et al. (2019) also confirm the causality relationship among oil prices, PM prices, and the USD/GBP exchange rate. Moreover, Mensi et al. (2020) show that there are weak average conditional correlations between PMs and exchange rates, except for the global financial crisis. Recent literature has used the time-domain and time-frequency spillover index to analyse the spillover intensity and its direction among markets. For example, Mensi et al. (2021b) examin the spillovers between PMs (gold, palladium, platinum, and silver) and currency markets (AUD, CAD, CHF, CNY, EUR, GBP, and JPY) using the spillover indices of Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). The authors find that silver, palladium, and platinum are the largest contributor of spillovers to the AUD and CAD currency markets irrespective of the time horizons considered. The spillovers between currency and PMs are asymmetric and influenced by international shocks. In fact, the PM assets serve as a diversifier and hedge asset for currency portfolios. Using the time-frequency spillover index and the implied volatility indices of oil, gold, and FX rates, Ding et al. (2021) show a higher spillover between these markets during the European debt crisis and the COVID-19 crisis. This result is also obtained by Shah et al. (2021). Recently, Mensi et al. (2022) examin the quantile dependence between PMs and the currency markets of Australia, Canada, China, the Eurozone, Japan, Switzerland, and the UK. The authors observe that gold and silver are net contributors of spillovers in the system. Moreover, the oil prices, the implied volatility index (VIX), the Economic Policy Uncertainty index, and the USD index represented the key drivers in determining the direction and size of spillovers among PMs and currency markets. Table A1 provides the further empirical studies addressing the relationships between PM and currency markets.

The motivation behind this study stems from the above studies that have revealed significant and complex relationships between PMs and FX markets. This relationship may be explained by the fact that the transactions of PMs involves the transaction of currencies through central bank PMs and currency reserves (Aizeman et al., 2020) and through international PM markets such as ones based in London, New York, Tokyo, and Shanghai (Hoang et al., 2016). All these transactions of PMs have led to changes in currency rates (appreciations and depreciations). Furthermore, there is evidence that a handful of critical variables, including oil price, amount of uncertainty, and investors' anticipation for future volatility, strongly explain spillovers. As an illustration, if the price of oil were to rise, it would have a multiplicative effect on inflation and, in turn, on currency exchange rate shocks. In order to mitigate the effects of inflation and the increasing volatility of the foreign exchange market, investors seek out the most suitable PM to hedge their currency portfolios (Barunk et al., 2018). According to Baur and McDermott (2010), gold purchases increase when market participants fear the future of the economy or the financial sector. The volatility index (VIX) is a superior hedging instrument and safe haven than gold (Hood and Malik, 2013).

Historically, the link between currencies and precious metals has been seen economically via the lens of the global oil price channel. Specifically, economies that import a sizeable amount of their oil consumption—like those of Europe, Japan, Australia, the United Kingdom, and the United States—experience larger inflationary and currency rate shocks as a result of the rise in oil prices. Branuik et al. (2018) argue that investors seek investments in precious metals in response to growing inflation and currency market volatility. This approach makes PMs an international money reserve and connects currency markets to the PM markets. Additionally, Jain and Ghosh (2013) show there is two-way relationships between currency and PM prices since demand is met through imports. PMs tend to increase in value as the value of other currencies declines, notably the US dollar. This is because after a drop in the value of the USD, foreign exchange dealers would often swap their currency for precious metals, causing the currency markets to be volatile and the price of gold to rise sharply. The economic theory and the previous research on the precious metals-currencies nexus are not unanimous in their conclusions (Jain and Ghosh, 2013). Given this, we examine the precious metals-currencies link from the angles of tails dependency and network downside and upside spillovers, which is a curious phenomenon in and of itself. Therefore, it is important for central banks, investors, and portfolio managers to have a firm grasp of the dependency structure and risk transmission between PMs and currencies. In particular, how to protect their investment portfolio from the potential negative effects of a health crisis on the market.

This paper aims to examine the tail dependence and the downside and upside risk spillovers between four major PMs (gold, palladium, platinum, and silver) and seven main currencies (AUD/USD, CAD/USD, CHF/USD, CNY/USD. EUR/USD, GBP/USD, and JPY/USD) before and during the COVID-19 crisis. We draw our empirical results by implementing copulas with time-varying parameters (TVP), and Value-at-Risk (VaR) and conditional Value-at-Risk (CoVaR) methods on two samples of daily frequency data spanning from August 22, 2018, to March 10, 2021 (before COVID-19), and from March 11, 2020, to September 28, 2021 (during the COVID-19). The breakpoint is the announcement by the WHO that COVID-19 is a global pandemic on March 11, 2020. For consistency, both subsamples are equal in terms of the number of observations (405 daily observations).

This study contributes to the relevant literature in two important ways. First, no previous study has investigated the time-varying average and tail dependence and downside and upside spillover effects between major PM and FX markets before and during the COVID-19 outbreak. This comparison is important because it measures for the first time the effect of an international health crisis on the return and volatility dependence structure during bear and bull market scenarios between two important markets such as the PMs and the FX, and their implications on risk management. We notice that currency investors were pessimistic during COVID-19 crisis episodes and sought alternative investment opportunities to hedge their currency portfolio from extreme risk exposure. Second, we use the results of the dynamics of dependence to quantify the impacts of the COVID-19 crisis spillover size and directions between the PM and FX markets. Specifically, we analyse the asymmetric (downside and upside) bidirectional spillovers among the markets under investigation. This study may help investors and portfolio managers to better hedge and manage their investment positions when markets are shocked by global health crises. It also provides important guidelines for policymakers (central banks) looking to implement suitable monetary policies during crisis times.

A plethora of empirical methods are used to examine cross-market information spillovers and dependencies among international markets. To achieve this, this study apply static and dynamic copula-based GARCH models including the Gaussian, Student's-t, Clayton, Rotated clayton, Umbel, Rotated gamble, and symmetrized Joe-Clayton models. Copula approach separates the marginal distributions from the dependence structure and allows the modeling of these distributions independently. This advantage is not considered in the time-domain spillover index of Diebold and Yilmaz (2012) which measure only the directional and size spillovers among markets. Besides, the time-domain spillover index fails to investigate the spillovers under extreme market conditions (bearish and bullish market scenarios). The Copula method offers valuable information not only on the average dependence but also on the probability that two markets would jointly experience extreme downwards or upwards movements (Hammoudeh et al., 2014). Archimedean and elliptical copula methods can overcome the deficiencies associated with linear correlation methods (Embrechts et al., 1999; Nelsen, 1997). The Copula method measures the nonlinear temporal dependence between two markets during bear and bull market conditions (Hanif et al., 2021). It constitutes a helpful metric for financial risk management as it helps investors and portfolio managers identify whether an asset is a hedge when it is negatively or uncorrelated with other assets or portfolios during a normal market status or if a safe haven is negatively or uncorrelated with other assets or portfolios during crisis periods. The downside and upside bidirectional risk spillover size between the studied markets is computed through the Conditional Value at Risk (CoVaR) measure implemented by Adrian and Brunnermeier (2016). The best Copula model is thereafter used to compute the CoVaR. The CoVaR technique measures the asymmetric bidirectional risk from one market to another and vice versa. Taking into account the both upside and downside systematic risk offers new insights to market participants on how they lose in one market if another market is in financial trouble.

The TVP Copula results indicate that prior to the COVID-19 period; all PMs have a symmetric dependence relationship with each of the currencies considered, with the Gaussian Copula providing the best fit for 95% of PM-FX pairs. However, the COVID-19 period caused both negative and positive tail asymmetric dependences, and a more pronounced symmetric tail dependence between the PM and FX pairs. The CoVaR spillover results indicate that the JPY transmits and receives the largest spillover to/from most of the PMs in the downside and upside. The exceptions are silver, which receives the largest spillover from the CNY and gold, which in turn has the largest spillover to the AUD and JPY. In both, the downside and upside, all PMs transmit weak spillover to the CNY, while the AUD receives the smallest spillover from most PMs, except for gold. With respect to the VaR, spillovers from PMs to currencies, for both the downside and upside, the largest spillover from each of the PMs are owed to the AUD while the smallest is attributed to the CNY. Finally, although the COVID-19 period do affect the spillover dynamics between PMs and currencies, the JPY currency maintain its role as the largest CoVaR spillover transmitter and receiver to/from the PMs. In turn, the EUR become one of the weakest spillover transmitters during the COVID-19 pandemic.

The rest of this paper is organised as follows: Section 2 discusses the methodology followed in this work; Section 3 presents the data samples and the preliminary statistics; Section 4 presents the empirical results; and Section 5 provides the conclusions.

2. Methodology

2.1. Time-varying parameter bivariate copulas

The concept of copulas has its origin in Sklar's (1959) theorem, which states that the following relationship holds:

$$F_{XY}(x,y) = C(u,v) \tag{1}$$

In Eq. (1), $F_{XY}(x,y)$ represents a joint distribution corresponding to the marginal distribution functions $F_X(x)$ and $F_y(y)$ of variables X and Y. The term C represents the copula function and is unique for the case of continuous marginal distributions. The terms $u = F_X(x)$ and $v = F_Y(y)$ are uniformly and marginally distributed bivariate copula functions. Through a differentiation with Eq. (1), the following can be obtained:

$$f_{XY}(x,y) = C(u,v)f_X(x)f_Y(y) \tag{2}$$

where $f_{XY}(x,y)$ is a probability density function and $f_X(x)$ and $f_Y(y)$ are the marginal density functions. The function $C(u,v) = \partial^2 C(u,v)/\partial u \partial v$. The lower and upper tail dependences based on a copula measure are estimated as follows:

$$\tau^U = \lim_{u \to 1} Pr\,[X \geq F_X^{-1}(u) | Y \geq F_Y^{-1}(u)] = \lim_{u \to 1} \frac{1-2u+C(u,u)}{1-u} \tag{3}$$

$$\tau^L = \lim_{u \to 1} Pr\,[X \leq F_X^{-1}(u) | Y \leq F_Y^{-1}(u)] = \lim_{u \to 1} \frac{C(u,u)}{1-u} \tag{4}$$

where $F_l^{-1}$and F_j^{-1} are the marginal quantile functions and $\tau^U, \tau^L \in [0,1]$. If the dependence in the tails (upper and lower) is greater than zero, the variables X and Y tend to be lower and upper tail-dependent.

The normal and the Student-t copulas have a linear dependence parameter ρ_t, as per the evolution in an ARMA (p,q) process: [3]

$$\rho_t = \Lambda\left(\psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q}\sum_{j=1}^{q} \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})\right) \tag{5}$$

[3] See Patton (2012) for details.

where $\Lambda(x) = (1 - e^{-x})(1 + e^{-x})^{-1}$ represents a logistic transformation to retain the dependence parameter ρ_t within the interval [-1, 1]. The termsψ_0, ψ_1, and ψ_2 are autoregressive coefficients. The Student-t copula function with TVP features is obtained by substituting a standard normal quantile function $\Phi^{-1}(x)$by $t_t^{-1}(x)$ in Eq. (5).

The tail-dependence parameters of the TVP rotated Gumbel and Gumbel copulas follow an ARMA (p, q) process and are estimated as follows:

$$\delta_t = \omega + \beta \delta_{t-1} + \alpha \frac{1}{q} \sum_{j=1}^{q} \left| u_{t-j} - v_{t-j} \right| \tag{6}$$

The symmetrized Joe-Clayton copula's tail dependence parameters are estimated as follows:

$$\tau_t^U = \Delta\left(\omega_U + \beta_U \rho_{t-1} + \alpha_U \frac{1}{q} \sum_{j=1}^{q} \left| u_{t-j} - v_{t-j} \right|\right) \tag{7}$$

$$\tau_t^L = \Delta\left(\omega_L + \beta_L \rho_{t-1} + \alpha_L \frac{1}{q} \sum_{j=1}^{q} \left| u_{t-j} - v_{t-j} \right|\right) \tag{8}$$

where $\Delta(x) = (1 + e^{-x})^{-1}$ indicates the logistic transformation to retain τ_t^U and τ_t^L within the interval $(0,1)$.

2.2. Downside and upside VaRs and CoVaRs

The VaR measures the investor's maximum losses according to a confidence level and a specific time horizon by holding a short (i.e., upside risk) or a long position (i.e., downside risk). The downside (upside) VaR at time t for a confidence level of $1 - \alpha$ is $Pr\left(r_t \leq VaR_{\alpha,t}\right) = \alpha\left(Pr\left(r_t \geq VaR_{1-\alpha,t}\right) = \alpha\right)$. We can express the downside and upside VaR as follows:

$$VaR_{\alpha,t}^{Downside} = \mu_t + t_{v,k}^{-1}(\alpha)\sigma_t \tag{9}$$

$$VaR_{\alpha,t}^{Upside} = \mu_t + t_{v,k}^{-1}(1-\alpha)\sigma_t \tag{10}$$

whereσ_t and μ_t respectively represent the standard deviation and conditional mean of the return series. The term $t_{v,k}^{-1}(\alpha)$ is the α-quantile of the skewed Student-t distribution. The CoVaR measure is defined as theVaR of asset i conditional on asset j suffering from a large movement.[4] Let r_t^S be the returns for an asset and r_t^C be the returns for another asset. The downside CoVaR for the returns of an asset given an extreme downward trend in returns of a certain PM at a confidence level of$(1-\beta)$ or β-quantile of the conditional distribution of r_t^S is as follows:

$$Pr\left(r_t^s \leq CoVaR_{\beta,t}^S | r_t^C \leq VaR_{\alpha,t}^C\right) = \beta \tag{11}$$

Likewise, the upside CoVaR is as follows:

$$Pr\left(r_t^S \geq CoVaR_{\beta,t}^S | r_t^C \geq VaR_{1-\alpha,t}^C\right) = \beta \tag{12}$$

Combining the copula measure with CoVaR, we can measure the systematic impact of returns of one asset on the returns of another asset using Eqs. (10)-(11) as follows:

$$C\left(F_{r_t^s}\left(CoVaR_{\beta,t}^s\right), F_{r_t^C}\left(VaR_{\alpha,t}^C\right)\right) = \alpha\beta \tag{13}$$

$$1 - F_{r_t^S}\left(CoVaR_{\beta,t}^S\right) - F_{r_t^C}\left(VaR_{t-\alpha,t}^C\right) + C\left(F_{r_t^S}\left(CoVaR_{\beta,t}^S\right), F_{r_t^C}\left(VaR_{1-\alpha,t}^C\right)\right) = \alpha\beta \tag{14}$$

where $F_{r_t^S}$ and $F_{r_t^C}$ are the marginal distributions of an asset and another asset return, respectively.

We use the Kolmogorov-Smirnov (KS) bootstrapping test (Abadie, 2002) to test for the downside (upside) risk spillover:

$$H_0: CoVaR_{\beta,t}^S = VaR_{\beta,t}^S.\ H_1: CoVaR_{\beta,t}^s < VaR_{\beta,t}^s \tag{15}$$

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{1/2} Sup_x |F_m(x) - G_n(x)| \tag{16}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative CoVaR and VaR distribution functions, respectively, and n and m are the sizes of the two samples.

3. Data

The data set on which we implement our modelling framework consists of the daily prices

[4] Refer to Adrian and Brunnermeier (2016) for more details.

