The euro to dollar exchange rate in the Covid-19 era: Evidence from spectral causality and Markov-switching estimation

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Abstract
In this paper, we analyse how the Covid-19 pandemic changed the dynamics of the euro to dollar exchange rate. To do so, we make use of spectral non-causality tests to uncover the determinants of the euro to dollar exchange rate, using data that cover the pre-Covid-19 and the actual Covid-19 era, by considering the exchange rate movements of other currencies, the stock market index of S&P 500, and the price of oil and gold, as well as their realized volatilities. Based on our findings, the Covid-19 pandemic has indeed significantly changed the determinants of the euro to dollar exchange rate. Also, to investigate the potential shifts in the regimes of the euro to dollar exchange rate, we formulate a Markov-switching model with two regimes, based on the determinants that have been found in the previous step. Based on our findings, the duration of the high volatility state in the Covid-19 era has doubled, from almost 3 to approximately 6 days, compared to the pre-Covid-19 era, whereas the high volatility state in the Covid-19 era is characterized by a statistically significant higher range of volatility compared to the pre-Covid-19 era.

KEYWORDS
Covid-19, euro to dollar, exchange rate, Markov-switching, spectral causality

JEL CLASSIFICATION
C22; C58; C50; C51

1 | INTRODUCTION

The Covid-19 pandemic has spread from one country to another, having its origin in Wuhan, Hubei, China (Liu, Gayle, Wilder-Smith, & Rocklöv, 2020). The spread of the SARS-COV-2 virus in a worldwide context has caused fear globally. The total confirmed cases are estimated to be several million people globally, showing the cruel face of this pandemic (World Health Organization, 2020). In an attempt to minimize the spread of the virus, most economies and policymakers have taken extreme lockdown measures that negatively affect the overall macroeconomic, macroeconomic, and financial conditions of each economy. However, the increased globalization and integration of trade and financial relations, among the various economies and institutions, makes clear that the global shock caused by the pandemic is tremendous (Lee & McKibbin, 2004).

The impact of the recent pandemic on the global economy can be roughly categorized into three major
The first pillar involves the “lockdown” and isolation measures undertaken at a global scale by the respective governments of most economies, which have an immediate impact on their trade relations, since the total volume of trade was estimated to decrease approximately by 13%–32% in 2020, based on official projections by the World Trade Organization (Trade Forecast Press-Conference, April 2020). On top of that, one should take into consideration the fact that political events have contributed to the increase of the volatility of crude oil prices, yielding an unprecedented drop in the price of oil, leading countries such as Saudi Arabia and Russia to take political measures to control the situation (Albulescu, 2020).

The second pillar involves the impact of the pandemic on the financial markets, in general, and on stock markets in particular. Analytically, many major stock markets around the world have lost almost 20% of their initial value (Segal & Gerstel, 2020). Also, the European Central Bank (ECB) and the Federal Reserve Bank (FED) announced generous stimulus packages both for the European Union and the US economies, respectively, setting at the same time their interest rate targets close to zero, in an attempt to minimize the effects of the “lockdowns” to the overall economic activity. As a result, the aforementioned dimensions of the pandemic have impacted large parts of the overall macroeconomic, fiscal, monetary, and financial aspects of economic activity. Therefore, it is apparent that the fundamental determinants of the exchange rate dynamics of predominant currencies, like the U.S. dollar and the euro have been substantially impacted by the Covid-19 pandemic.

In this context, the present paper attempts to shed light on the research question that arises which can be formulated as follows: What is the impact of the Covid-19 pandemic on the dynamics of exchange rate currencies? During periods of crisis, the exchange rates of predominant currencies like the US dollar and the euro are affected in various ways. For instance, evidence regarding the movement of dominant currencies during the global financial crisis of 2007–2009, show that the two currencies appreciated with respect to other currencies like the Japanese yen, the Canadian dollar, and the Australian dollar (Kohler, 2010). Nonetheless, this did not happen in previous crises like the Asian 1997–1998 crisis or the Russian crisis that followed. Behind this fact, there are two factors that are likely to have contributed to such a development. The first factor could be summarized as a “safe-heaven” effect, which could lead the financial behaviour of traders and investors against the typical pattern of crisis-related flows. On the other hand, the interest rate differentials could explain more of the crisis-related exchange rate movements. This is probably reflected by the structural changes in the determinants of exchange rate dynamics, such as the increased role of carrying trade activity (Kohler, 2010).

The present paper makes use of spectral (non-)causality tests to uncover the determinants of the euro to dollar exchange rate, using data that cover the pre-Covid-19, and the actual Covid-19 era per se, by considering the exchange rate movements of other currencies, the stock market index of S&P 500, and the prices of oil and gold, as well as their realized volatilities. Then, the present paper formulates a Markov-Switching (MS) model with two regimes, to study the difference in the movements of the euro to dollar exchange rate, before and after the outbreak of the Covid-19 pandemic.

The paper is structured as follows: Section 2 presents the review of the literature; Section 3 sets out the methodology used; Section 4 presents the results; Section 5 discusses the paper, and finally, Section 6 concludes the paper.

2 | LITERATURE REVIEW

The present paper deals with the exchange rate movements of predominant currencies in times of crisis, using a MS model. In this context, the related literature consists of two subsections, one that focuses on the movement of exchange rates in times of crisis and one that focuses on the application of MS modelling in exchange rate dynamics.

2.1 | Crisis and exchange rates

Based on the related literature, there are two main strands regarding the factors that affect the movements of predominant exchange rates in times of crisis. The first strand focuses on the impact of the stock market on the movements of exchange rates, whereas the second strand examines the impact of other factors on the exchange rate dynamics.

Starting with the first strand, in a prominent paper, Gavin (1989) examined the linkage between monetary policy and exchange rates in a general equilibrium model, accounting for the presence of a stock market. Based on the author’s findings, the stock market reduces the impact of monetary policy on the real exchange rate. In a similar context, Ajayi and Mougué (1996) showed that an increase in the stock price index has a negative short-run impact on the domestic currency value. Nonetheless, in the long run, increases in stock prices have a positive effect on the domestic currency value. In policy-oriented research, Gould and Kamin (2000) showed that credit spreads and stock prices exert significant effects on
exchange rates during financial crises. Analytically, they argued that although the monetary policy does exert an important influence on exchange rates, this most likely takes place slowly, as central banks attempt to establish credibility, over longer periods of time. In a research on the impact of the Asian financial crisis, Nagayasu (2001), using high-frequency data of exchange rates and stock indices, showed that although stock indices often fail to provide valuable insights into currency crises, developments in the sectoral indices seem to cause upward pressure on exchange rates. Similarly, Phylaktis and Ravazzolo (2005), using data on a group of Pacific Basin economies over the period 1980–1998, found that stock and foreign exchange markets are positively related and that the U.S. stock market acts as a conduit for these links.

Moreover, Lin (2012) investigated the co-movement between exchange rates and stock prices. The results showed that the co-movement between exchange rates and stock prices becomes stronger during crisis periods, consistent with contagion or spillover between asset prices when compared with tranquil periods. Moreover, most of the spillovers during crisis periods can be attributed to the channel running from stock price shocks to exchange rates. A study by Caporale, Hunter, and Ali (2014) uncovered the nature of the linkages between stock market prices and exchange rates on the banking crisis between 2007 and 2010. Based on their findings, the dependence between the two variables increased during the financial crisis.