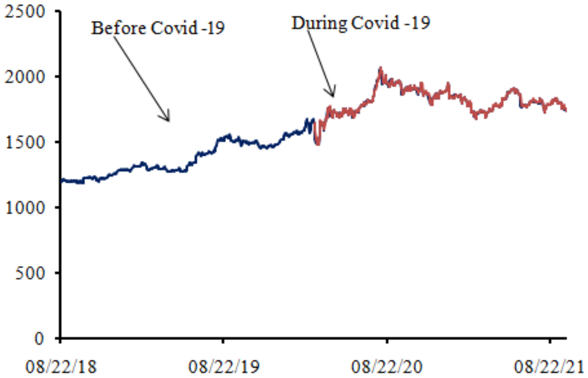
of four major PMs (gold, palladium, platinum, and silver) as well as seven major currencies quoted against the US dollar such as the Euro (EUR), British Pound (GBP), Swiss Franc (CHF), Japanese Yen (JPY), Canadian Dollar (CAD), Australian Dollar (AUD), and Chinese Yuan (CNY). The choice of daily data series is guided by the fact that daily data contain richer information over monthly and quarterly data (Bannigidadmath and Narayan, 2016). Daily data allow to account for the exact moment of each news announcement (financial, economic, and political, among others) and to identify the instant market responsiveness to that particular news (Pastor and Veronesi 2012). This allows us to assess how market shocks are instantaneously transmitted to other markets. We notice that with low frequency data such as weekly, monthly, and quarterly data, the identification of the transmission of news announcement shock to the system will be complicated (Selmi et al., 2018). The selected currencies (EUR, GBP, JPY, CAD, AUD, CHF, and CNY) are marked by their large trading volumes and high liquidity. The US dollar is the world's most traded currency in the world followed by EUR rate. Precious metals (gold, silver, platinum, and palladium) are commonly accepted as a refuge asset. For example, gold, as a store value, serves as a safe-haven asset against extreme downward prices of stock (Baur and Lucey, 2010), oil (Selmi et al., 2018), US dollar (Reboredo, 2013), and inflation (Jaffe, 1989). Balli et al. (2019) argue that precious metals are immune against uncertainty and international shocks. It is worth noting that white metals such as silver have recently experienced a sharp rise in demand in the automotive industry. Palladium helps transform toxic pollutants into less harmful CO_2 and water vapor (Bloomberg, 2019). The sample period studies ranges from August 22, 2018, to September 28, 2021. To examine the impact of the COVID-19 crisis on the dependence and spillovers between PMs and FXs, we split the whole sampling period into two subperiods: the pre-COVID-19 period spanning from August 22, 2018, to March 10, 2020, and the ongoing COVID-19 period from March 11, 2020, to September 28, 2021. We used the WHO announcement from March 11, 2020, to define the breakpoint. The two subsamples have the same number of observations (405 daily observations). The data is compiled from Datastream. We transform the daily prices into daily logarithmic returns.

Figure 1 plots the time-variations of the daily price series of PMs and FXs; the prices of gold and silver exhibits the most similar behavior, while those of palladium and platinum followed very different paths before the pandemic crisis. This may be explained by the important role of gold and silver as alternative investment assets for portfolio diversification purposes (e.g., O'Connor et al., 2015; Vigne et al., 2017). However, the prices of all four PMs exhibited increasing tends before the COVID-19 crisis, with the highest increase being recorded for gold prices. It is worth noting that the prices of PMs, except gold, show a downward evolution pattern in 2021. Most of the considered currencies have a continuous and decreasing (depreciation) tendency during the pandemic period, except for the GBP and AUD. This may be explained by various quantitative easing campaigns following the recent COVID-19 crisis. For example, the EUR FX returns show a downside trend before the pandemic as well as during the first wave of COVID-19.

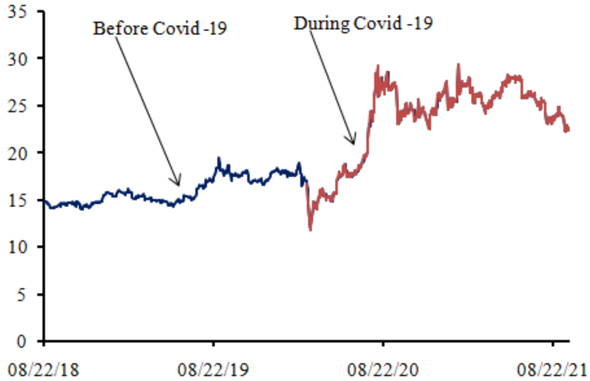
Fig. 1. Price dynamics of precious metals (PMs) and currencies.

Panel A: Precious Metals

1. Gold

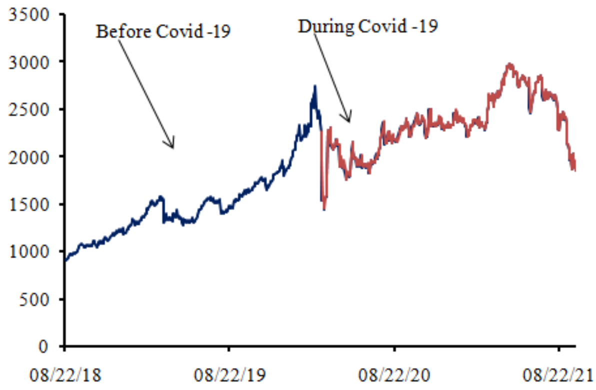


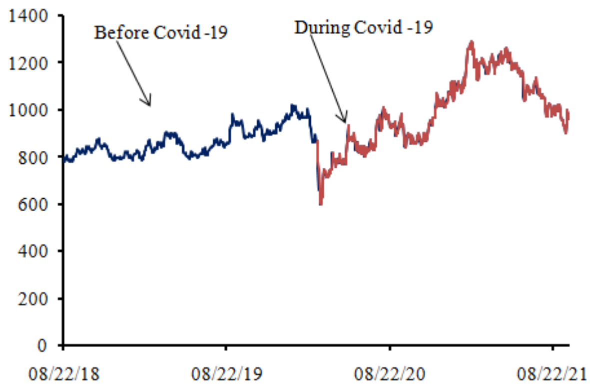
2. Silver



3. Platinum

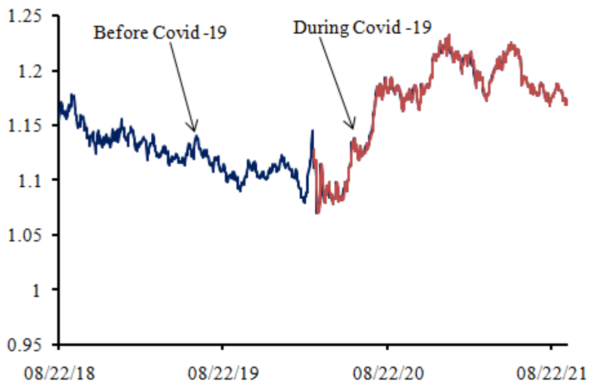
4. Palladium



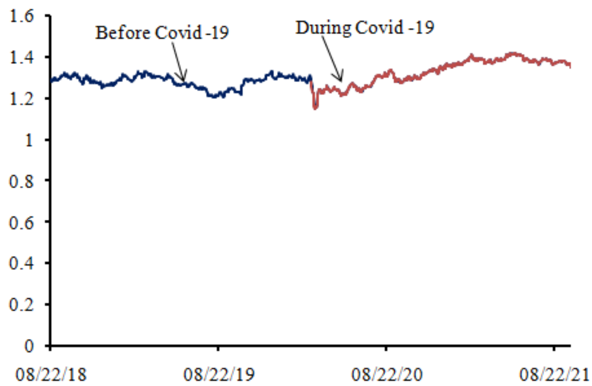


Panel B: Major currencies

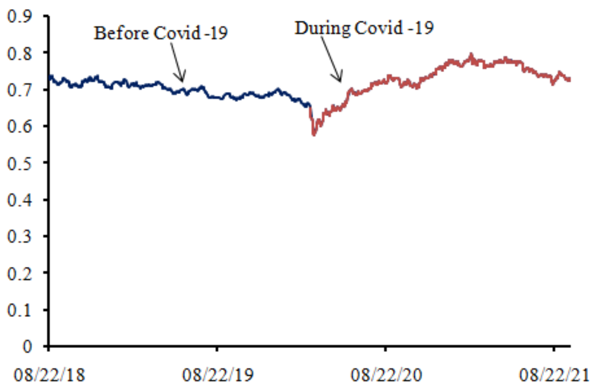
1. EUR



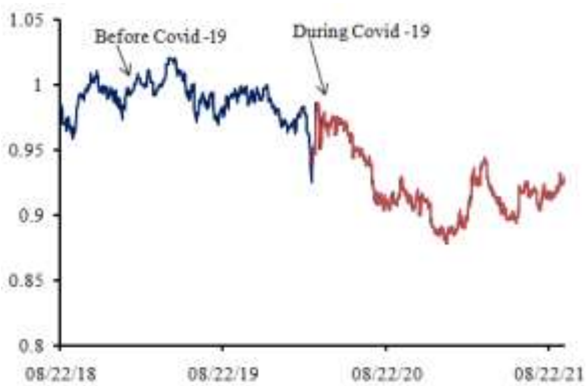
2. GBP



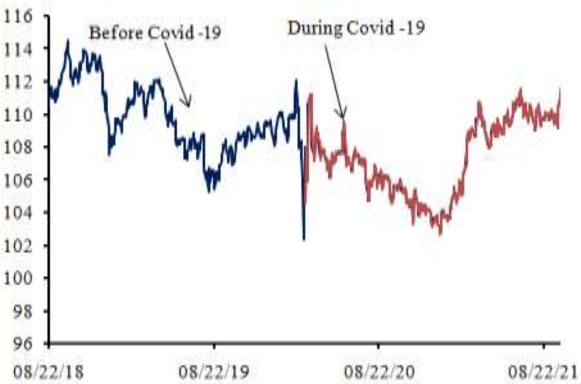
3. AUD



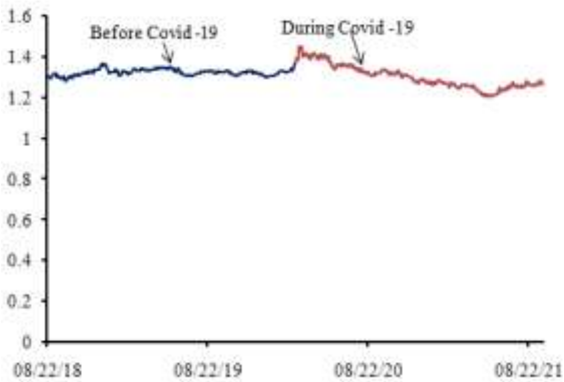
4. CHF



5. JPY



6. CAD



7. CNY

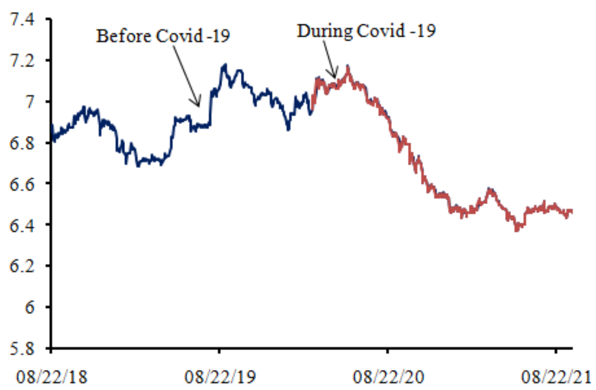


Table 1 displays the main descriptive statistics of the data samples before and during the COVID-19 period. Panel A of Figure 1 shows that the EUR, AUD, CHF, and JPY currencies have a negative mean return. The mean returns for the remaining currencies are in the range of zero. The PMs have a positive mean return where platinum exhibited the highest return. During the pandemic, the mean return of the EUR, GBP, AUD, and JPY currencies shift to positive values whereas those of the CAD and CNY currencies became negative. The CHF returns are negative before and during the pandemic. In relation to standard deviations, all markets are more volatile during the pandemic than before it, except for CNY. Among all considered currencies, the GBP and AUD have the largest standard deviations while the CNY and CAD have the smallest. We note that the volatility (measured by the standard deviation of returns) is much higher for PMs than for currencies. We can thus suggest that the demand for PMs is much more volatile than that of the exchange rates during the studied period. This may have been due to the role of hedges and safe havens attributes to PMs (e.g., Baur and Lucey, 2010; Beckmann et al., 2019). Surprisingly, the price of gold is less volatile than that of the other considered PMs, while platinum and palladium prices are the most volatile (e.g., Sensoy, 2013). This may be explained by a higher demand of these two PMs for industrial use (e.g., Chaston, 1982; Bloomberg, 2019). All kurtosis values are larger than three, indicating leptokurtic behaviors, fat tails, and the absence of a Gaussian distribution in the return series of the PMs and currencies. The skewness differs from zero for all series, suggesting asymmetric distributions. The Jarque-Bera test is significant for all markets, confirming that their return series are not normally distributed.

Table 1. Descriptive statistics of precious metals (PMs) and currencies.

	Mean	St.Dev	Minimum	Maximum	Skewness	Kurtosis	J-B
Panel A: Before COVID-19							
Gold	0.080	0.760	-4.725	3.504	-0.212	5.573	533.86***
Silver	0.034	1.246	-7.479	4.764	-0.501	4.694	394.04***
Platinum	0.232	1.833	-9.616	7.519	-1.105	5.118	530.78***
Palladium	0.023	1.321	-5.248	4.581	-0.198	1.287	31.466***
EUR	-0.007	0.360	-1.452	1.255	0.026	0.998	17.48***
GBP	0.000	0.540	-1.819	1.994	0.269	1.470	42.376***
AUD	-0.030	0.471	-1.630	1.834	0.046	0.860	13.165***
CHF	-0.011	0.374	-1.438	1.587	-0.141	1.529	41.861***
JPY	-0.011	0.442	-3.003	3.169	-0.234	11.852	2398***
CAD	0.013	0.351	-1.040	2.146	0.401	3.310	198.78***
CNY	0.004	0.265	-1.098	1.532	0.479	5.095	459.44***
Panel B: During COVID-19							
Gold	0.014	1.205	-5.114	5.775	-0.280	4.410	338.14***
Silver	0.072	2.640	-12.345	8.896	-0.770	4.297	356.3***
Platinum	-0.049	2.996	-23.400	22.598	-0.464	19.095	6223.3***
Palladium	0.025	2.443	-12.316	11.176	-0.419	3.855	266.55***
EUR	0.009	0.420	-2.039	1.345	-0.338	1.436	43.514***
GBP	0.013	0.589	-3.738	2.722	-0.572	5.471	533.93***
AUD	0.027	0.708	-3.835	2.033	-0.740	4.002	311.48***
CHF	-0.003	0.436	-1.379	1.790	0.303	1.149	29.248***
JPY	0.016	0.425	-1.937	3.131	1.292	11.191	2247.9***
CAD	-0.020	0.500	-1.912	2.207	0.327	1.831	65.203***
CNY	-0.018	0.246	-1.386	0.989	-0.145	3.963	270.44***

Notes: The symbol *** indicates the significance at a 1% level.