Turning to the second strand of the literature, a number of research articles study the impact of interest rates on exchange rates in times of crisis. See, among others, Dekle, Hsiao, and Wang (2002), di Giovanni and Shambaugh (2008), and Hnatkovska, Amartya, and Carlos (2013). In general, the findings suggest rising interest rates have had a small impact on nominal exchange rates during the crisis period.

Another part of research on exchange rate movements in times of crisis focuses on the effect between exchange rate currencies. Dungey and Martin (2004) using a multifactor model of exchange rates measured the contribution of contagion to the volatilities of exchange rates during the East Asian currency crisis. The researchers argue that there exists significant contagion to the volatilities of exchange rates during the crisis. In general, there is evidence that the Japanese currency (Yen) affects the dollar–euro exchange rate (Hillebrand & Schnabl, 2008) in many ways. In more detail, during crises, the impact on the US dollar and Japanese yen is negative, whereas for the British pound, the Canadian dollar, and the euro the impact is positive, consistent with the findings of Lizardo and Mollick (2010).

Of course, there is a part of the literature that focuses on forecasting the exchange rates in times of crisis. In this context, Morales-Arias and Moura (2013) investigated the economic implications of adaptive forecasting of exchange rates, using a panel data methodology. Their results showed that combining exchange rate forecasts generated from a wide range of information sets reduces uncertainty, improves forecasting precision and also leads to better market timing than most single predictors. In another attempt, Caraiani (2017) performed an evaluation of exchange rate forecasts of reference models in time and frequency. The author studied the uniformity of random walk performance along with different frequencies to find out whether uniformity exists, or it is driven by certain frequencies. Based on the author’s findings, the predictability of exchange rates seems to vary along with the different frequencies. Furthermore, the absence of a high-frequency component leads to many cases in which the random walk is outperformed.

Finally, there is an emerging part of the literature that focuses on the effect of oil prices on the movement of exchange rates. In a seminal paper, Chen, Liu, Wang, and Zhu (2016) investigated the impacts of oil price shocks on the bilateral exchange rates of the US dollar against currencies in 16 OECD countries. The authors argued that the responses of dollar exchange rates to oil price shocks differ, depending on whether changes in oil prices are driven by supply or aggregate demand. According to them, oil price shocks can explain about 10%–20% of long-term variations in exchange rates. Peng, Hu, Chen, Zeng, and Yang (2019) investigated the volatility index (VIX) and the oil price influence on the foreign exchange rates, based on a conditional autoregressive value at risk model. The authors argued that the oil price affects the value at risk (VaR) of exchange rates of oil-importing and oil-exporting countries differently. Moreover, according to the authors, the VIX can influence the tail risk of the currencies when the U.S. financial market fluctuates significantly, while after the financial crisis it seems to be a significant increase in the volatility of the VaR of the currencies.

In what follows, we turn to the recent literature on MS models employed for exchange rate modeling.

### 2.2 Exchange rate and MS modelling

Probably one of the first works on exchange rates, using MS modeling, was conducted by Engel (1994). The researcher fitted an MS model for 18 exchange rates at a quarterly and monthly frequency and argued that there appeared to be evidence that the forecasting performance of the MS model was superior. Later on, Marsh (2000),
using MS models for three daily exchange rate currencies, investigated their forecasting profitability dynamics. Based on the author’s findings, despite the fact that the MS model fitted the exchange rate currencies data very well, its forecasting ability on the profitability of the currencies was rather poor. Caporale and Spagnolo (2004) compared the ability of nonlinear and standard linear models to capture the dynamics of foreign exchange rates in the presence of structural breaks. The researchers argued that an MS model with shifts in the mean and variance was better in capturing the nonlinearities in the exchange rates. Moreover, Frkmella, Macdonald, and Menkhoff (2005) used Markov regime switches for exchange rates and found a non-linear relationship between exchange rates and underlying fundamentals. According to the authors, the key fundamental that determined the regimes turned out to be the interest rate, while the established relationship was stable in several respects.

Furthermore, Cheung and Erlandsson (2005) made use of MS dynamics in dollar-based exchange rates. In their approach, they considered two data frequencies, two sample periods, and various specifications. The results indicated that the quarterly data yielded inconclusive evidence. As for the case of monthly data, unambiguous evidence was found, in the presence of MS dynamics. The authors suggested that data frequency, in addition to sample size, is crucial for determining the number of regimes. Lee and Chen (2006) also used the MS approach by showing that this kind of time series process is consistent with the exchange rate regime. The authors argue that the results show that a higher probability of a central bank’s future interventions raises the rational expectations discrepancy between the exchange rate and its fundamentals, even though the bank does not step in the foreign exchange market during that period. In the same context, Chen (2006) implemented an MS specification of the nominal exchange rate with time-varying transition probabilities, from six developing countries: Indonesia, South Korea, the Philippines, Thailand, Mexico, and Turkey. The results showed that raising nominal interest rates led to a higher probability of switching to a crisis regime. According to the author, the implemented model had multiple equilibria, and under plausible conditions, higher exchange rate volatility is associated with higher interest rates.

Moreover, Walil, Chaker, Masood, and Fry (2011) employed an MS model and investigated the dynamic linkage between stock price volatility and exchange rate changes. The results uncovered two different regimes with the first corresponding to a high mean-low variance regime. Nikolsko-Rzhevskyy and Prodan (2012) modeled the drift using the two-state MS stochastic segmented trend model for monthly exchange rates and showed that long-run predictability declines as the forecasting horizon increases. Last but not least, Basher, Haugb, and Sadorsky (2016) used MS models to investigate the impact of oil shocks on exchange rates for a sample of oil exporting and oil-importing countries. The findings showed that global economic demand shocks affect exchange rates in both oil-exporting and importing countries, though there did not seem to exist any systematic pattern of appreciating and depreciating exchange rates. The results supported the presence of regime-switching for the effects of oil shocks on real exchange rates.

3 METHODOLOGY

3.1 Markov Switching

A MS regression model with $s_t = 1, ..., k$ states has the following general representation:

$$ y_t = \mu_{s_t} + \mathbf{x}_t \mathbf{a} + \mathbf{z}_t \mathbf{b}_{s_t} + \epsilon_{s_t}, s_t = 1, 2, ..., k $$

where $y_t$ is a dependent variable, $\mu_{s_t}$ is a state-dependent intercept, $\mathbf{x}_t$ is a vector of state-independent exogenous variables, $\mathbf{a}$ is a vector of the state-independent coefficients, $\mathbf{z}_t$ is a vector of state-dependent exogenous variables, and $\mathbf{b}_{s_t}$ is a vector of the state-dependent coefficients and $\epsilon_{s_t} \sim \text{IID}(0, \sigma^2_{s_t})$ are the state-dependent error terms, which are characterized by a state-dependent variance. It should be noted that $\mathbf{x}_t$ or $\mathbf{z}_t$ may also contain lags of the dependent variable.

In this specification, the state $s_t$ is not observed, and it follows a Markov chain process. $s_t$ is an irreducible, aperiodic Markov chain starting from its ergodic distribution $\pi = (\pi_1, ..., \pi_k)$ see Hamilton (2008). The probability that $s_t$ equal to $j \in (1, ..., k)$ depends only on the most recent realization, $s_{t-1}$, and is given by:

$$ Pr(s_t = j | s_{t-1} = i) = p_{ij} $$

All possible transitions from one state to the other can be collected in a $k \times k$ transition matrix:

$$ \mathbf{P} = \begin{pmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{pmatrix} $$

which governs the evolution of the Markov-chain. All elements of $\mathbf{P}$ are nonnegative and each column sums to 1. See Fruhwirth-Schnatter (2006). The fact that $\sum_{j=1}^{k} p_{ij} = 1$
causes numerical complications. To handle these complications we estimate functions of \( p_{ji} \) and by normalizing by \( p_{ki} \). In particular, we estimate \( q_{ji} \) in:

\[
p_{ji} = \frac{e^{-q_{ji}}}{1 + \sum_{j=1}^{k-1} e^{-q_{ji}}}, j = 1, \ldots, k - 1
\]

and we normalize \( p_{ki} \) by imposing:

\[
p_{ki} = \frac{1}{1 + \sum_{j=1}^{k-1} e^{-q_{ji}}}
\]

### 3.2 Likelihood function

The conditional density of \( y_t \) is given by \( f(y_t/s_t = i, y_{t-1}; \theta) \) for \( i = 1, \ldots, k \). The marginal density of \( y_t \) is obtained by weighting the conditional densities by their respective probabilities. This is written as follows:

\[
f(y_t/\theta) = \sum_{i=1}^{k} f(y_t/s_t = i, y_{t-1}; \theta)Pr(s_t = i; \theta)
\]

Let \( \eta_t \) be a \( k \times 1 \) vector of conditional densities. Constructing the likelihood function requires estimating the probability that \( s_t \) takes on a specific value using the data through time \( t \) and model parameters \( \theta \). Let \( Pr(s_t = i/y_t; \theta) \) denote the conditional probability of observing \( s_t = i \), based on data until time \( t \). Then

\[
Pr(s_t = i/y_{t-1}; \theta) = \frac{f(y_t/s_t = i, y_{t-1}; \theta)Pr(s_t = i; \theta)}{f(y_t/y_{t-1}; \theta)}
\]

where \( f(y_t/y_{t-1}; \theta) \) is the likelihood of \( y_t \) and \( Pr(s_t = i; \theta) \) is the forecasted probability of \( s_t = i \) given the observation until time \( t - 1 \). Then

\[
Pr(s_t = 1/y_{t-1}; \theta) = \sum_{i=1}^{k} Pr(s_t = i/s_{t-1} = j, y_{t-1}; \theta)
\]

Let \( \xi_{t/t} \) and \( \xi_{t/t-1} \) denote a \( k \times 1 \) vectors of conditional probabilities \( Pr(s_t = i/y_t; \theta) \) and \( Pr(s_t = i/y_{t-1}; \theta) \) the likelihood is then obtained (Hamilton, 2008) by iterating the following equations:

\[
\xi_{t+1/t} = P\xi_{t/t}
\]

where \( P' \) is the transpose of a \( k \times 1 \) vector of ones and \( P \) is the transition matrix defined earlier. The log-likelihood function is obtained as:

\[
L(\theta) = \sum_{i=1}^{T} \log(f(y_t/y_{t-1}; \theta))
\]

where

\[
f(y_t/y_{t-1}; \theta) = P'(\xi_{t-1/t} \otimes \eta_t)
\]

In the next section, we apply the aforementioned methodology and derive the maximum Likelihood estimates empirically.

### 3.3 Spectral causality

Spectral causality (Breitung and Calderon, 2006) is very useful if causal links between variables change according to frequency (Tastan, 2015). Granger (1969), Geweke (1982), Hosoya (1991), and Breitung and Candelaon (2006) developed a Granger causality test in the frequency domain. The test can be used to determine whether a particular component of the “cause” variable at frequency \( \omega \) is useful in predicting the component of the “effect” variable at the same frequency, one period ahead.

Let \( Y_t = (x_t, y_t)' \) be a covariance-stationary vector time series represented by a finite-order vector autoregressive model—VAR(p).

\[
\Theta(L)Y_t = \epsilon_t
\]

where \( \Theta(L) = I_2 - \Theta_1 L - \Theta_2 L^2 - \ldots - \Theta_p L^p \) a \( 2 \times 2 \) lag polynomial with backshift operator \( Y_t L^i = Y_{t-i} \). \( I_2 \) is the identity matrix; \( \Theta_i, \ i = 1, 2, \ldots, p \) is a \( 2 \times 2 \) coefficient matrix associated with lag \( i \) and \( \epsilon_t = (\epsilon_{t1}, \ epsilon_{t2})' \) denotes a vector white-noise process with \( E(\epsilon_t) = 0 \) and positive-definite covariance matrix \( \Sigma = E(\epsilon_t \epsilon_t') \). By applying Cholesky factorization, \( GG' = \Sigma^{-1} \), \( G \) being a lower-triangular matrix, we have a moving average representation of the system in Equation (13):

\[
\begin{pmatrix} x_t \\ y_t \end{pmatrix} = \Phi(L)\epsilon_t = \begin{pmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{pmatrix} \begin{pmatrix} \epsilon_{t1} \\ \epsilon_{t2} \end{pmatrix} = \Psi(L)\eta_t
\]
where \( \eta_t = Ge_t, \ E(\eta_t) = I, \ \Phi(L) = \Theta(L)^{-1} \) and \( \Psi(L) = \Phi(L)G^{-1} \).

Applying Fourier transformation of the moving average polynomial terms, we rewrite the spectral density of \( x_t \) as:

\[
f_x(\omega) = \frac{1}{2\pi} \left( |\Psi_{11}(e^{-i\omega})|^2 + |\Psi_{12}(e^{-i\omega})|^2 \right)
\]

Geweke's measure of linear feedback from \( y_t \) to \( x_t \) at frequency \( \omega \) (Geweke, 1982) is defined by:

\[
M_{y-x}(\omega) = \log \left( \frac{2|f_x(\omega)|}{|\Psi_{11}(e^{-i\omega})|^2} \right) = \log \left( 1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2} \right)
\]

If \( |\Psi_{12}(e^{-i\omega})|^2 = 0 \), then \( M_{y-x}(\omega) = 0 \). In this case, \( y_t \) does not Granger cause \( x_t \) at frequency \( \omega \) if the following condition is satisfied:

\[
|\Theta_{12}(e^{-i\omega})| = \left| \sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) - \sum_{k=1}^{p} \theta_{12,k} \sin(k\omega) i \right| = 0
\]

\( \theta_{12,k} \) is the (1,2)-element of \( \Theta_k \). In this case, the necessary and sufficient conditions for \( |\Theta_{12}(e^{-i\omega})| \) are:

\[
\sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) = 0
\]

\[
\sum_{k=1}^{p} \theta_{12,k} \sin(k\omega) i = 0
\]

Breitung and Candelon (2006) wrote the equation for \( x_t \) in the VAR(p) system:

\[
x_t = c_1 + a_1 x_{t-1} + ... + a_p x_{t-p} + b_1 y_{t-1} + ... + b_p y_{t-p} + \epsilon_{1t}
\]

where \( a_j = \theta_{11,j} \) and \( b_j = \theta_{12,j} \). The null hypothesis is equivalent to:

\[
H_0 : R(\omega)b = 0
\]

where \( b = (b_1, ..., b_p)' \) and \( R(\omega) \) is a 2Xp restriction matrix:

\[
R(\omega) = \begin{bmatrix}
\cos(\omega) & \cos(2\omega) & ... & \cos(2\omega) \\
\sin(\omega) & \sin(2\omega) & ... & \sin(2\omega)
\end{bmatrix}
\]