Table 2 reports the unconditional correlations between the PM and FX returns. The results show positive and weak correlations between PMs and EUR, GBP, and AUD before and during the pandemic period. In contrast, the CHF, JPY, CAD, and CNY currency returns are negatively correlated with PMs. These results indicate that the PM assets provide diversification benefits for currency investors (mutual funds, hedge funds, retail investors…). Overall, the degree of correlation between PMs and currencies is crisis-sensitive and varies across currencies.

Table 2. Correlation matrix between precious metals (PMs) and currencies.

	EUR	GBP	AUD	CHF	JPY	CAD	CNY
Panel A: Before COVID-19							
$\rho_{Gold,Currency}$	0.378	0.197	0.267	-0.423	-0.328	-0.219	-0.185
$\rho_{Silver,Currency}$	0.255	0.144	0.289	-0.268	-0.141	-0.285	-0.245
$\rho_{Platinum,Currency}$	0.138	0.213	0.244	-0.044	0.134	-0.203	-0.173
$\rho_{Palladium,Currency}$	0.220	0.179	0.381	-0.111	0.101	-0.342	-0.266
Panel B: During COVID-9							
$\rho_{Gold,Currency}$	0.303	0.268	0.373	-0.340	-0.286	-0.158	-0.379
$\rho_{Silver,Currency}$	0.337	0.316	0.419	-0.302	-0.179	-0.329	-0.306
$\rho_{Platinum,Currency}$	0.254	0.381	0.380	-0.194	-0.133	-0.365	-0.163
$\rho_{Palladium,Currency}$	0.348	0.420	0.526	-0.311	-0.132	-0.470	-0.306

4. Empirical results

In the first subsection, we present the results of the TVP copulas before and during the COVID-19 crisis. In the second subsection, we present the results corresponding to the downside and upside VaR and CoVaR spillovers among PMs and currencies.

4.1. Time-varying parameter copula results

The standardized residuals are used for fitting the TVP copulas. Different GARCH family models are used with different lags. The standardized residuals are generated from the fit of the ARMA (p, q)-TGARCH (1, 1) model. The minimization of the Akaike Information Criterion (AIC) is used to select the best-fitted copulas. We show that the time-varying copula outperforms the time-invariant copula according to AIC, suggesting a temporal dependence between PMs and

FXs.[5] Table 3.1 displays the results of TVP copulas for the gold-currencies pairs corresponding to the pre-COVID-19 period. To save space, we only present the table with the best-fitted copulas. The full details of best fit copula for metals and currency pairs are provided in the online Appendix. An analysis of the fit of the time-varying-parameter copulas shows that the *TVP-Gaussian* copula best captures the dynamic relationship for the *Gold–EUR*, *Gold-GBP*, *Gold-CHF*, and *Gold-CAD* pairs.

Table 3.1. Results of the time-varying parameter (TVP) copulas between the gold and currencies before the COVID-19 crisis.

	Gold–EUR	**Gold– GBP**	**Gold– AUD**	**Gold– CHF**	**Gold– JPY**	**Gold– CAD**	**Gold– CNY**
1. TVP-Gaussian							
Ψ_0	1.511***	0.432***	0.109***	-2.018***	-0.102***	-0.011***	-0.001***
	(0.260)	(0.730)	(0.014)	(0.250)	(0.282)	(0.018)	(0.001)
Ψ_1	0.859***	0.074***	0.459***	0.155**	0.118***	0.137***	0.102***
	(0.239)	(0.262)	(0.025)	(0.284)	(0.130)	(0.065)	(0.009)
Ψ_2	-2.360***	0.020***	1.174***	-2.511***	1.833***	1.896***	1.977***
	(0.089)	(3.298)	(0.056)	(0.094)	(0.696)	(0.111)	(0.017)
AIC	**-81.647**	**-20.364**	-46.127	**-91.665**	-88.582	**-35.392**	-47.194
2. TVP-Clayton							
ω	1.109***	0.471***	1.998***	0.000	0.000	0.000	0.000
	(0.547)	(0.426)	(0.212)	(0.326)	(0.490)	(0.324)	(0.495)
α	-0.059**	-0.819***	-0.501***	-1.082***	-1.079***	-1.062	-1.005***
	(0.540)	(0.213)	(0.091)	(0.999)	(0.999)	(13.409)	(1.000)
β	-1.535***	0.933***	-5.238***	-0.000	-0.000	-0.000	0.000
	(1.238)	(1.325)	(0.579)	(0.807)	(1.272)	(3.520)	(0.969)
AIC	-49.601	-19.606	-30.985	0.038	0.035	0.030	0.025
3. TVP-Rotated Clayton							
ω_U	1.263	0.583***	2.324***	0.000	0.000	0.000	0.000
	()	(0.645)	(0.209)	(0.098)	(0.282)	(0.306)	(0.487)
α_U	-1.712	-0.682***	-0.633***	-1.103	-1.089***	-1.047***	-1.008***
	()	(2.744)	(0.080)	(1.674)	(1.000)	(1.176)	(0.995)
β_U	-0.863	0.074	-6.042***	-0.000	0.000	-0.000	0.000
	()	(1.491)	(0.536)	(0.236)	(0.690)	(0.657)	(0.962)
AIC	-56.295	-11.298	-47.859	0.042	0.042	0.027	0.025
4. TVP-Gumbel							
ω	1.408***	-0.383***	0.079***	0.000***	0.000	0.000	1.601***

[5] The results of the marginal models and static copula are available upon request from the corresponding author.

	(1.296)	(2.560)	(0.221)	(4.747)	(5.748)	(5.466)	(1.564)
α	-0.270***	0.636***	0.533***	-0.000***	0.000	0.000	-1.821***
	(0.751)	(2.321)	(0.094)	(4.925)	(5.952)	(5.787)	(1.441)
β	-1.778***	0.086***	-1.087***	0.000***	0.000	0.000	0.455***
	(1.223)	(0.517)	(0.441)	(0.717)	(0.781)	(0.973)	(0.321)
AIC	-79.012	-14.798	-46.452	0.624	1.027	0.853	0.645
5.TVP Rotated Gumbel							
ω_L	2.165***	-0.288***	2.240***	-0.000***	0.000	0.000	1.783***
	(0.151)	(2.118)	(0.158)	(6.016)	(13.836)	(5.195)	(1.942)
α_L	-0.788***	0.560***	-0.607***	0.000***	0.000	0.000	-1.977***
	(0.070)	(1.914)	(0.109)	(6.120)	(13.940)	(5.414)	(1.865)
β_L	-2.241***	9.938***	-4.218***	-0.000**	0.000	0.000	0.438***
	(0.815)	(0.548)	(0.500)	(0.617)	(0.865)	(0.787)	(0.302)
AIC	-65.871	-18.516	-40.527	0.673	0.790	0.745	0.612
6. TVP-SJC							
ω_U	2.805***	-3.898***	3.859***	-18.537***	-18.376	-22.972***	-22.164
	(5.766)	(2.354)	(0.095)	(251.149)	(253.063)	(2606.704)	(2610.178)
α_U	-12.050***	-0.888***	-17.797***	-0.506**	-0.791	-6.011**	-5.675
	(39.648)	(4.541)	(0.322)	(98.685)	(96.307)	(1107.372)	(1181.887)
β_U	-2.536***	22.718***	-5.534***	-0.001	-0.002	-0.015	-0.013
	(10.264)	(36.179)	(0.246)	(1.031)	(1.027)	(3.001)	(2.820)
ω_L	-1.107***	-3.676***	0.108***	-21.395***	-20.567	-17.936***	-18.216
	(3.436)	(2.810)	(0.321)	(2694.749)	(2407.046)	(239.842)	(292.140)
α_L	-3.528***	3.205***	-10.974***	-4.717	-4.803	-0.282	-0.450
	(10.825)	(9.275)	(0.725)	(1051.741)	(948.104)	(98.216)	(132.264)
β_L	4.546	4.142***	-0.719***	-0.013	-0.015	-0.001	-0.001
	(1.017)	(9.129)	(0.302)	(3.053)	(3.030)	(1.022)	(1.036)
AIC	-79.786	-19.952	-49.033	26.623	25.250	15.510	12.500
7. TVP-Student's-t							
Ψ_0	1.513***	0.367***	0.017***	-0.509***	-0.015	-0.008***	-0.000
	(0.278)	(1.631)	(0.029)	(0.852)	(0.478)	(0.017)	(0.008)
Ψ_1	0.169***	-0.024***	0.126***	-0.044***	0.049***	0.082***	0.048***
	(0.011)	(0.176)	(0.063)	(0.111)	(0.087)	(0.045)	(0.025)
Ψ_2	0.098***	0.318	1.791***	1.019***	2.099***	1.887***	2.010***
	(0.037)	(7.583)	(0.197)	(1.928)	(1.074)	(0.123)	(0.039)
ν	5.000***	5.000***	4.991***	5.000***	5.000***	5.000***	4.571***
	(0.967)	(0.958)	(1.508)	(1.062)	(1.299)	(0.959)	(1.312)
AIC	-71.453	-11.570	**-53.608**	-84.183	**-104.598**	-26.009	**-60.618**

Notes: The table displays the fit of multiple copulas with time-varying parameters. We employed the Akaike information criterion (AIC) to identify the copula the best fits the data. TVP denotes the time-varying parameter. Standard errors values are indicate in brackets. The symbol*** indicates a significance at the 1% level. The parameters for the TVP-Gaussian and Student's-t copulas Ψ_0,Ψ_1,and Ψ2 capture the dependence, persistence, and adjustments respectively. For the TVP Gumbel, SJC, and Clay ton copulas, the ω, α, and β parameters capture the dependence, persistence, and time variations, respectively. The s ubscripts U and L indicate the upper and lower dependences in tail, respectively.

Table 3.2. Results of TVP copulas between gold and currencies during the COVID-19 crisis.

	Gold–EUR	Gold– GBP	Gold– AUD	Gold– CHF	Gold–JPY	Gold– CAD	Gold– CNY
1. TVP-Gaussian							
Ψ_0	1.260***	0.822***	0.815***	-1.178***	0.003	-1.159***	-0.831***
	(0.314)	(0.439)	(1.011)	(0.376)	(0.055)	(0.198)	(0.404)
Ψ_1	0.405***	0.108***	0.078***	0.457***	0.101***	-0.364***	-0.482***
	(0.330)	(0.191)	(0.169)	(0.328)	(0.073)	(0.155)	(0.245)
Ψ_2	-1.548***	-1.000***	-0.180***	-1.231***	2.064***	-2.156***	0.626***
	(0.591)	(1.440)	(2.729)	(0.869)	(0.206)	(0.051)	(0.783)
AIC	-63.154	-32.673	-4.302	-69.348	-60.703	**-31.896**	-79.093
2. TVP-Clayton							
ω	1.918***	0.873***	1.127***	0.000	0.000	0.156***	0.000
	(0.203)	(0.043)	(0.339)	(0.297)	(0.301)	(0.920)	(0.421)
α	-0.704***	-2.292***	-0.570***	-1.095***	-1.117***	-0.685**	-1.088***
	(0.063)	(0.209)	(0.278)	(0.999)	(1.001)	(6.298)	(1.000)
β	-3.688***	-0.644***	-0.438***	-0.000	-0.000	-0.407***	0.000
	(0.771)	(0.083)	(1.102)	(0.738)	(0.788)	(2.048)	(1.096)
AIC	-59.014	-25.866	0.072	0.038	0.035	0.004	0.036
3. TVP-Rotated Clayton							
ω_U	0.571***	1.344***	0.418***	0.000	0.000	-0.204***	0.000
	(0.081)	(0.197)	(0.191)	(0.288)	(0.262)	(1.350)	(0.275)
α_U	0.521***	-0.731***	0.536***	-1.099***	-1.111***	-1.203***	-1.102***
	(0.051)	(0.102)	(0.451)	(1.002)	(0.996)	(1.021)	(0.991)
β_U	-0.514***	-1.723***	0.068***	-0.000	0.000	0.598***	0.000
	(0.252)	(0.816)	(0.228)	(0.718)	(0.653)	(3.176)	(0.695)
AIC	-63.108	0.072	-0.550	0.037	0.035	-0.018	0.039
4. TVP-Gumbel							
ω	2.540***	0.958***	4.257***	0.000	0.902*	-1.654***	-0.000
	(0.133)	(1.180)	(4.426)	(5.094)	(10.214)	(1.034)	(2.941)
α	-0.802***	-0.167***	-3.693***	0.000	-0.901*	1.926***	0.000
	(0.059)	(0.810)	(4.582)	(5.054)	(10.146)	(0.966)	(3.045)
β	-3.469***	-1.145***	-1.343***	0.000	-0.002	-0.872***	-0.000
	(0.559)	(0.970)	(1.286)	(0.567)	(0.488)	(0.492)	(0.711)
AIC	-86.178	-33.395	-0.197	-0.043	-0.215	-0.741	0.213
5.TVP Rotated Gumbel							
ω_L	2.375***	1.976***	1.544***	0.000	0.000	1.830***	-0.000
	(0.193)	(0.119)	(1.013)	(3.779)	(5.411)	(1.818)	(3.257)
α_L	-0.840***	-1.032***	-0.679***	0.000	0.000	-2.063***	0.000
	(0.074)	(0.151)	(0.701)	(3.726)	(5.322)	(1.712)	(3.350)
β_L	-2.803***	-1.104***	-0.367***	0.000	0.000	0.683***	-0.000
	(0.784)	(0.593)	(0.843)	(0.540)	(0.576)	(0.516)	(0.713)
AIC	-73.136	-34.187	0.093	0.038	-0.300	-0.034	0.292
6. TVP-SJC							

ω_U	2.302***	2.263***	-2.622***	-22.219	-18.410	-17.923	-18.481***
	(1.476)	(0.488)	(0.376)	(2517.692)	(262.090)	(260.035)	(254.510)
α_U	-10.516***	-11.164***	0.734***	-4.668	-0.479	-0.260	-0.477***
	(5.091)	(1.773)	(1.193)	(992.940)	(101.213)	(94.002)	(98.432)
β_U	-3.444***	-15.589***	5.002***	-0.012	-0.001	-0.001	-0.001***
	(2.407)	(4.971)	(1.115)	(2.766)	(1.032)	(1.032)	(1.033)
ω_L	3.007***	0.109**	0.999***	-18.410	-22.487	-23.126	-21.785***
	(0.808)	(1.007)	(1.578)	(247.071)	(4896.122)	(2311.313)	(2634.806)
α_L	-12.964***	-24.999***	-3.832***	-0.467	-4.153	-4.907	-4.843
	(3.407)	(31.648)	(6.425)	(96.718)	(1807.770)	(876.943)	(1017.104)
β_L	-6.037***	0.356***	-4.784***	-0.001	-0.011	-0.013	-0.013
	(1.082)	(2.497)	(1.178)	(1.028)	(5.039)	(2.525)	(2.950)
AIC	**-87.748**	**-48.258**	1.301	23.570	21.546	13.976	23.709
7. TVP-Student's-t							
Ψ_0	1.234***	0.820***	0.019***	-1.082***	-0.088***	-0.540***	-0.785***
	(0.424)	(0.308)	(0.102)	(0.346)	(0.192)	(0.472)	(0.388)
Ψ_1	0.114***	0.148***	0.025***	0.460***	0.088***	0.098***	-0.228***
	(0.190)	(0.144)	(0.035)	(0.220)	(0.089)	(0.196)	(0.133)
Ψ_2	-1.460***	-1.317***	2.004***	-1.345***	1.750***	-0.405***	0.520***
	(0.964)	(0.939)	(0.327)	(0.747)	(0.651)	(1.902)	(0.828)
ν	3.996***	5.000***	4.825***	5.000***	5.000***	5.000***	5.000***
	(1.122)	(1.125)	(1.633)	(1.261)	(1.213)	(1.514)	(1.276)
AIC	-78.103	-33.360	**-1.932**	**-74.116**	**-62.283**	-30.386	**-82.646**

Notes: See notes of Table 3.1

This finding implies a symmetric dependence for the above-mentioned gold-FX pairs. Indeed, the Gaussian copula has a greater mass concentration in the center and represented a symmetric copula. More precisely, the joint dependence is rejected during extreme movements in gold and FX prices for the above-mentioned pairs. Further analysis shows that the TVP-Student's-t copula best captures the dynamic relationship for the Gold-AUD, Gold-CNY, and Gold-JPY pairs. This finding indicates the presence of a symmetric tail dependence between the prices of gold and those of the AUD, JPY, and CNY currencies. This implies a joint dependence during extreme movements between gold prices and the AUD/USD, JPY/USD, and CNY/USD exchange rates. Table 3.2 shows the results for the COVID-19 crisis and reveals that the COVID-19 period caused an asymmetric tail dependence for the Gold-AUD, Gold-CHF, Gold-JPY, and Gold-CNY pairs.