Due to the fact that there are linear restrictions, the usual Wald statistic can be used. Let \( \gamma = [c_1, a_1, ..., a_p, b_1, ..., b_p]' \) be \( (2p + 1)X1 \) vector of parameters, and let \( V \) be a qXq covariance matrix from the unrestricted regression (14). The Wald statistic is the following:

\[
W = (Q')^{-1}(Q')\tilde{X}_2^2
\]

where \( Q \) is 2Xq restriction matrix:

\[
Q = \begin{bmatrix}
0_{2X(p+1)} & R(\omega)
\end{bmatrix}
\]

To prevent indirect causality, we can extend the framework to the case of additional variables. In that case, the frequency test is computed on these variables (Tastan, 2015). A way of conditioning is to include lagged values of additional variables in the regression test (Geweke, 1984). For simplicity, assume that there is only one additional variable, \( z_t \). Testing the null hypothesis, \( H_0 : M_{y-x}(\omega) = 0 \), we then can run the following regression:

\[
x_t = c_1 + \sum_{j=1}^{p} a_j x_{t-j} + \sum_{j=1}^{p} b_j y_{t-j} + \sum_{j=1}^{p} d_j z_{t-j} + \epsilon_t
\]

We can then apply the testing procedure on the parameters of lagged \( y_t \). Let \( w_t \) be the projection residuals from the regression of \( z_t \) on \( x_t, x_{t-1}, ..., x_{t-p}, y_t, y_{t-1}, ..., y_{t-p}, \) and \( z_{t-1}, ..., z_{t-p} \). Based on Hosoya (2001), conditional Granger causality can be tested in the following model:

\[
x_t = c_1 + \sum_{j=1}^{p} a_j x_{t-j} + \sum_{j=1}^{p} b_j y_{t-j} + \sum_{j=0}^{p} d_j w_{t-j} + \epsilon_t
\]

Breitung and Candelon (2006), mention in Hosoya's (2001) approach, that the variable \( w_t \) carries the contemporaneous information in \( z_t \), which may not fit well with Granger causality. Furthermore, ignoring the contemporaneous information in \( z_t \), as in Geweke's
The variables in the system are assumed to be I(0) and can be represented by a stationary VAR. If the variables in the system appear to be nonstationary, then we must establish integration and cointegration properties of the data. If each variable is I(1), then the system must be tested for cointegration, for instance using the Johansen test. If the variables are cointegrated, then at least one-directional Granger causality exists between variables. If the system seems to not be cointegrated, then we can estimate a VAR in first-differences and implement Granger causality tests (Tastan, 2015).

Moreover, Toda and Yamamoto (1995) and Dolado and Lutkepohl (1996) suggested that the usual Wald test statistic will be valid for Granger causality on p-lags of a variable in an overfitted VAR \((p + d_{\text{max}})\) model, where \(d_{\text{max}}\) is the highest order of integration in the system. Breitung and Candelon (2006) suggested that this approach can be used for the frequency domain test. Assuming that \(d_{\text{max}} > 0\), we can then write the test regression as:

\[
x_t = c_t + \sum_{j=1}^{p} a_j x_{t-j} + \sum_{j=1}^{p} b_j y_{t-j} + \sum_{k=p+1}^{p+d_{\text{max}}} a_k x_{t-k} + \sum_{k=p+1}^{p+d_{\text{max}}} b_k y_{t-k} + e_t
\]

The null hypothesis of \(M_p \sim \chi^2(\alpha) = 0\) involving only \(b_j, j = 1, ..., p\) can be tested using the Wald statistic. The coefficients on the additional lagged variables are not included in the computation of the Wald statistic. For a bivariate system with I(1) variables, the optimal lag order is chosen by a data-dependent information criterion, such as the Akaike information criterion (AIC). Then, we fit a VAR(p) model conducting the Granger causality test using p lags.

4 | EMPIRICAL RESULTS

4.1 | Data and variables

The exchange rate data used in our analysis were the exchange rates of the foreign country and the USA dollar. These currencies are the Australian dollar (AUD), the Swiss Franc (CHF), the euro (EUR), the British pound or sterling (GBP), the Japanese yen (JPY), and the Hong Kong dollar (HKD). Moreover, we included in our analysis the S&P500, the crude-oil, and the gold commodities. The aforementioned exchange rates and the S&P500 were downloaded from https://www.histdata.com/download-free-forex-data/ and were in minute frequency. These were transformed into realized volatility of daily frequency, as follows:

The realized variance of a variable \(X\) is measured as:

\[
RV_X = \sum_{t=1}^{T} \ln(X_{t+1}) - \ln(X_t)
\]

where \(T\) is the number of minute averages for each day.

The gold and crude-oil commodities were downloaded in daily format from: https://finance.yahoo.com/, and the Covid-19 data we used in the present paper, were the confirmed cases and the deaths, as found in https://github.com/CSSEGISandData/COVID-19.

The whole sample is divided into two sub-samples that capture the pre- and the actual Covid-19 era, per se. The stochastic properties for the two sub-sample periods regarding the time series data employed in the analysis are compactly presented in Table 1 and Table 2.

4.2 | Result analysis

For the two sub-samples, we test for spectral non-causality using the Breitung and Calderon (2006) methodology described earlier. To consistently model the non-causality equation for the pre-Covid-19 era, we make use of all the exchange rate variables and the daily realized volatilities, as well as the returns of S&P 500, crude oil and gold. Before proceeding, we examine the stochastic properties of our time series by testing against the existence of unit roots, using the Phillips–Perron unit root test. We rejected the null hypothesis of a unit root for all the time series, so our data are considered to be integrated of zero degree, that is, I(0).

To a priori avoid any collinearity trap we estimate the correlation matrix among the variables for the two sub-sample periods, see Tables 3 and 4.

Based on the correlations reported in Table 3, the returns of the euro exchange rate to dollar appear to have a high correlation with its intraday realized volatility, whereas in the actual Covid-19 era, there is a high correlation between the returns of the CHF exchange rate to dollar.

The lag structure for spectral non-causality tests in the pre-Covid-19 era are presented in Table 5 through the relevant information criteria, that is, final prediction error (FPE), Hannan–Quinn (HQIC), and Schwartz–Bayes (SBIC) information criteria.

Based on Table 5, in our spectral causality investigation, all the variables should enter with up to one lag. The results of the spectral non-causality tests, for the pre-Covid-19 era, on the evolution of the returns on the euro exchange rate are presented in Figure 1.
Based on the results presented in Figure 1, the evolution of the returns of the euro exchange rate is statistically significantly affected by the realized volatilities of the exchange rate of the euro, GB pound, and the HK dollar, as well as by the returns of HK dollar, JP yen, GB pound, crude oil, and gold. Table 6 presents the frequency ranges for the causalities as well as the respective time range in days.

According to Table 6, the realized volatility of the euro exchange rate, the realized volatility of the GB

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**Table 1** Summary statistics, pre-Covid-19 era

| Variables            | Obs | Mean | Std. Dev. | Min | Max | p1 | p99 | Skew. | Kurt. |
|----------------------|-----|------|-----------|-----|-----|----|-----|-------|-------|
| Realized volatility AUD | 95  | 0    | 0         | 0   | 0   | 0  | 0   | .259  | 3.482 |
| Realized volatility CHF | 95  | 0    | 0         | 0   | 0   | 0  | 0   | −.258 | 2.864 |
| Realized volatility EUR | 95  | 0    | 0         | 0   | 0   | 0  | 0   | −.141 | 2.618 |
| Realized volatility GBP | 95  | 0    | 0         | 0   | 0   | 0  | 0   | .738  | 4.397 |
| Realized volatility HKD | 95  | 0    | 0         | 0   | 0   | 0  | 0   | −.429 | 4.888 |
| Realized volatility JPY | 95  | 0    | 0         | 0   | 0   | 0  | 0   | .316  | 3.523 |
| Realized volatility S&P500 | 95  | 0    | 0         | 0   | 0   | 0  | 0   | −.386 | 3.998 |
| CHF returns          | 94  | 0    | .002      | −.007| .004| −.007| .004| −.589| 2.892 |
| EUR returns          | 94  | 0    | .002      | −.005| .005| −.005| .005| .122 | 2.671 |
| HKD returns          | 94  | 0    | 0         | −.002| .001| −.002| .001| −1.22| 5.497 |
| JPY returns          | 94  | −.028| .272      | −2.635| .005| −2.635| .005| −9.539| 91.999|
| S&P500 returns       | 94  | .001 | .005      | −.02 | .014| −.02 | .014| −.923| 6.831 |
| Crude oil returns    | 94  | .001 | .022      | −.058| .137| −.058| .137| 2.209| 16.677|
| Gold returns         | 94  | 0    | .007      | −.023| .018| −.023| .018| −.667| 4.304 |
| AUD returns          | 94  | 0    | .003      | −.009| .01 | −.009| .01 | .114 | 3.141 |
| GBP returns          | 94  | .001 | .005      | −.013| .019| −.013| .019| .68  | 5.593 |

**Table 2** Summary statistics, actual Covid-19 era

| Variables            | Obs | Mean | Std. Dev. | Min  | Max  | p1   | p99  | Skew. | Kurt. |
|----------------------|-----|------|-----------|------|------|------|------|-------|-------|
| Realized volatility AUD | 66  | 0    | 0         | 0    | 0    | 0    | 0    | −1.193| 9.807 |
| Realized volatility CHF | 66  | 0    | 0         | 0    | 0    | 0    | 0    | −1.396| 9.356 |
| Realized volatility EUR | 66  | 0    | 0         | 0    | 0    | 0    | 0    | .623  | 6.256 |
| Realized volatility GBP | 66  | 0    | 0         | 0    | 0    | 0    | 0    | −1.251| 8.672 |
| Realized volatility HKD | 66  | 0    | 0         | 0    | 0    | 0    | 0    | −1.396| 10.657|
| Realized volatility JPY | 66  | 0    | 0         | 0    | 0    | 0    | 0    | −1.396| 10.657|
| Realized volatility S&P500 | 66  | 0    | 0         | −.002| 0    | −.002| 0    | −7.728| 61.79 |
| CHF returns          | 66  | 0    | .005      | −.012| .014| −.012| .014| .116  | 4.067 |
| EUR returns          | 66  | 0    | .005      | −.016| .013| −.016| .013| −.297 | 4.028 |
| HKD returns          | 66  | 0    | 0         | −.001| .001| −.001| .001| .24   | 4.338 |
| JPY returns          | 66  | 0    | 0         | −.001| .001| −.001| .001| .24   | 4.338 |
| S&P500 returns       | 66  | −.003| .025      | −.093| .057| −.093| .057| −1.048| 5.893 |
| Crude oil returns    | 66  | −.014| .092      | −.344| .238| −.344| .238| −.742 | 7.004 |
| Gold returns         | 66  | .002 | .02       | −.049| .074| −.049| .074| .478  | 5.543 |
| AUD returns          | 66  | −.001| .009      | −.033| .021| −.033| .021| −.571 | 4.867 |
| GBP returns          | 66  | −.001| .008      | −.031| .019| −.031| .019| −.559 | 5.522 |
| Daily confirmed cases | 65  | 24,535.31| 41,487.45| 99 | 249,184| 99 | 249,184| 2.971| 14.711|
| Daily deaths         | 65  | 1,468.277| 2,735.951| 1  | 15,778| 1  | 15,778| 2.881| 13.236|
**TABLE 3**  Correlation coefficients, pre-Covid-19 era

| Variables                        | (1) | (2)   | (3)  | (4) | (5)  | (6)  | (7)  | (8)  | (9)  | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
|----------------------------------|-----|-------|------|-----|------|------|------|------|------|------|------|------|------|------|------|------|
| (1) Realized volatility AUD      | 1.000 |       |      |     |      |      |      |      |      |      |      |      |      |      |      |      |
| (2) Realized volatility CHF      | −0.365 | 1.000 |      |     |      |      |      |      |      |      |      |      |      |      |      |      |
| (3) Realized volatility EUR      | 0.644 | −0.609 | 1.000 |     |      |      |      |      |      |      |      |      |      |      |      |      |
| (4) Realized volatility GBP      | 0.455 | −0.168 | 0.589 | 1.000 |      |      |      |      |      |      |      |      |      |      |      |      |
| (5) Realized volatility HKD      | −0.007 | −0.052 | 0.031 | 0.095 | 1.000 |      |      |      |      |      |      |      |      |      |      |      |
| (6) Realized volatility JPY      | 0.170 | 0.311 | 0.023 | 0.288 | −0.032 | 1.000 |      |      |      |      |      |      |      |      |      |      |
| (7) Realized volatility S&P500   | 0.217 | 0.205 | −0.027 | 0.241 | −0.178 | 0.512 | 1.000 |      |      |      |      |      |      |      |      |      |
| (8) CHF returns                  | −0.294 | 0.800 | −0.518 | −0.233 | −0.037 | 0.305 | 0.095 | 1.000 |      |      |      |      |      |      |      |      |
| (9) EUR returns                  | 0.515 | −0.552 | 0.777 | 0.555 | −0.004 | −0.115 | −0.017 | −0.664 | 1.000 |      |      |      |      |      |      |      |
| (10) HKD returns                 | −0.116 | 0.003 | −0.153 | −0.040 | 0.634 | −0.079 | −0.132 | 0.025 | −0.100 | 1.000 |      |      |      |      |      |      |
| (11) JPY returns                 | 0.141 | −0.015 | 0.096 | 0.112 | 0.137 | 0.045 | 0.040 | −0.156 | 0.152 | −0.067 | 1.000 |      |      |      |      |      |
| (12) S&P500 returns              | 0.114 | 0.059 | −0.026 | 0.165 | −0.116 | 0.535 | 0.631 | 0.170 | 0.013 | −0.120 | −0.127 | 1.000 |      |      |      |
| (13) Crude oil returns           | −0.097 | 0.053 | −0.129 | −0.010 | −0.188 | 0.254 | 0.176 | 0.038 | −0.127 | −0.185 | −0.005 | 0.038 | 1.000 |      |      |
| (14) Gold returns                | −0.041 | −0.343 | 0.204 | −0.129 | −0.120 | −0.514 | −0.228 | −0.334 | 0.177 | −0.119 | −0.049 | −0.368 | 0.101 | 1.000 |      |
| (15) AUD returns                 | 0.688 | −0.264 | 0.395 | 0.396 | −0.120 | 0.054 | 0.186 | −0.350 | 0.572 | −0.120 | 0.132 | 0.166 | 0.036 | −0.043 | 1.000 |
| (16) GBP returns                 | 0.245 | −0.214 | 0.397 | 0.779 | 0.030 | 0.133 | 0.184 | −0.244 | 0.589 | −0.021 | 0.068 | 0.281 | 0.072 | −0.062 | 0.422 | 1.000 |
### Table 4: Correlation coefficients, actual Covid-19 era