Specifically, the relationship between those pairs is best captured by the TVP-Student's-t copula which has a positive asymmetric tail dependence while this effect is not present prior to the COVID-19 pandemic.

To save space, we do not present all TVP copula results tables in the text because they followed the same principle as in Tables 3.1 and 3.2. All the tables for all the possible pairs between each PM and FX are presented in the online Appendix while the main findings from these tables are presented below.

Table A3 (in the Appendix) displays the results of the TVP copulas for the seven silver-currencies pairs before the COVID-19 pandemic period. The resulting AICs indicate that the TVP-Gaussian copula best captures the dynamic relationship between silver and each of the currencies under consideration. An exception to this is the GBP which is best captured by TVP-SJC in addition to the JPY and CNY currencies which are best captured by the TVP-Student's-t copula. This information suggests that silver prices do not exhibit any tail co-movement with any of the seven currencies considered. An additional feature is that the dependence structure is symmetric. This result means that the dependence structure is similar in the left and right regions of the distribution, i.e., during both market downturns and upturns. On the other hand, Table A4 (in the online Appendix) for the COVID-19 period indicates the presence of a tail asymmetric-dependence between silver and some currencies. Specifically, the dependence for the silver-EUR and silver-GBP pairs is best captured by the TVP-SJC copula, while that for the silver-CHF, silver-JPY, silver-CAD, and silver-CNY pairs is best captured by the TVP-Student's-t copula. However, these effects are not recognized prior to the COVID-19 period.

Continuing with the analysis of dependence with Table A5 (in the online Appendix), we observe that the dependence dynamics between platinum and CHF, CAD, and CNY are best captured by the TVP Gaussian copula prior to the COVID-19 period, while the platinum-EUR, platinum-GBP, and platinum-AUD pairs are best captured by TVP-SJR. This implies symmetric dependence dynamics and the absence of a tail dependence. Hence, we can only expect a symmetric joint tail dependence during extreme co-movements for the platinum-JPY pair (with TVP-Student's-t copula). Table A6 (in the online Appendix) for the COVID-19 period evidences the presence of a negative tail asymmetric dependence. Indeed, the dependence for the platinum-CHF, platinum-JPY, platinum-CAD, and platinum-CNY pairs is best captured by the TVP-Gaussian copula. For the platinum-AUD and platinum-GBP, their dependence structure is best fitted by the TVP-SJC copula. We also notice a more pronounce negative and positive symmetric tail dependence during the COVID-19 pandemic as the dependence for the platinum-EUR pair is best captured by the TVP-Student's-t copula. These effects are not identified prior to the COVID-19 period.

Regarding palladium and its dependence relationship with the seven considered currencies in Table A7 (in the online Appendix) before the COVID-19 crisis, we observe that the Gaussian copula is best fitted for the EUR, CAD, and CNY currencies. This result indicates a symmetry in the dependence relationship between palladium and the above mentioned currencies. This result also indicates the absence of a tail dependence and joint co-movement during extreme price movements for both PMs and currencies. Table A8 (in the online Appendix) for the COVID-19 period indicates the presence of positive and negative tail asymmetric dependences for the palladium-AUD and palladium-JPY pairs. These latter are indeed best fitted by the TVP-SJC and TVP-Gaussian copulas, respectively. We also observe both positive and negative symmetric tail dependences for the palladium-CHF pair. These effects are not recognized prior to the COVID-19 period.

In summary, the TVP copula analysis in this sub-section allows us to detect a significant change in the dependence structure between currencies and PMs during the COVID-19 period. Indeed, before the COVID-19 outbreak, the relationship between currencies and precious is symmetric, with no tail dependence, as indicate by the presence of Gaussian copulas in 95% of the PM-FX pairs. During the COVID-19 period, the dependence dynamics became asymmetric and tail-dependent for most of the PM-FX pairs. Our results are consistent with the findings of Shah et al. (2021) who show that market volatility is associated with an abnormally significant increase in spillovers. Similar findings regarding increased spillover between these markets during the European financial crisis and the COVID-19 issue were shown by Ding et al. (2021). Our findings also corroborate those of Mensi et al. (2020), who examine the long-term relationship between four key precious metals (gold, silver, palladium, and platinum) and 20 major U.S. exchange rates. The correlation between PM prices and the USD/GBP exchange rate has also been verified as causative by Churchill et al. (2019).

To further understand the spillover effect between major PMs and currencies before and during the COVID-19 pandemic, the next sub-section provides an analysis of the results regarding the downside and upside VaR and CoVaR spillovers.

4.2. Downside and upside spillover results

The VaR and CoVaR risk measures for the PM and FX markets are quantified to study the implications of our copula results in terms of the risk spillovers between the PM-FX pairs. Table 4.1 presents the downsides and upsides of the VaR and CoVaR spillovers between gold and the seven considered currencies prior to the COVID-19 period. According to Panel A of Table 4.1 (spillover from currencies to gold), in both the downside and upside, the largest CoVaR spillovers to gold is transmitted from the AUD, while the smallest spillover is transmitted from the CHF. For the COVID-19 period, the AUD still exerts the largest CoVaR spillover to gold and the CAD has the lowest (Panel A of Table 4.2). In relation to spillovers from gold to currencies prior to the COVID-19 period, Panel B of Tables 4.1 and 4.2 indicate that, in the downside, the largest VaR and CoVaR spillovers from gold occurred to the AUD, while the smallest were to the CHF and CNY. According to Panel B of Table 4.2, during the COVID-19 period, in the downside the largest VaR and CoVaR spillover transmission from gold to the AUD while the smallest to the CAD and the CNY. On the upside, prior to the COVID-19 period, the largest CoVaR spillover transmits from gold to the AUD while the smallest to the CHF. On the other hand, the largest upside VaR spillover transmits from gold to the GBP, while the smallest to the CNY. Finally, on the upside, during the COVID-19 period, the largest CoVaR spillover transmitted by gold is to the AUD while the smallest is to the CAD. On the other hand, the largest upside VaR spillover transmitted by gold is to the AUD, while the smallest are to the CNY.

To save space, we do not present all the Dow/Up VaR and CoVaR tables in the text. All the tables are presented in the online Appendix while the main findings from these tables are presented below.

Table 4.1. Dow/Up VaR and CoVaR spillover between gold and currencies before COVID-19 crisis

	Downside			**Upside**		
	VaR	CoVaR	H_0:CoVaR = VaR H_1:CoVaR<VaR	VaR	CoVaR	H_0:CoVaR = VaR H_1:CoVaR>VaR
Panel A: From currencies to gold						
USDEUR	-1.170	-2.737	0.980	1.228	1.988	0.884
	(0.009)	(0.029)	[0.000]	(0.009)	(0.019)	[0.000]
USDGBP	-1.170	-1.979	0.958	1.228	1.543	0.634
	(0.009)	(0.015)	[0.000]	(0.009)	(0.011)	[0.000]
USDAUD	-1.170	-3.627	1.000	1.228	2.507	0.990
	(0.009)	(0.028)	[0.000]	(0.009)	(0.019)	[0.000]
USDCHF	-1.170	-0.219	0.000	1.228	0.438	0.000
	(0.009)	(0.005)	[1.000]	(0.009)	(0.005)	[1.000]
USDJPY	-1.170	-2.460	0.988	1.228	1.826	0.861
	(0.009)	(0.021)	[0.000]	(0.009)	(0.015)	[0.000]
USDCAD	-1.170	-0.740	0.089	1.228	0.783	0.010
	(0.009)	(0.026)	[0.038]	(0.009)	(0.018)	[0.961]
USDCNY	-1.170	-3.029	0.988	1.228	2.158	0.921
	(0.009)	(0.037)	[0.000]	(0.009)	(0.024)	[0.000]
Panel: B: From gold to currencies						
USDEUR	-0.564	-0.986	0.921	0.567	0.674	0.399
	(0.004	(0.009)	[0.000]	(0.004)	(0.006)	[0.000]
USDGBP	-0.845	-1.038	0.592	0.868	1.229	0.842
	(0.005	(0.007)	[0.000]	(0.005)	(0.008)	[0.000]
USDAUD	-0.849	-1.048	0.587	0.745	1.784	1.000
	(0.005	(0.007)	[0.000]	(0.004)	(0.012)	[0.000]
USDCHF	-0.639	-0.234	0.000	0.574	0.165	0.000

	(0.005	(0.003)	[1.000]	(0.005)	(0.003)	[1.000]
USDJPY	-0.605	-0.569	0.000	0.592	1.199	0.928
	(0.008	(0.008)	[1.000]	(0.008)	(0.017)	[0.000]
USDCAD	-0.570	-0.387	0.000	0.598	0.341	0.000
	(0.005	(0.009)	[1.000]	(0.005)	(0.004)	[1.000]
USDCNY	-0.388	-0.518	0.733	0.369	1.025	0.993
	(0.003	(0.004)	[0.000]	(0.004)	(0.011)	[0.000]

Notes: This table shows the magnitude of the spillovers. Values in parentheses are the standard errors. Values in [ ] are the p-values of the Kolmogorov-Smirnov (K-S) test.

Table 4.2. Dow/Up VaR and CoVaR spillover between gold and currencies during COVID-19 crisis

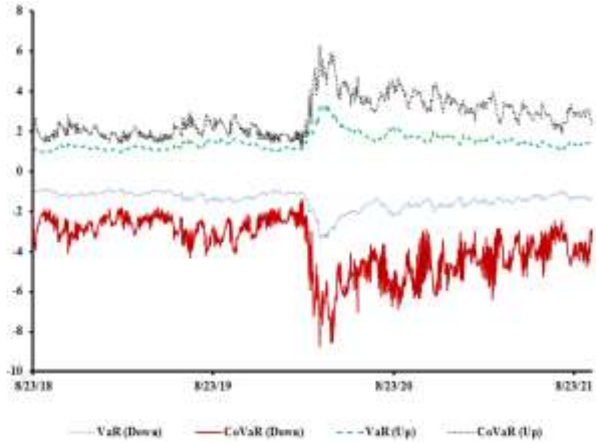
Panel A:	**From currencies to gold**					
	Downside			Upside		
	VaR	CoVaR	$H_{0:}$CoVaR=VaR $H_{1:}$CoVaR<VaR	VaR	CoVaR	$H_{\ 0:}$CoVaR = VaR $H_{\ 1:}$CoVaR>VaR
USDEUR	-1.683	-4.712	0.938	1.720	3.468	0.889
	(0.023)	(0.057	[0.000]	(0.022)	(0.037)	[0.000]
USDGBP	-1.683	-2.653	0.699	1.720	2.808	0.565
	(0.023)	(0.041	[0.000]	(0.022)	(0.051)	[0.000]
USDAUD	-1.683	-5.398	0.990	1.720	3.667	0.909
	(0.023)	(0.075	[0.000]	(0.022)	(0.050)	[0.000]
USDCHF	-1.683	-3.814	0.919	1.720	2.744	0.736
	(0.023)	(0.058	[0.000]	(0.022)	(0.039)	[0.000]
USDJPY	-1.683	-3.889	0.919	1.720	2.788	0.753
	(0.023)	(0.058	[0.000]	(0.022)	(0.039)	[0.000]
USDCAD	-1.683	-0.907	0.010	1.720	0.989	0.003
	(0.023)	(0.025	[0.961]	(0.022)	(0.018)	[0.998]
USDCNY	-1.683	-3.813	0.906	1.720	2.743	0.726
	(0.023)	(0.056	[0.000]	(0.022)	(0.038)	[0.000]
Panel B:	**From gold to currencies**					
USDEUR	-0.666	-1.272	0.911	0.670	0.872	0.580
	(0.007)	(0.012)	[0.000]	(0.007)	(0.008)	[0.000]
USDGBP	-0.874	-1.035	0.462	0.897	1.521	0.780
	(0.011)	(0.014)	[0.000]	(0.011)	(0.024)	[0.000]
USDAUD	-1.106	-1.398	0.617	0.988	2.430	0.975
	(0.012)	(0.016)	[0.000]	(0.011)	(0.028)	[0.000]
USDCHF	-0.715	-0.894	0.694	0.646	1.170	0.961
	(0.006)	(0.008)	[0.000]	(0.006)	(0.010)	[0.000]
USDJPY	-0.620	-0.605	0.003	0.607	1.322	0.956
	(0.010)	(0.010)	[0.998]	(0.010)	(0.022)	[0.000]
USDCAD	-0.716	-0.461	0.010	0.752	0.428	0.000
	(0.011)	(0.014)	[0.961]	(0.010)	(0.006)	[1.000]

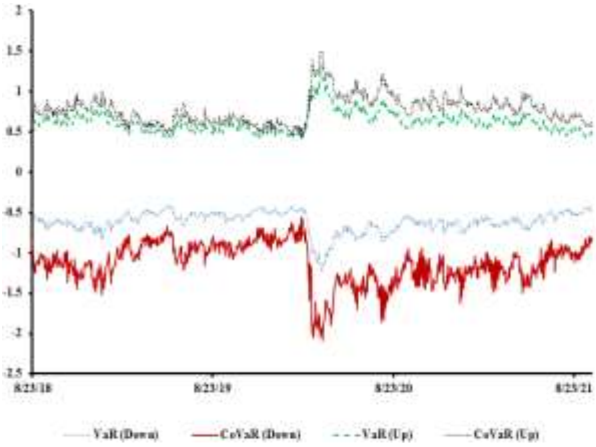
USDCNY	-0.387	-0.478	0.622	0.373	0.919	0.993
	(0.003)	(0.004)	[0.000]	(0.004)	(0.009)	[0.000]

Notes: See table 4.1.