| Variables          | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   | (7)   | (8)   | (9)   | (10)  | (11)  | (12)  | (13)  | (14)  | (15)  | (16)  | (17)  | (18)  |
|--------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| (1) Realized volatility AUD | 1.000 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| (2) Realized volatility CHF  | −0.038 | 1.000 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| (3) Realized volatility EUR  | 0.104 | −0.937 | 1.000 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| (4) Realized volatility GBP  | 0.680 | −0.560 | 0.598 | 1.000 |       |       |       |       |       |       |       |       |       |       |       |       |       |       |
| (5) Realized volatility HKD  | −0.080 | 0.254 | −0.313 | −0.163 | 1.000 |       |       |       |       |       |       |       |       |       |       |       |       |       |
| (6) Realized volatility JPY  | −0.080 | 0.254 | −0.313 | −0.163 | 1.000 | 1.000 |       |       |       |       |       |       |       |       |       |       |       |       |
| (7) Realized volatility S&P500 | 0.092 | 0.111 | −0.193 | −0.180 | 0.052 | 0.052 | 1.000 |       |       |       |       |       |       |       |       |       |       |       |
| (8) CHF returns            | −0.159 | 0.649 | −0.657 | −0.444 | −0.002 | −0.002 | 0.043 | 1.000 |       |       |       |       |       |       |       |       |       |       |
| (9) EUR returns            | 0.208 | −0.602 | 0.673 | 0.431 | −0.054 | −0.054 | −0.013 | −0.957 | 1.000 |       |       |       |       |       |       |       |       |       |
| (10) HKD returns           | −0.120 | 0.064 | −0.066 | −0.147 | 0.653 | 0.653 | 0.186 | −0.003 | −0.039 | 1.000 |       |       |       |       |       |       |       |       |
| (11) JPY returns           | −0.120 | 0.064 | −0.066 | −0.147 | 0.653 | 0.653 | 0.186 | −0.003 | −0.039 | 1.000 | 1.000 |       |       |       |       |       |       |       |
| (12) S&P500 returns        | 0.479 | 0.039 | −0.020 | 0.305 | −0.219 | −0.219 | 0.016 | −0.007 | 0.122 | −0.363 | −0.363 | 1.000 |       |       |       |       |       |       |
| (13) Crude oil returns     | 0.075 | 0.368 | −0.304 | −0.118 | 0.177 | 0.177 | 0.133 | 0.000 | 0.047 | 0.086 | 0.086 | 0.150 | 1.000 |       |       |       |       |       |
| (14) Gold returns          | 0.073 | −0.042 | −0.012 | −0.027 | 0.356 | 0.356 | 0.307 | −0.208 | 0.198 | 0.209 | 0.209 | 0.081 | 0.147 | 1.000 |       |       |       |       |
| (15) AUD returns           | 0.627 | −0.155 | 0.197 | 0.515 | −0.035 | −0.035 | 0.201 | −0.491 | 0.563 | −0.187 | −0.187 | 0.657 | 0.294 | 0.308 | 1.000 |       |       |
| (16) GBP returns           | 0.406 | −0.398 | 0.377 | 0.660 | −0.013 | −0.013 | 0.154 | −0.678 | 0.666 | −0.136 | −0.136 | 0.377 | 0.168 | 0.194 | 0.789 | 1.000 |       |
sub-samples. An interesting finding here is the fact that modeled with the use of fewer causal variables for both state (1), whereas the high volatility state (2) can be are able to capture a large part of the variability of the returns of the euro exchange rates. Most causal variables causality tests have a statistically significant effect on the majority of the causal variables dictated by the spectral high and low volatility states for both sub-samples the valid hypothesis. In addition, we witness that across the states, which implies that the two-state specification is a section results, the volatility between the two states, that is, the duration is less than 7 days. Nonetheless, these small durations could play a significant role in the duration of the high/low volatile periods of the euro.

Next, we turn to the spectral causalities regarding the Covid-19 era. Figure 2, presents the results. Based on Figure 2, the evolution of the returns on the euro exchange rate in the Covid-19 era is statistically significantly affected by the intra-day realized volatility of the AU dollar and S&P 500, as well as by the returns of the GB pound, crude oil, and gold. Table 7 presents the causal frequencies as well as the respective time ranges. According to Table 7, it is worth noticing that the returns of crude oil and gold as well as the realized volatility of S&P500 cause the evolution of the returns on the euro exchange rate, for almost the entire sub-sample period. On the other hand, the causal effect of the GB pound and the AU dollar realized volatility on the returns of the euro exchange rate is rather limited since its duration is less than 7 days.

We then turn to the MS estimation results, regarding the effect of all the causal variables in each period on the returns of the euro exchange rate for two states. According to Table 8, which summarizes the estimation results, the volatility between the two states, that is, the Insigma variable, is statistically significant in both states, which implies that the two-state specification is a valid hypothesis. In addition, we witness that across the high and low volatility states for both sub-samples the majority of the causal variables dictated by the spectral causality tests have a statistically significant effect on the returns of the euro exchange rates. Most causal variables are able to capture a large part of the variability of the returns on the euro exchange rate in the low volatility state (1), whereas the high volatility state (2) can be modeled with the use of fewer causal variables for both sub-samples. An interesting finding here is the fact that state independent variables that capture the impact of Covid-19, namely the accumulated number of daily deaths as well as the accumulated number of daily cases, have a statistically significant effect on the returns of the euro exchange rates.

Additionally, based on the estimation results, we can obtain the expected duration of each volatility state in the pre- and the actual Covid-19 era in Table 9. Based on our findings, in both sub-sample periods, the low volatility state on the returns of the euro to dollar exchange rate has a smaller duration in both sub-sample periods. It is worth noticing though, that based on the 95% confidence intervals, the high volatility state has a statistically significantly increased duration, compared with the low volatility state in the Covid-19 era, whereas this duration has almost tripled compared with the pre-Covid-19 era.

The transition probabilities across the two volatility states for each sub-sample are presented in Table 10. According to our findings, in the pre-Covid-19 era, the most probable switch is from the low to the high volatility state, whereas staying at the high volatility state when the returns on the euro exchange rate are in the high volatility state is approximately equally probable. On the other hand, in the Covid-19 era, the predominant probabilities are the ones that lead to the high volatility states irrespectively of the current state. The probability for the returns on the euro exchange rate to move to a low volatility state, when the current state is characterized by high volatility is less than 20%.

The overall findings of the dynamic MS model employed are supported by the excellent fitting properties of our model, both for the returns of the euro exchange rate to the dollar as well as for the actual euro to dollar exchange rate, presented in Figure 3.