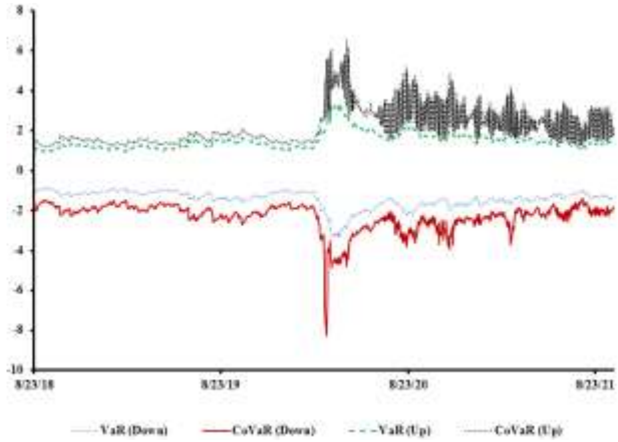
Panel A). From Currencies to Gold **Panel B). From Gold to Currencies**

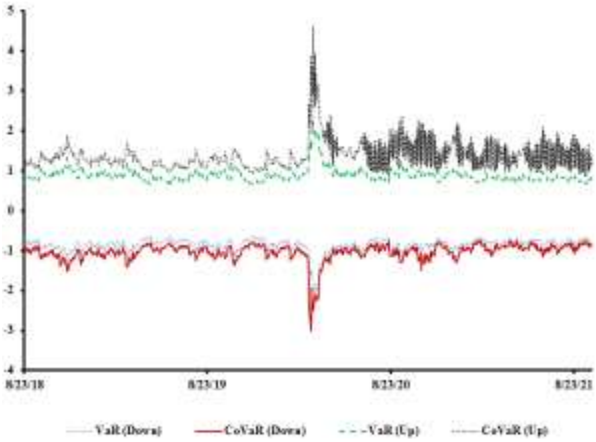
1. EUR



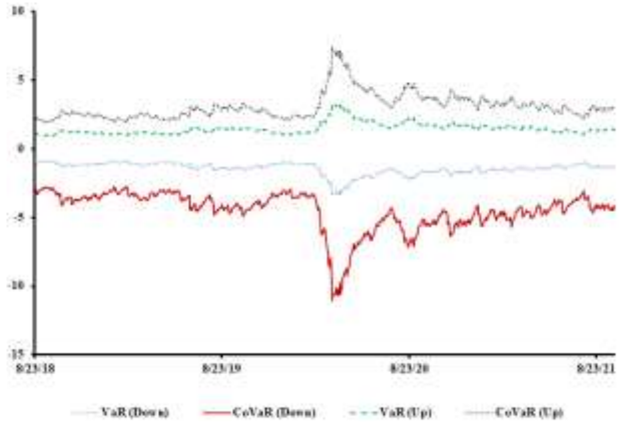


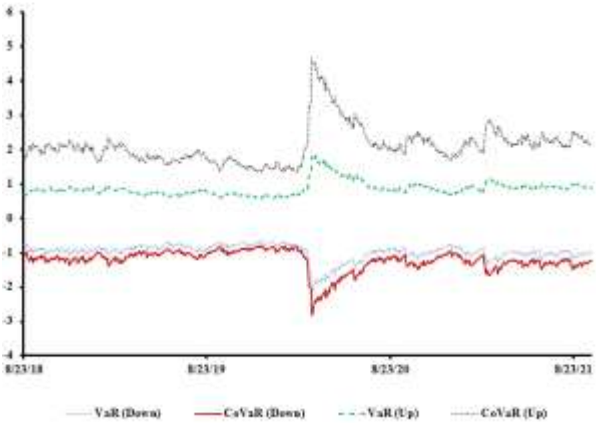
2. GBP



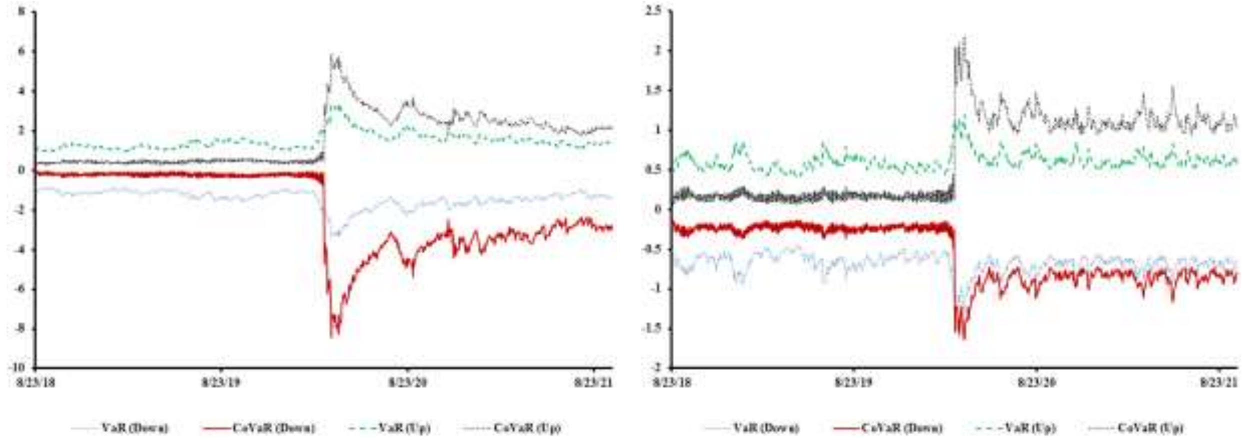


3. AUD

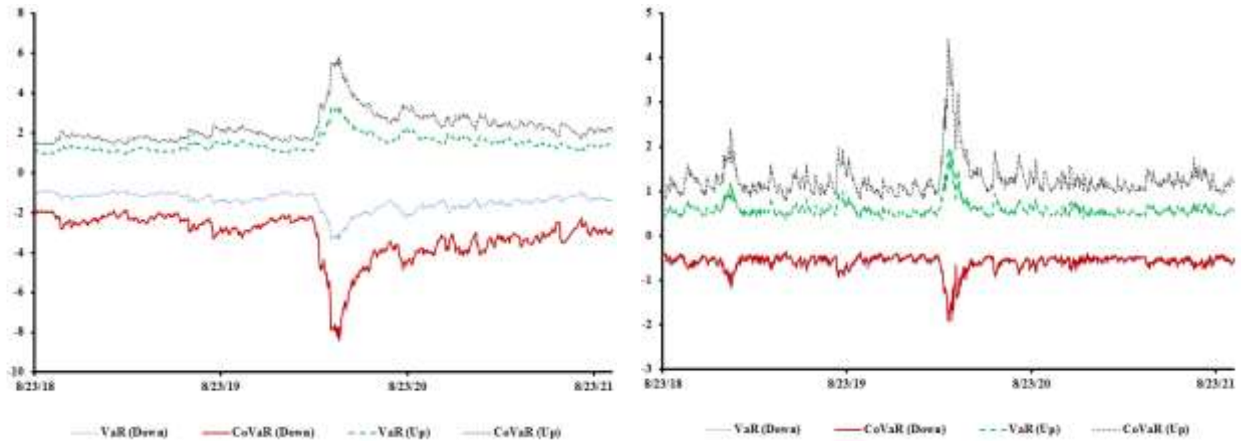




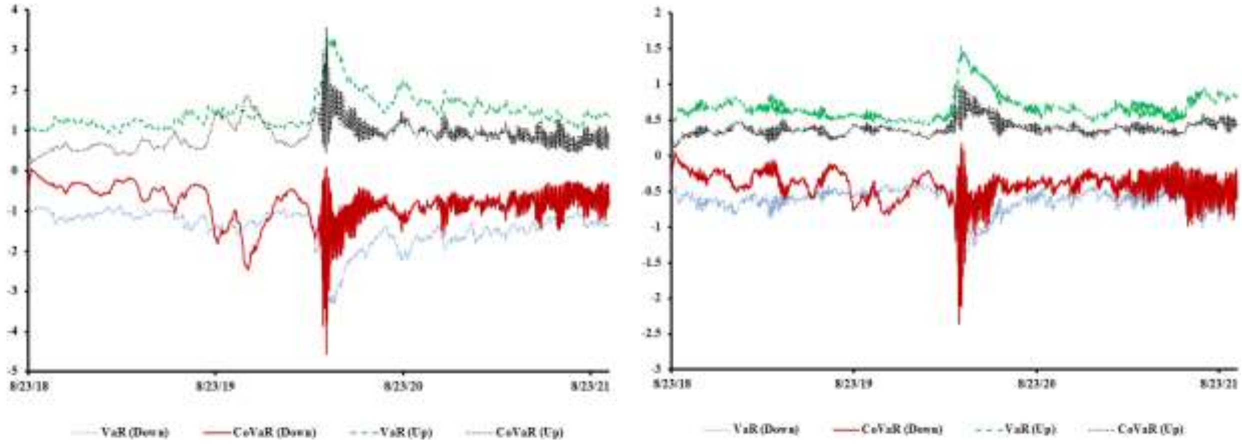
4. CHF



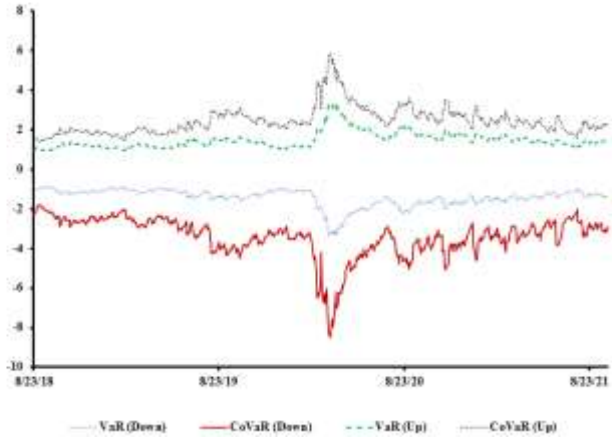
5. JPY



6. CAD



7. CNY



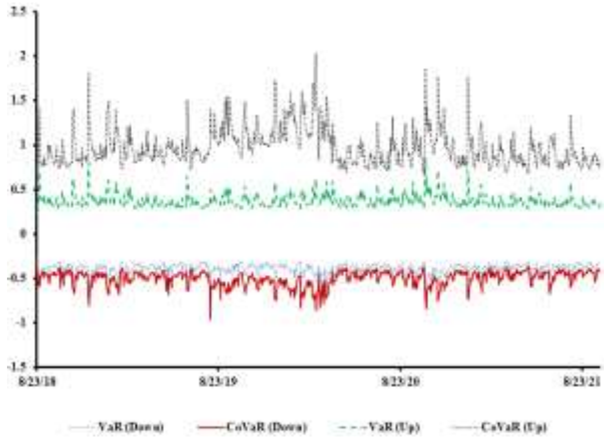
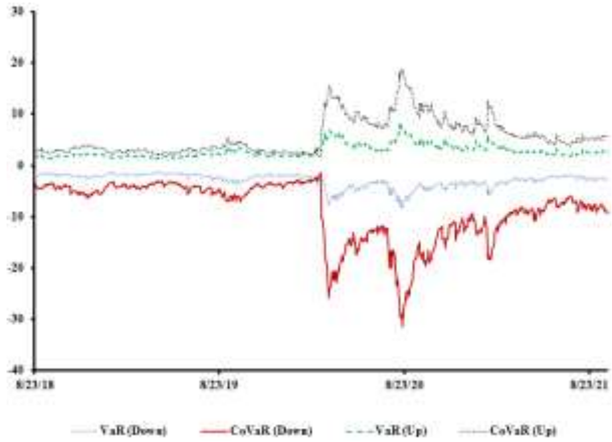
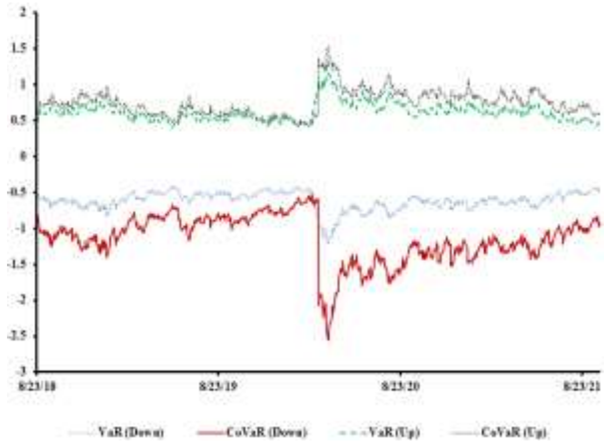


Fig. 2. Risk spillover between gold and currencies before and during COVID-19.

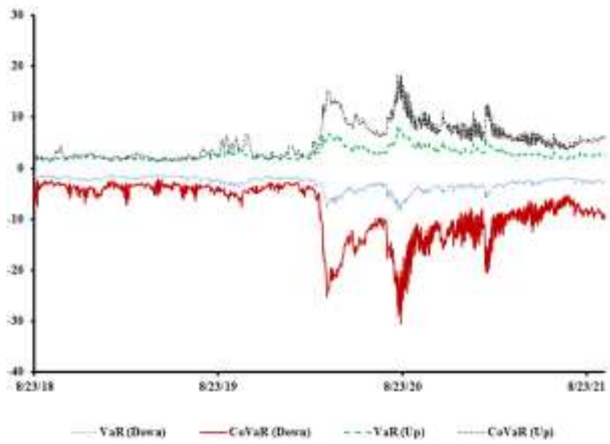
Panel A). From Currencies to Silver **Panel B). From Silver to Currencies**

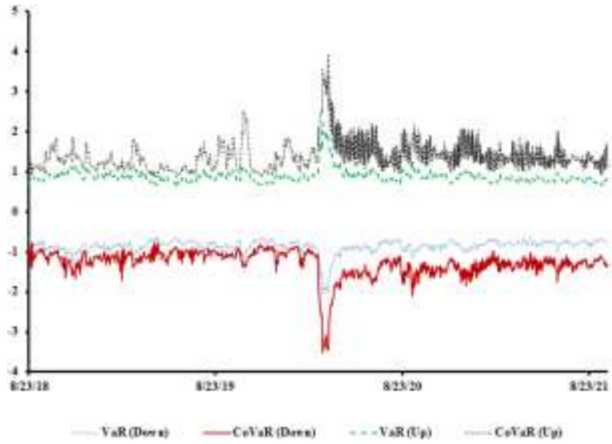
1. EUR



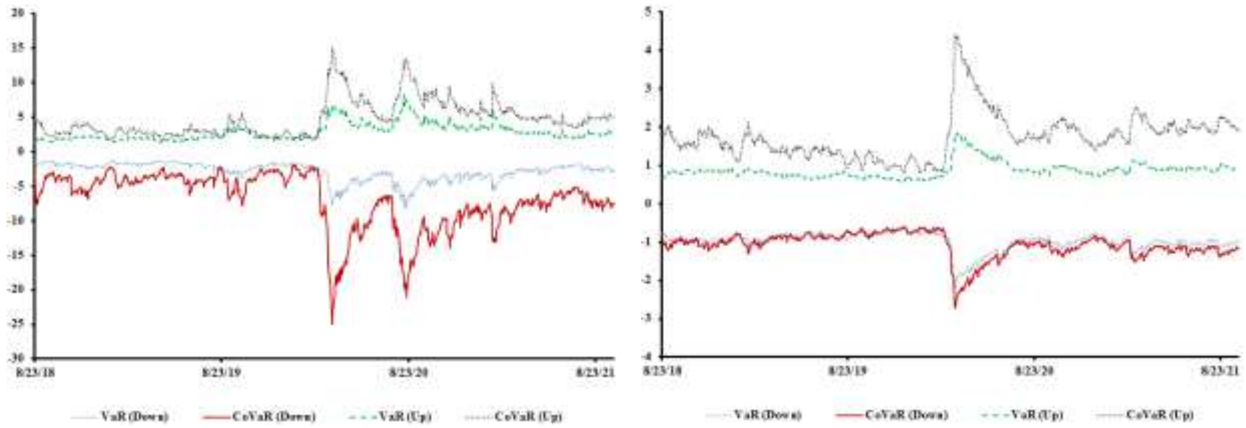


2. GBP

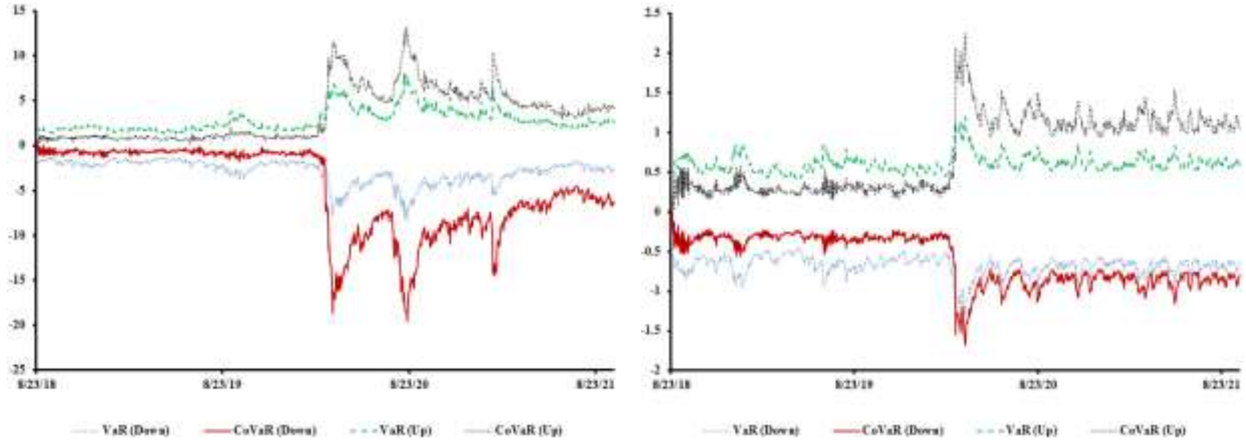




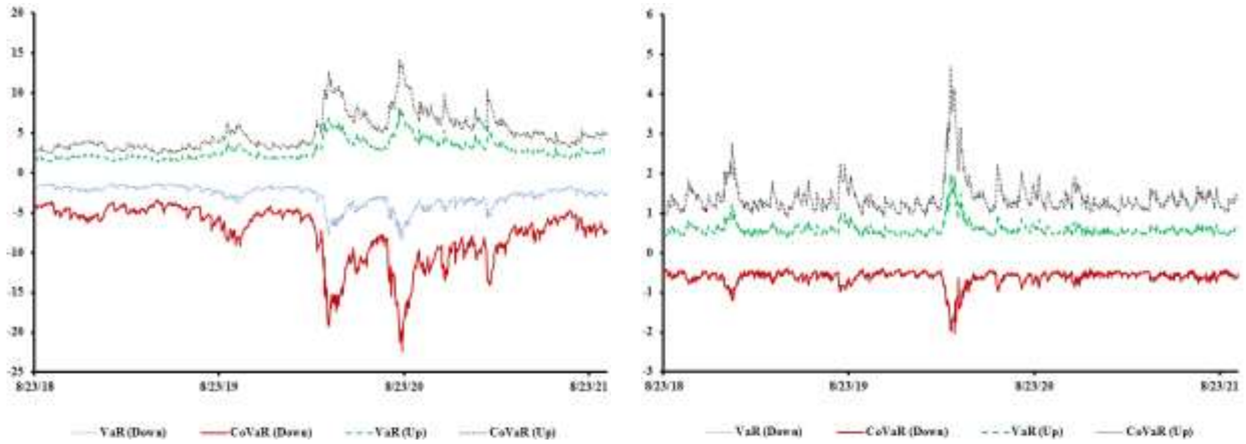
3. AUD



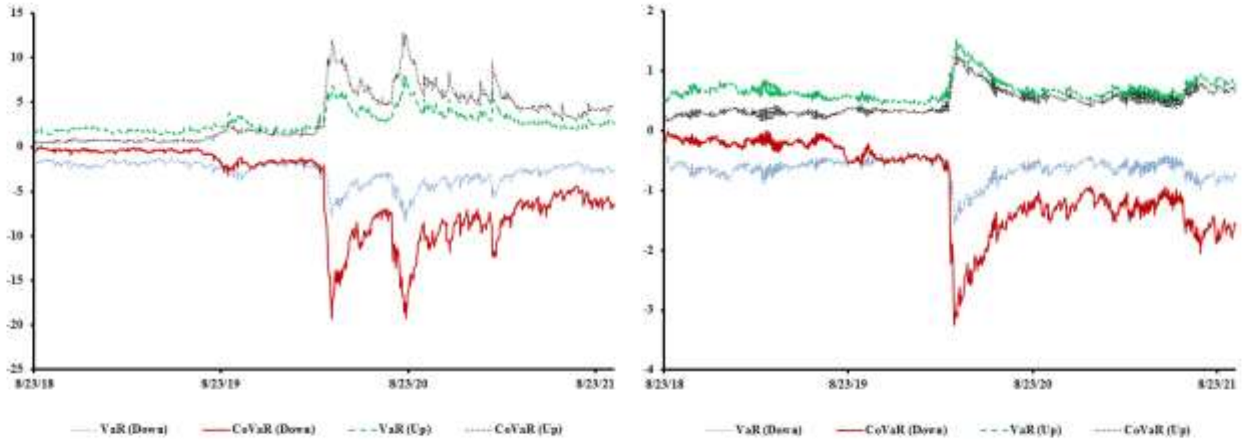
4. CHF



5. JPY



6. CAD



7. CNY

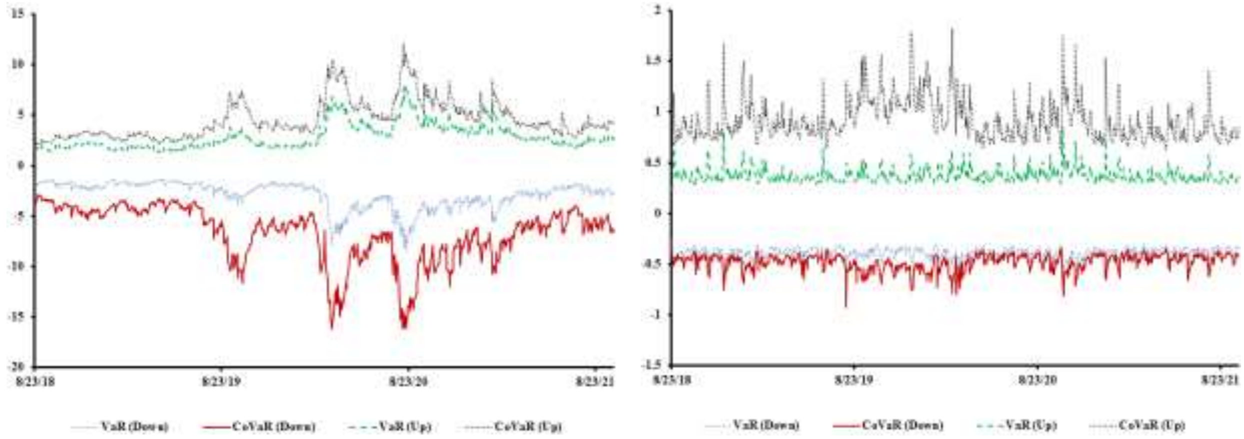
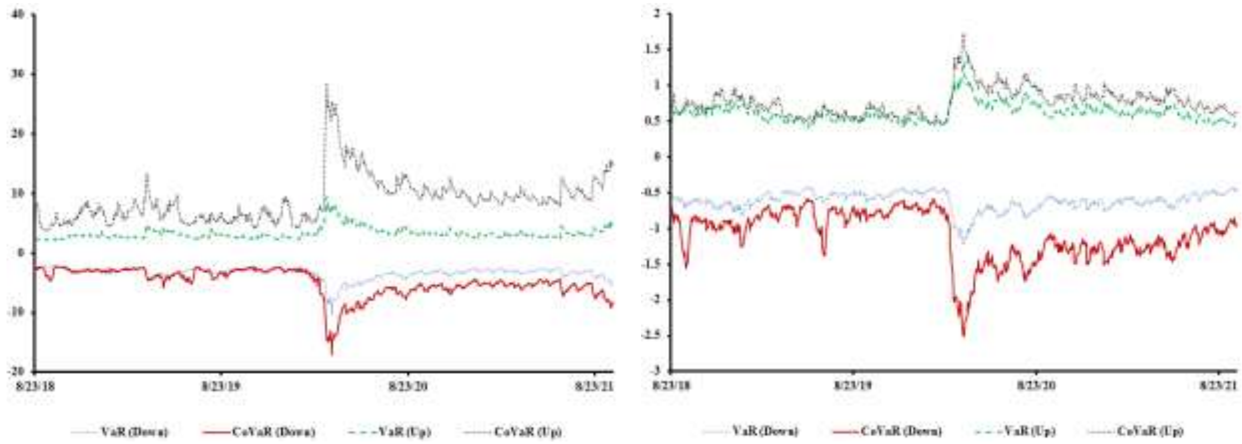


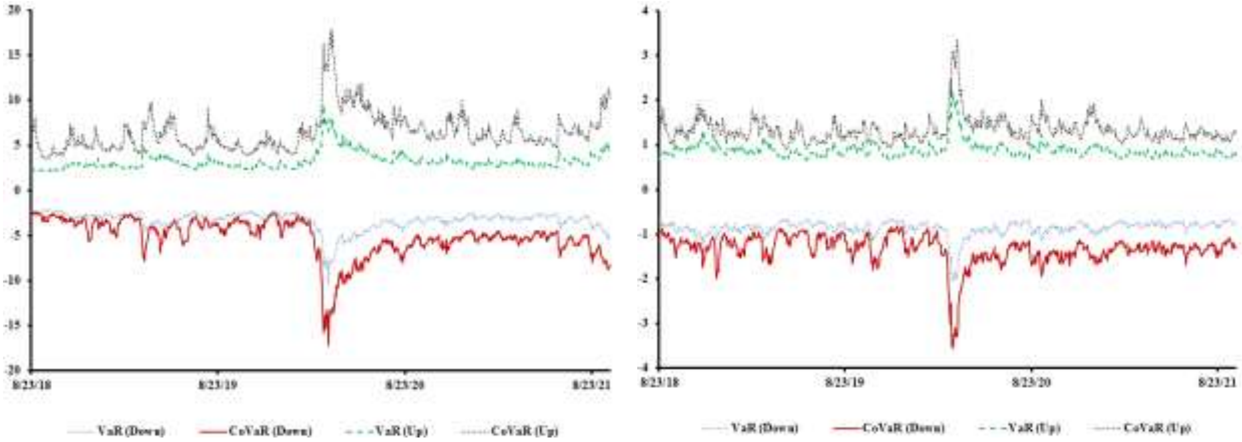
Fig. 3. Risk spillover between silver and currencies before and during COVID-19.