### TABLE 5 Optimal lag length

| Lags | FPE    | HQIC   | SBIC   |
|------|--------|--------|--------|
| 1    | 7.1e-126 | −285.355 | −281.112 |
| 2    | 4.1e-125 | −281.246 | −272.760 |
| 3    | 1.1e-124 | −279.904 | −266.175 |
| 4    | 6.1e-125 | −280.273 | −263.300 |

#### DISCUSSION AND POLICY IMPLICATIONS

The literature on exchange rate dynamics hypothesizes that exchange rates often exhibit different states, based on their volatility dynamics (Schnabl & Hillebrand, 2006). These different volatility states are attributed to either direct monetary policies implemented by the central banks to regulate their currency circulation or to trends and movements of key financial indices, such as stock exchange indices, commodity indices, and so on, as well as to spillover effects across currencies.

In this paper, using daily data for dominant currencies and financial indices we modeled in the pre- and the actual Covid-19 era, the volatility states of the euro exchange rate to dollar through dynamic MS estimations.
In this context, for uncovering the causal determinants of the returns on the euro exchange rate for the two periods, we made use of spectral Granger (non-)causality tests. Based on our findings, in the pre-Covid-19 era, the returns on the euro exchange rates are statistically significantly caused for almost the whole era from the intra-day
realized volatility of the euro to dollar exchange rate, as well as from the returns on the GB pound. The fact that intra-day realized volatility of the euro exchange rate causes significantly the returns on the euro to dollar could be attributed to arbitrage conditions in the sense that foreign currency traders try to make profits by selling or buying options when expected volatility rises above or below what is implied in currency option premiums (Clarida, Davis, & Pedersen, 2009). In the same context, the causal effect of the GB pounds returns on the euro returns could be attributed to the fact that the two currencies are closely related in the sense that the Bank of England targeted in politics (Janjusevic & Chegeni, 2020) to maintain a relatively steady exchange rate with the euro to facilitate the overall procedures that will follow the Brexit decision. Another interesting finding is that the returns on the euro exchange rate are caused by the returns of the HKD. This, in turn, could be attributed to the fact that the price of HKD remains pegged at a certain range to the US dollar, by the Central Bank of Hong Kong, to exploit the overall trading and financial international linkages between the Hong-Kong hub and the rest of the world.

The Granger spectral causality analysis for the actual Covid-19 era offered some interesting findings, compared to the pre-Covid-19 era regarding the returns of the euro exchange rate. Firstly, in the Covid-19 era, the evolution of the returns on the euro exchange rate are caused, for almost the entire subsample, by the realized volatility of S&P500, which did not have any causal relationship in the pre-Covid-19 era. This implies that, in the actual Covid-19 era, traders and investors try to explore the increased volatility, induced by the pandemic, in various financial markets, to minimize their expected losses. In other words, traders and investors try to benefit from the volatile environment by shorting large amounts in different financial markets, that is, exchange rate market, stock market, and so on (Neha, 2017).

Moreover, in the actual Covid-19 era, the evolution of the returns on the euro exchange rate is caused by the returns on gold and the returns on crude oil prices, for almost the entire subsample. In contrast, these causal effects were limited to less than 3 days in the pre-Covid-19 era. This significant causal differentiation between the two eras could be attributed to the fact that investors and traders in the Covid-19 era, turned to the “safe heaven” investment of gold, leaving their position from the European financial markets, a movement that was moderated by the ECB’s announcement, regarding the measures to mitigate the adverse consequences of the Covid-19 pandemic in EU the economies (Nuno, 2020). As far as crude oil prices are concerned, their causal relationship with the returns on the euro exchange rate could be attributed to the substantially decreased demanded quantities for oil from the EU, during the Covid-19 era, due to the “lockdowns” implemented in the majority of EU economies (Mzoughi, Urom, Uddin, & Guesmi, 2020).

Turning to the MS analysis in the two sub-samples of our investigation, the most striking finding is that the duration of the high volatility state in the actual Covid-19 era has doubled, from almost 3 to approximately 6 days, compared to the pre-Covid-19 era. This fact gives credit to the view that the Covid-19 pandemic has substantially changed the dynamics in many exchange rate markets globally (Bakar & Rosbi, 2020). Based on our findings, the predominant probability in the Covid-19 era is the probability that the returns of the euro exchange rate will remain at a high volatility state. It is worth noticing, that based on the analysis between the two eras, the high volatility state in the actual Covid-19 era is characterized by a statistically significant higher range of volatility compared to the pre-Covid-19 era.

Finally, another important finding of our analysis is that, for both eras, the high volatility state is modeled with fewer statistically significant variables than the respective low volatility state. This, in turn, gives credit to the view that in turbulent times, non-fundamental variables like investors’ herding behaviour could play a significant role in capturing the volatility movements in key financial indicators. In this context, the statistically

| Causal variables     | Frequency range $\omega$ (in rads) | Time range (in days) |
|----------------------|-------------------------------------|----------------------|
| Realized volatility EUR | 0 - 3.14                           | 2.00 - 96            |
| Realized volatility GBP | 2.01 - 3.14                         | 0.83 - 7.96          |
| Realized volatility HKD | 0.25 - 3.14                         | 2.00 - 25.12         |
| JPY returns           | 1.1 - 2.48                           | 2.53 - 5.71          |
| GBP returns           | 0 - 0.83                            | 7.57 - 96            |
| Crude oil returns     | 1.49 - 2.17                          | 2.89 - 4.21          |
| Gold returns          | 1.99 - 3.14                          | 2.00 - 3.16          |
FIGURE 2  Breitung and Calderon spectral non-causality tests, actual Covid-19 era [Colour figure can be viewed at wileyonlinelibrary.com]
significant negative effect of the accumulated number of deaths induced by the SARS-COV-2 virus on the return of the euro exchange rate captures the fear of investors who realize that the pandemic has an actual cost on human life, and thus, abandon their long-term investment positions on exchange rates and look for “safe heaven” investments to minimize their long-term losses.

On the other hand, the positive and statistically significant effect of the accumulated number of confirmed cases caused by the pandemic captures the opportunistic behaviour of investors and traders who try to exploit the volatility jumps to maximize their short-run profits.

Taking into consideration, on the one hand, the globalization and financial interaction concerning both economies and enterprises, as well as, on the other hand, the high volatility of the euro to dollar exchange rate in the Covid-19 era, it is clear that measures are particularly important and should be implemented in this regard, to minimize the relevant risks which arise due to the aforementioned volatility. There are many policy measures for dealing with the impact of the Covid-19 pandemic, among which is the foreign exchange hedge (FOREX hedge), which is a method used by companies to eliminate (or hedge) their so-called foreign exchange risks, resulting from transactions in foreign currencies, by transferring the relevant risk to a business that carries the risk, for example, a bank. In this context, taking into account the aforementioned volatility of the euro to dollar exchange rate during the Covid-19 era, it is even more important for companies to use relevant econometric models to estimate such risks.

In this work, the econometric model that has been developed can be used to examine the fluctuations of the euro to dollar exchange rate in the Covid-19 era that is characterized by high volatility regimes. It can be used for analyzing the determinants of the exchange rate, in a global as well as domestic setting. As we know, financial and currency markets are increasingly vulnerable to the fluctuations in global and local economies in which they are exposed. Hence, the risk analyses need to take into consideration domestic as well as international economic conditions of regions that directly or even indirectly influence the institution’s and the government’s exposure to the exchange rate, without neglecting the crucial role of the recent pandemic.