Panel A). From Currencies to Platinum **Panel B). From Platinum to Currencies**

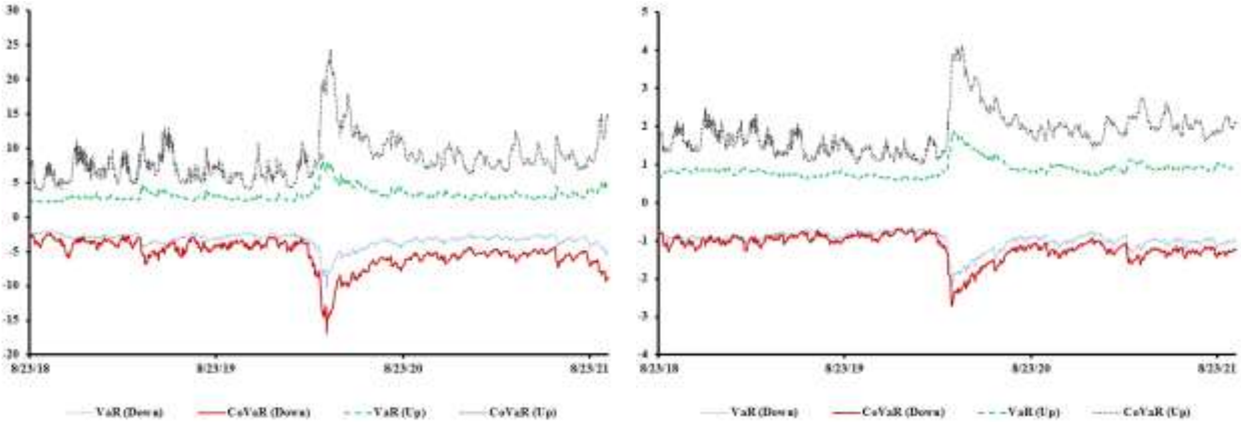
1. EUR



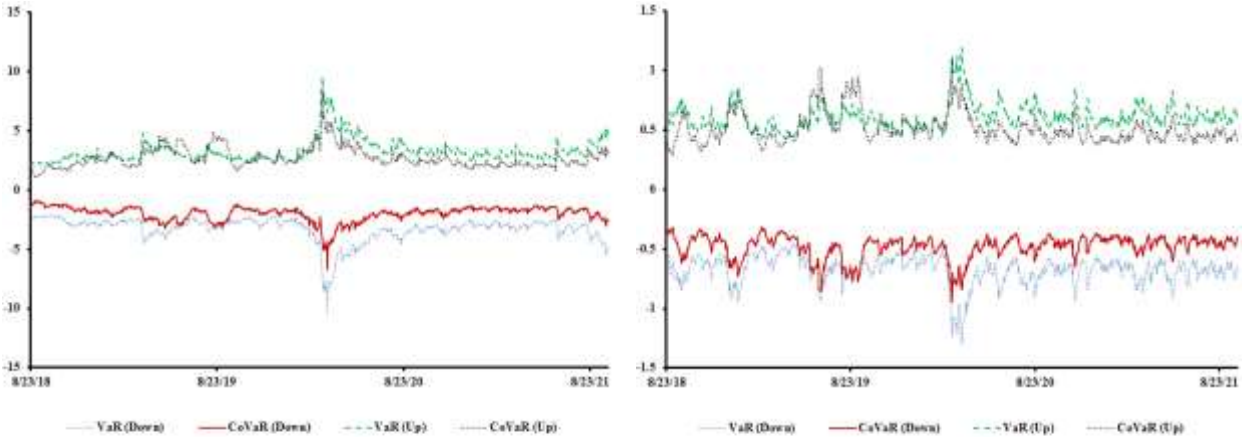
2. GBP



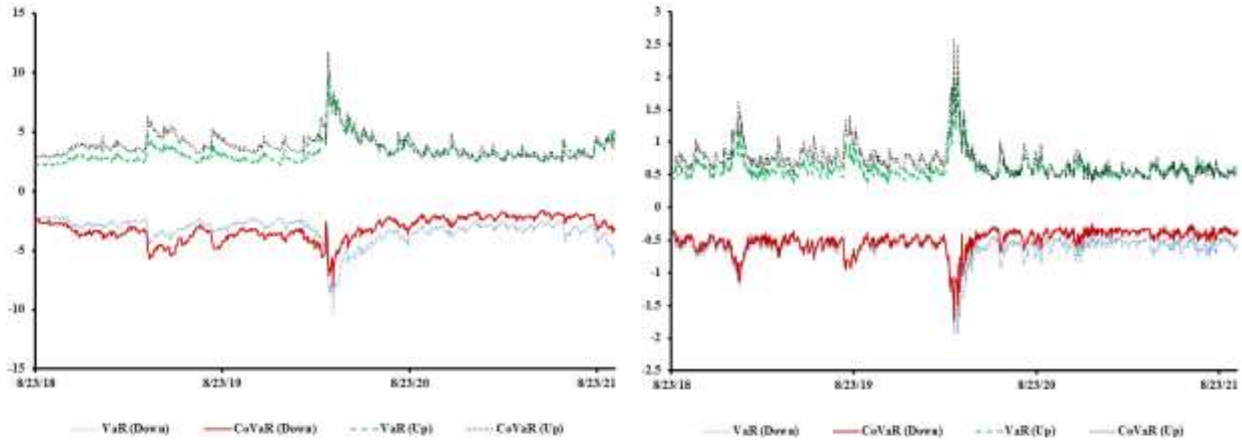
3. AUD



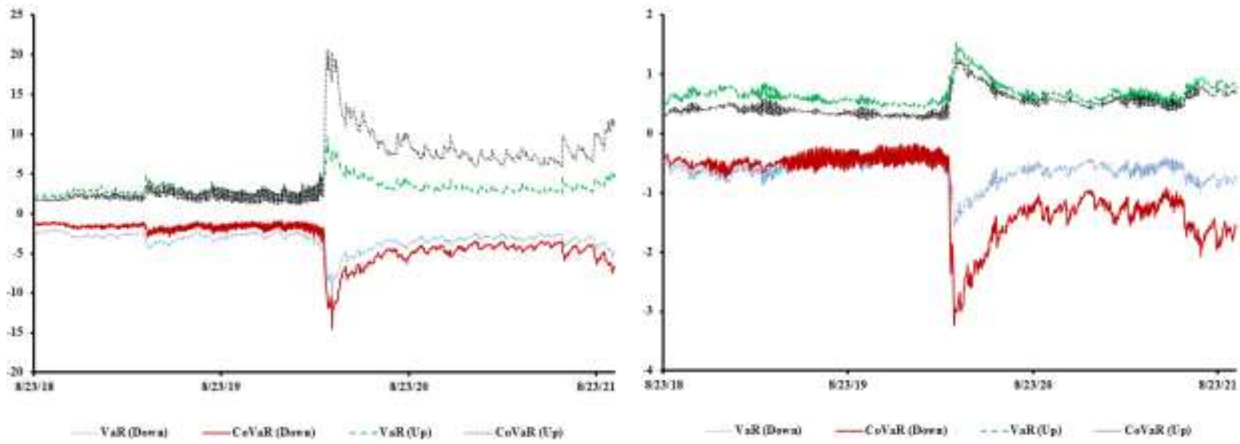
4. CHF



5. JPY



6. CAD



7. CNY

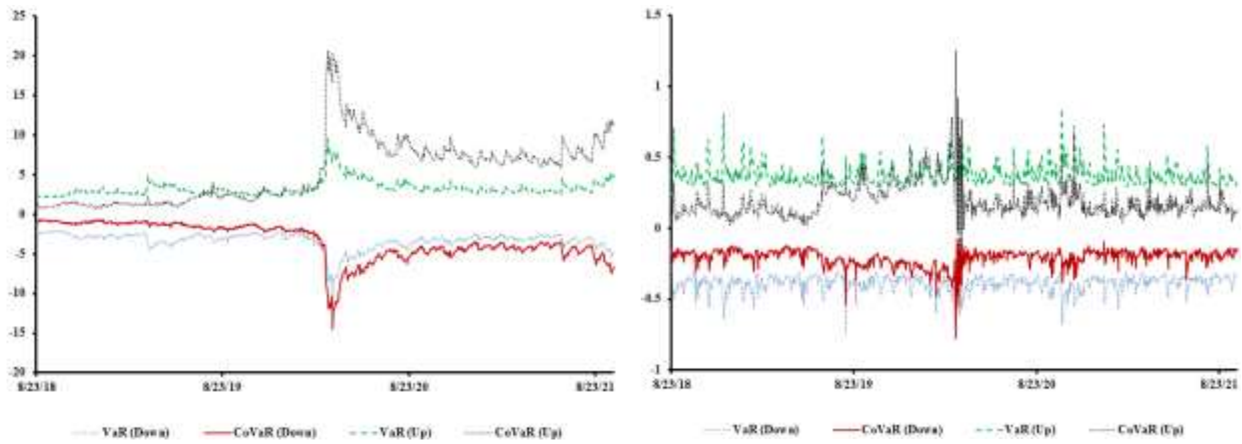
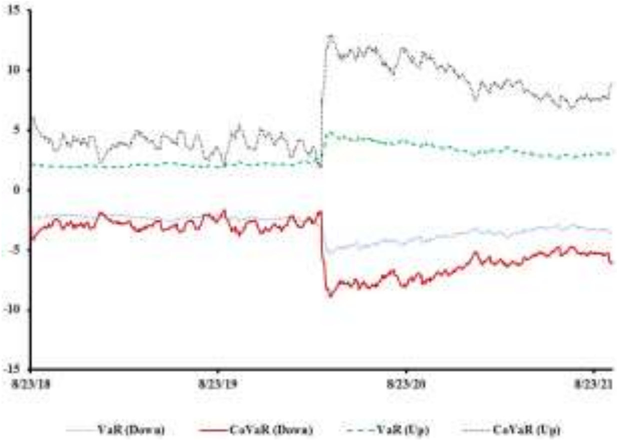
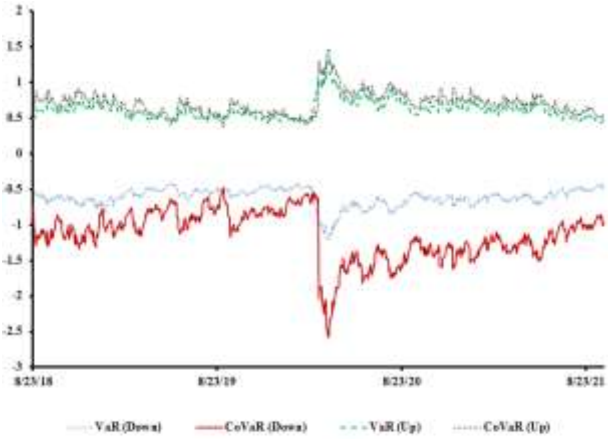


Fig. 4. Risk spillover between Platinum and Currencies before and during COVID-19.

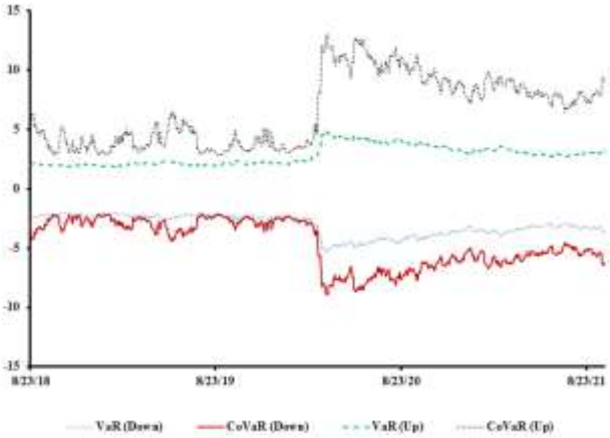
Panel A). From Currencies to Palladium **Panel B). From Palladium to Currencies**

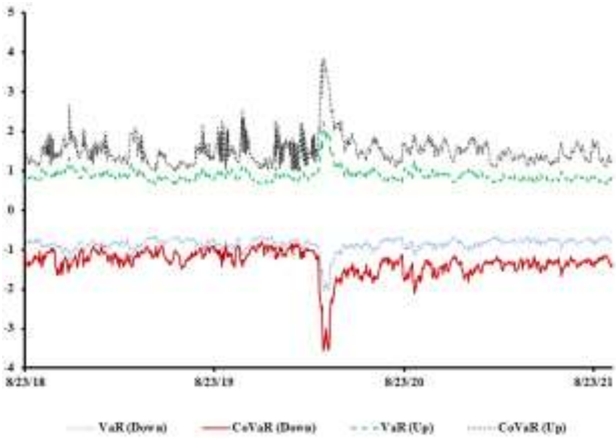
1. EUR



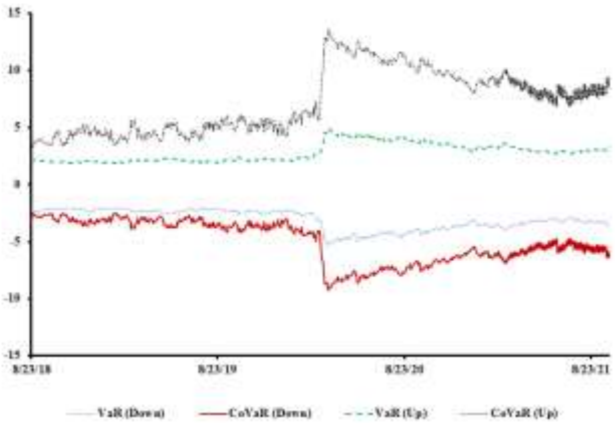


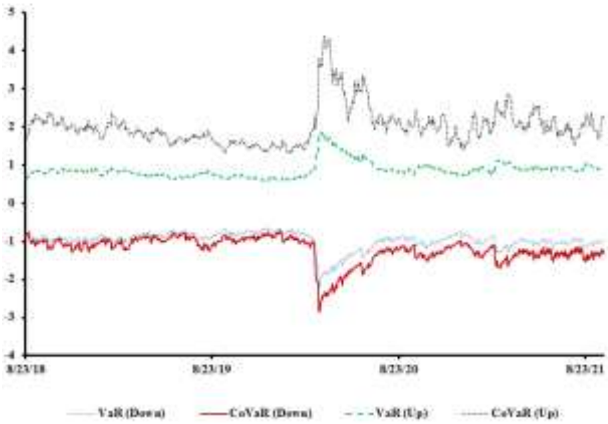
2. GBP



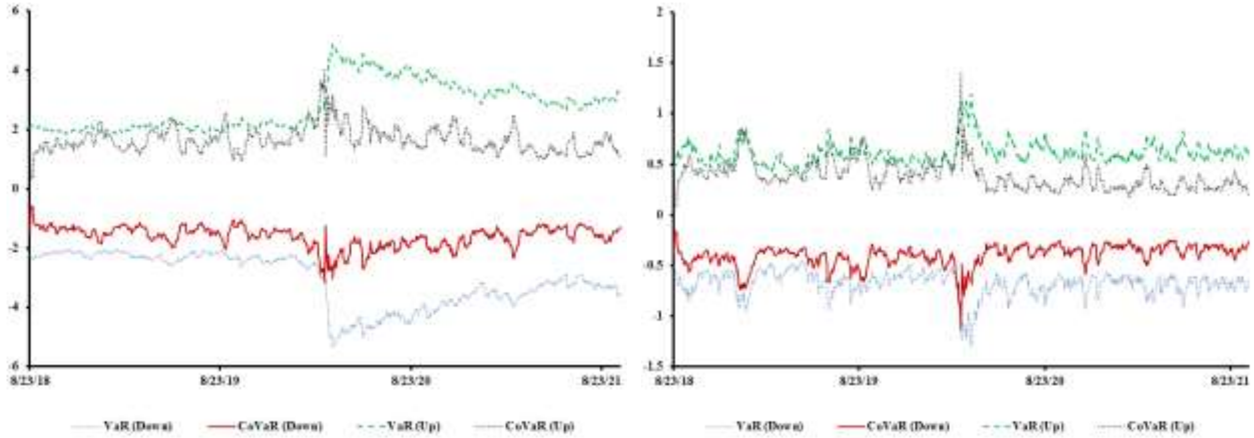


3. AUD

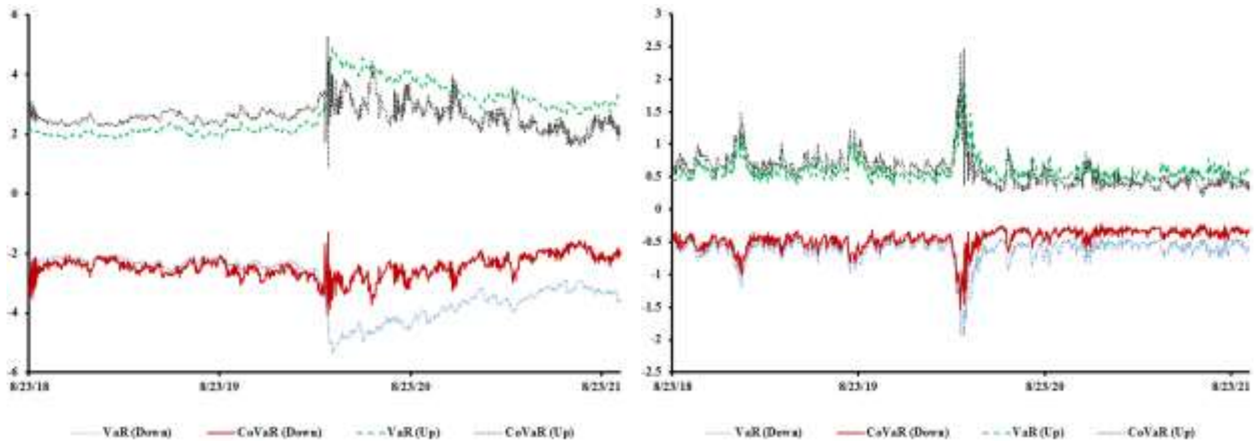




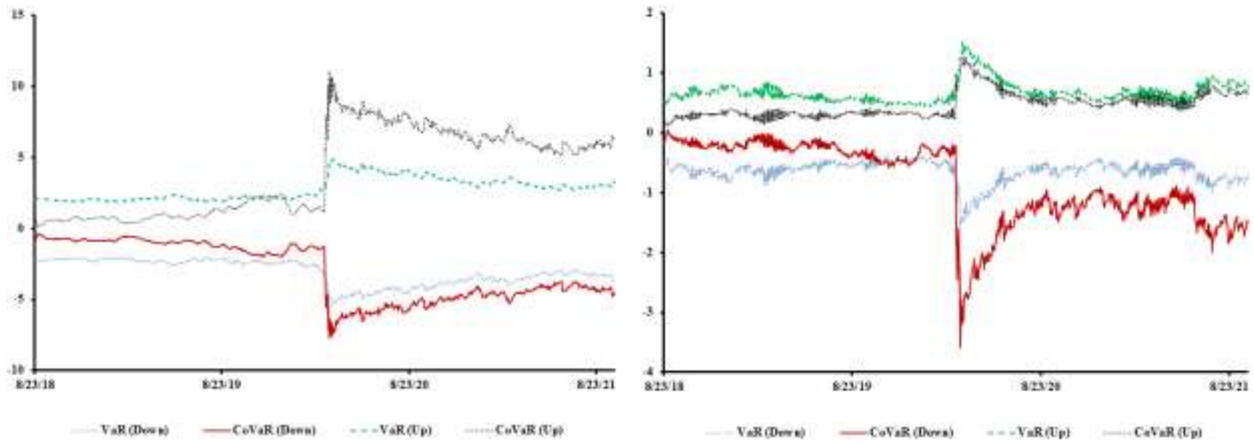
4. CHF



5. JPY



6. CAD



7. CNY

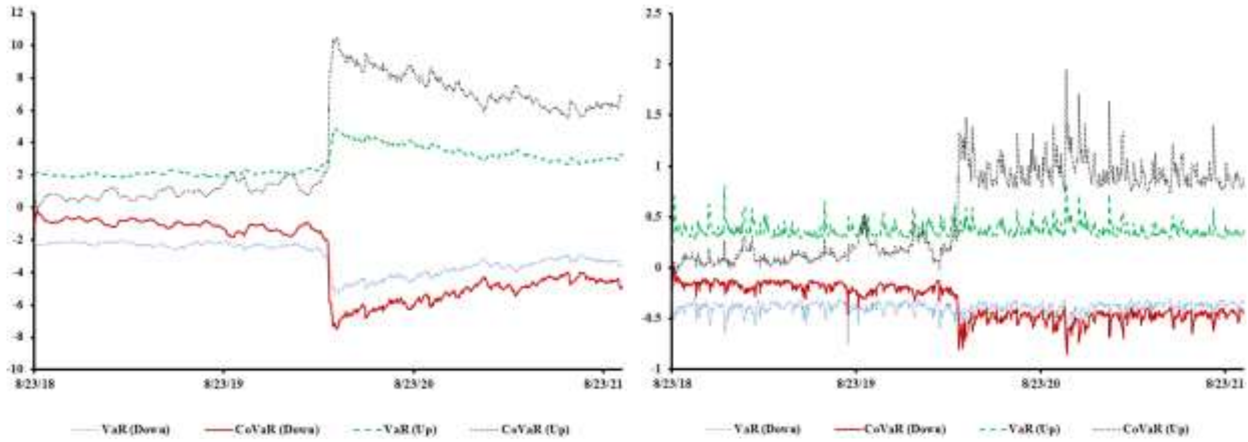


Fig. 5. Risk spillover between palladium and currencies before and during COVID-19

Table A9 (in the online Appendix) displays the downside and upside VaR and CoVaR spillovers between silver and the seven considered currencies prior to the COVID-19 period. According Panel A of Table A9, in both the downside and upside, the largest CoVaR spillovers on silver are transmitted from the CNY, while the smallest are transmitted from the CHF. The VaR spillover from all currencies to silver is similar in the downside and upside. According to Panel A of Table A10 (in the online Appendix), the largest downside CoVaR spillover on silver during the COVID-19 period are transmitted from the EUR and the lowest by the CNY. On the upside, the EUR has the largest CoVaR spillover on silver while the CAD has the lowest.

With respect to spillovers from silver to currencies prior to the COVID-19 period, Panel B of Table A9 indicates that in the downside, the largest CoVaR spillover from silver are received by the GBP, while the smallest is received by the CAD. Moreover, on the downside, the largest VaR spillover transmitted from silver is to the AUD while the smallest is to the CNY. On the upside, the largest CoVaR spillover from silver is received by the AUD while the smallest is to the CHF. For the VaR, the largest spillover from silver is transmitted to the GBP while the smallest is to the CHF. Panel B of Table A10 shows that during the COVID-19 period, the largest downside CoVaR spillover from silver transmits to the CAD, while the smallest is to the CNY. The largest downside

VaR spillovers from silver are exerted on the AUD, while the lowest are transmitted to the CNY. On the upside, the largest CoVaR spillovers from silver are exerted on the AUD, while the lowest are received by the CAD. The largest VaR spillover silver is transmitted to the AUD while the lowest is to the CNY.

Table A11 (in the online Appendix) displays the downside and upside VaR and CoVaR spillovers between platinum and the considered currencies prior to the COVID-19 period. According to Panel A of Table A11, in both the downside and upside, the largest CoVaR spillovers on platinum are transmitted from the AUD, while the smallest are transmitted from the CNY. The VaR spillovers from all currencies to platinum are similar in the downside and upside, although they varied in size. According to Panel A of Table A12 (in the online Appendix), the largest downside CoVaR spillover on platinum during the COVID-19 pandemic is transmitted from the AUD, and the lowest by the CHF. On the upside, the EUR exerts the largest CoVaR spillover on platinum, while the CHF exerts the smallest on the latter. Regarding the spillover from platinum to currencies prior to the COVID-19, Panel B of Table A11 indicates that, on the downside, the largest CoVaR spillover transmitted from platinum is to the GBP, while the smallest is to the CNY. Moreover, in the downside, the largest VaR spillover from platinum is transmitted to the AUD, while the smallest is transmitted to the CNY. On the upside, the largest CoVaR spillover from platinum is transmitted to the AUD while the smallest is to the CNY. Furthermore, the largest upside VaR spillovers from platinum are to GBP while the smallest are to CNY. According to Panel B of Table A12, under the COVID-19 period, the largest downside CoVaR spillover is transmitted from platinum are to the CAD, and the lowest is to the CNY. On the upside, platinum has the largest CoVaR spillover transmitted to the GBP and the smallest to the CNY. Finally, the largest both downside and upside VaR spillovers transmitted from platinum are to the AUD and the smallest to the CNY currencies.

Table A13 (in the online Appendix) displays the downside and upside VaR and CoVaR spillovers between palladium and the currencies consider prior to the COVID-19 period. According to Panel A of Table A13, in both the downside and upside, the largest CoVaR spillovers transmit to palladium are transmitted from the AUD, while the smallest is from the CNY. The VaR spillover from all currencies to palladium is similar in the downside and upside, although they varied in size. According to Panel A of Table A14 (in the online Appendix), the largest and smallest downside and upside CoVaR spillovers received by palladium during the COVID-19 period are transmitted from the AUD and the CHF, respectively. In relation to the spillovers from palladium to the currencies considered prior to the COVID-19 period, Panel B of Table A13 shows that in the downside, the largest CoVaR spillovers transmitted from palladium are to the GBP, while the smallest are to the CNY. Moreover, in the downside, the largest VaR spillover transmitted from palladium is to the AUD, while the smallest is to the CNY. On the upside, the largest CoVaR spillover transmitted from palladium is to AUD while the smallest is to CNY. Also in the upside, the largest VaR spillover transmitted from palladium is to GBP while the smallest is to CNY. According to Panel B of Table A14, during the COVID-19 period, the largest downside (upside) CoVaR spillover from palladium is transmitted to the GBP (AUD) and the smallest is to the CHF. Finally, for the VaR, the largest both downside and upside VAR spillover transmitted is to AUD while the smallest is to CNY.

Figures 2–5 depict the evolution of the upside and downside VaRs and CoVaRs for FX and PM market returns. The graphical graph demonstrates that the downside and upside VaRs for the FX markets (Panel B) are notably higher than those for PMs markets (Panel A), implying that the FX market is riskier than that of the PMs under both downside and upside market conditions. This graphical evidence coincides with the descriptive statistics outlined in Tables 4.1, 4.12, and A8–A13. These findings are critical for managing and monitoring currency risks. The upside and downside CoVaR trends, on the other hand, show a similar trend for all cases, with minor variations in magnitude across currencies. More intriguingly, the influence of the COVID-19 crisis on the FX and PM markets is clearly evident, with significant sudden and unexpected changes occurring on March 11, 2020. We discover that where the downside CoVaR sharply fall or the upside CoVaR pick up substantially more than the downside and upside VaRs for all currencies and PMs during this period, implying that each market has a systemic impact on the other market. Overall, this finding indicates significant bidirectional risk spillover effects between the PM and FX markets. Identifying the source of PMs shocks is an important factor in determining risk spillovers between the PMs and FX markets.

We use the Kolmogorov-Smirnov (K-S) test to confirm the graphical representations in Figures 2–5 and to test for the significance of systematic risks. More specifically, we look for a significant difference between downside and upside VaRs and CoVaRs. Tables 4.1, 4.2, and A8–A14 present the estimation results of the K-S test, which show significant differences in VaRs and CoVaRs (for both risk spillovers from FX to PM markets and from PM to FX markets) for all cases, confirming the importance of risk spillovers.

In addition, we examine whether the upside and downside systemic risks in the FX and PM markets are asymmetric. However, even though investor behaviour differs during downturn and upturn markets, this stylize fact (asymmetry) has direct implications for portfolio risk management and hedging. We test the presence of asymmetry in risk spillovers using these arguments. The estimates (see Tables 4.1., 4.2 and online A8–A14) reject the null hypothesis of symmetric risk spillovers. We discover the asymmetric downside risk spillover effects from FX to PM markets and vice versa. Then, we investigate the asymmetric downside/upside risk spillover effects using the K-S statistic to test for significant differences between downside and upside spillovers between PM and FX markets. The findings summarized in Tables 4.1, 4.2, and online A8–A14 demonstrate the asymmetric behavior of the upside and downside risk spillovers to the FX and PM markets.

Overall, the above results extend our limited understanding of the propagation of extreme returns shocks within the system of connectedness of currencies. They show evidence of asymmetry is present during extreme events. These results are generally in line with those of Mensi et al. (2021b), who found that international shocks had an asymmetrical impact between the currency markets and precious metals (PMs) such as gold, palladium, platinum, and silver. Moreover, the results complement previous studies (e.g., Antonakakis and Kizys, 2015; Sakemoto, 2018; Mensi et al., 2020).

5. Conclusion

To better understand how the COVID-19 outbreak impacts the relationship and spillover between currencies and PMs, this research work applies TVP copulas as well as VaR and CoVaR spillover measures on four major PMs (gold, silver, palladium, and platinum) and seven major exchange rates (AUD/USD, CAD/USD, CNY/USD, JPY/USD, EUR/USD, CHF/USD, and GBP/USD) before and during the COVID-19 outbreak.

The TVP copula results show that the dependence dynamics between currencies and PMs become asymmetric with increased density in the tails during the COVID-19 period. These results evidence the unique character of the COVID-19 crisis which strongly affect the relationship between FX and PM assets. Although these results are relatively novel in relation to the COVID-19 crisis, the findings partially confirm those of Antonakakis and Kizys (2015) following which the relationship between commodity and currencies intensified during the global financial crisis. Furthermore, the different results for different PMs also confirm those Sakemoto (2018) who underlined the time-varying property of the relationship between PMs and currencies since the hedge and safe haven characteristics of PMs weakened after 2000.

The results regarding the VaR and CoVaR spillover effects between currencies and PMs before and during the COVID-19 crisis shows that the magnitude of the spillovers became larger during the COVID-19 outbreak. This result implies that the COVID-19 crisis in fact strengthen the relationship between PMs and currencies. For central banks, investors, and portfolio managers, this finding suggests that diversification strategies should adapt better to construct optimal portfolios including PMs and currencies. Furthermore, similar results in the tail dependence downside and upside regarding the spillover effects between currencies and PMs imply that investors and portfolio managers may have to consider a symmetric dependence in the movement of their prices.

Our findings have important implications for central banks, portfolio managers, and individual investors. Indeed, our results suggest that central banks should revise the equilibrium between PMs and foreign currencies in their reserves when FX and PM markets are shocked by events such the COVID-19 outbreak (the S&P Global) which have led to an increasing volatility in the metals market. Indeed, the financial uncertainty caused by the outbreak has led international investors to rebalance their currency portfolios and to use PMs to hedge downside risks. Trade flows among countries have changed due to national lockdown measures and social distancing and international currency flows have naturally also been impacted as a result. The asymmetric dependence dynamics between PMs and currencies caused by the COVID-19 outbreak also suggests that the relationship between these two is more complex and harder to predict, thus making it more difficult and expensive for investors to diversify and manage their FX-PMs portfolio positions. In future studies, it would be insightful to further investigate how the changes in the dependence dynamics between currencies and PMs could affect their respective roles as hedge and safe haven assets in stock portfolios (e.g., Wong, 2018; Balilar et al., 2019).

Appendix

Table A1. Summary of literature review.

Authors	**Data and sample**	**Empirical methods**	**Main findings**

Balcilar et al. (2015)	Weekly data from January 1987 to February 2012. dollar/euro exchange, WTI crude oil, gold, silver, platinum, and palladium	Markov-switching vector error correction model	Gold contains useful information during high-volatility regime. Gold, palladium, and platinum are the most informative in the low volatility regime. Strong correlations between palladium and platinum. Gold is a safe haven asset.
Awartani et al. (2016)	Daily data from July 2012 and the 3rd of June 2015. silver, wheat, corn, and soybeans, crude oil, US equity, and Euro/Dollar rate	Spillover index of Diebold and Yilmaz (2014, 2016)	Significant volatility spillovers from oil to equities. A weak volatility transmission from oil to agricultural commodities
Ciner (2017)	Daily data from October 1996 to July 2016. Silver, palladium, platinum, and ZAR rate	Structural break test, impulse response and asymmetric causality test of Hatemi-J (2012)	Unidirectional causality from South African currency (ZAR) to white metals.
Qureshi et al. (2018)	daily data from January 1992 to July 2015. A set of currencies against Pakistani currency and gold	Wavelet coherence and Wavelet Granger coherence analysis approaches	Gold is a short-term hedge against currency rate. The relationship between gold and currencies varies across frequencies.
Peng (2020)	Daily data from October 2006 to October 2018. China Securities Index, Aggregate Bond index, CSI Commodity Futures Composite index, and CNY/US Dollar Real Effective	DCC–GARCH model	Precious metals are strong hedges for the bond market and diversifiers for other financial markets. In addition, precious metals play the role of safe haven during crisis period.

	Exchange Rate index.		
Mensi et al. (2020)	Daily data from January 2000 to May 2016. Precious metals futures (gold, silver, palladium and platinum), and 20 spot U.S. exchange rates.	Spillover index of Diebold and Yilmaz (2014, 2016) and DECO marginal model	Precious metals with the exception of platinum and almost all exchange rates are net shock receivers. Precious metals provide strong risk and downside-risk reductions.
Mensi et al. (2022)	Daily data from January 2000 to March 2021. gold, palladium, platinum, and silver, as well as major US foreign exchange rates (AUD, CAD, CHF, CNY, EUR, GBP, and JPY).	Frequency spillover index of Baruník and Křehlík (2018)	Gold, palladium, platinum, and silver serve as a safe haven asset against currency rates. Oil prices and uncertainty indexes affect the long-term spillover effects.
Kunkler (2022)	daily data from December 1989 to December 2019. Gold, silver, platinum, and ten currencies	Standard hedge ratio decomposition	all standard hedge ratios are negative for all combinations of currencies and precious metals.
Antonakakis et al. (2023)	Daily data from March 2011 to March 2021. Implied volatility of oil, energy, stock, precious metals, bonds, and exchange rates	TVP-VAR connectedness method	High connectedness among different asset classes during COVID-19 crisis. Oil is more integrated with financial markets.

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