Analytically, the proposed approach is capable of sufficiently answering one of the fundamental questions of every exchange rate model, which refers to the determinants of the exchange rate, while taking into consideration the recent pandemic. The appropriate model is crucial for policymakers, as it detects the factors that determine the exchange rate so that policy actions can be implemented in time to be effective. For instance, in contrast to monetary policy, where it takes usually a year for interest rates to impact inflation, this relationship is less well understood. For instance, banks have one year to comply with increased capital requirements under the countercyclical framework of Basel III (Basel Committee, 2010). In addition, data are reported with lags and policymakers do not act immediately on developments, but observe trends for some time before changing policies (Bernanke, 2004). This urges the use of models, which take the current global pandemic into consideration, as is the case with the suggested approach.

Our model could substantially aid policymakers worldwide. The validity of this argument lies in the fact that whilst tools and actual policies differ across countries and the financial institution, the key objective of macro-prudential policies, which is the reduction of systemic risk, is universal (e.g., Disyatat, 2010). Hence, one key challenge for policymakers is the identification of the different states in real-time, with particular emphasis on detecting the unsustainably high volatility (and hence risk) regimes that may end up in a financial crisis. Our model offers a solution for policymakers to the aforementioned problem.

### 6 Conclusion

In times of crisis that are characterized by turbulent macroeconomic and financial environments, exchange rates tend to exhibit persistent high volatilities (Walid et al., 2011). The global pandemic, induced by the SARS-COV-2 virus, has significantly changed the day-to-day operations of the business and financial institutions around the world. This, in turn, led central banks around the globe to decrease their overall interest rates and provide stimulus packages to support the real economy. In addition, the world trade chain has been heavily impacted by the Covid-19 pandemic. Therefore, the fundamental determinants of exchange rate regimes have substantially changed during the pandemic.
|                        | Pre Covid-19 era |                      | Actual Covid-19 era |                      | State-independent variables |
|------------------------|------------------|----------------------|---------------------|----------------------|-----------------------------|
|                        | Low volatility   | High volatility      | Prob 1 → 1          | Prob 2 → 1           |                             |
|                        | state (1)        | state (2)            |                     |                      |                             |
|                        |                  |                      |                     |                      |                             |
| GBP returns            | 0.212***         | 0.376***             |                     | −0.0917***           |                             |
|                        | (6.10)           | (9.27)               |                     | (−5.59)             |                             |
| HKD returns            | 0.786            | 0.0441               |                     |                      |                             |
|                        | (1.27)           | (0.17)               |                     |                      |                             |
| JPY returns            | 0.150*           | 0.000673***          |                     |                      |                             |
|                        | (1.71)           | (6.19)               |                     |                      |                             |
| Crude oil returns      | 0.0202*          | −0.0175*             | −0.0393***          | 0.00536              |                             |
|                        | (2.25)           | (−2.00)              | (−47.55)            | (1.23)               |                             |
| Gold returns           | −0.0635*         | 0.0212               | −0.0398***          | 0.0599*              |                             |
|                        | (−2.28)          | (1.43)               | (−11.08)            | (2.30)               |                             |
| Realized volatility    | 1,040.0***       | 609.6***             |                     |                      |                             |
| EUR                    |                  |                      |                     |                      |                             |
|                        | (6.40)           | (4.62)               |                     |                      |                             |
| Realized volatility    | −387.8***        | −86.73               |                     |                      |                             |
| GBP                    |                  |                      |                     |                      |                             |
|                        | (−7.45)          | (−1.58)              |                     |                      |                             |
| Realized volatility    | −112.7           | −386.4               |                     |                      |                             |
| HKD                    |                  |                      |                     |                      |                             |
|                        | (−0.15)          | (−1.07)              |                     |                      |                             |
| AUD returns            |                  |                      | 0.387***            | 0.101                |                             |
|                        |                  |                      | (32.05)             | (0.87)               |                             |
| Realized volatility    | −115.5***        | −95.29*              |                     |                      |                             |
| AUR                    |                  |                      | (−6.71)             | (−2.01)              |                             |
| Realized volatility    | 37.39***         | −4.017***            |                     |                      |                             |
| S&P500                 |                  |                      | (9.50)              | (−7.30)              |                             |
| Deaths                 |                  |                      |                      | 0.000482***         |                             |
|                        |                  |                      |                      | (7.79)               |                             |
| Confirmed cases        | −0.000312***     |                      |                     |                     |                             |
|                        |                  |                      |                     | (−7.56)              |                             |
| Lnsigma                | −7.607***        | −6.974***            | 0.298               | −8.743***            | −5.794***                   |
|                        | (−29.59)         | (−55.72)             | 0.310               | (−38.96)             | (−55.05)                   |
|                        |                  |                      |                     |                      |                             |

Note: t statistics in parentheses.

*p < 0.10, **p < 0.01, ***p < 0.001.
### Table 9 Expected duration of each volatility state

| Expected duration       | Pre- Covid-19 era | Actual Covid-19 era |
|-------------------------|-------------------|---------------------|
|                         | Estimate          | Std error           | 95% CI  | Estimate          | Std error           | 95% CI  |
| Low volatility state (1)| 1.425             | 0.808               | 1.01–18.66 | 1.695             | 0.466               | 1.187–3.586 |
| High volatility state (2)| 3.237             | 1.892               | 1.42–12.73 | 6.073             | 1.934               | 3.404–11.711 |

### Table 10 Transition probabilities across volatility states

| Transition probabilities | Pre- Covid-19 era | Actual Covid-19 era |
|--------------------------|-------------------|---------------------|
|                         | Estimate          | Std error           | 95% CI  | Estimate          | Std error           | 95% CI  |
| Low → low                | 0.298             | 0.398               | 0.010–0.946 | 0.410             | 0.162               | 0.157–0.721 |
| Low → high               | 0.702             | 0.398               | 0.054–0.990 | 0.590             | 0.162               | 0.279–0.843 |
| High → low               | 0.309             | 0.181               | 0.079–0.701 | 0.165             | 0.052               | 0.085–0.294 |
| High → high              | 0.691             | 0.181               | 0.299–0.922 | 0.835             | 0.052               | 0.706–0.915 |

#### Figure 3 Fitting of low volatility state on the euro to dollar returns and on the actual euro to dollar exchange rate.

(A) Low volatility state on the EUR returns, pre-Covid-19 era. (B) Low volatility state on the EUR returns, actual Covid-19 era. (C) Low volatility state on the actual EUR/USD exchange rate, pre-Covid-19 era. (D) Low volatility state on the actual EUR/USD exchange rate, actual Covid-19 era [Colour figure can be viewed at wileyonlinelibrary.com]
In this paper, we analyzed how the Covid-19 pandemic changed the dynamics of the euro to dollar exchange rate. To do so, we made use of spectral non-causality tests to study the determinants of euro to dollar exchange rate, utilizing data that cover the pre-Covid-19 and the actual Covid-19 era per se, by considering the exchange rate movements of other currencies, the stock market index of S&P 500, and the price of crude oil and gold, as well as their realized volatilities. Based on our findings, the Covid-19 pandemic has significantly changed the determinants of the euro to dollar exchange rate.

Furthermore, to investigate the potential shifts in the regimes of the euro to dollar exchange rate because of the pandemic, the present paper formulated a MS model with two regimes, based on the determinants that have been found significant. Based on the paper’s findings, the duration of the high volatility state in the Covid-19 era has doubled, from almost 3 to approximately 6 days, compared to the pre-Covid-19 era, whereas the high volatility state in the Covid-19 era is characterized by statistically significantly higher range of volatility, compared to the pre-Covid-19 era. The present paper is the first, to the best of our knowledge, that investigates the impact of Covid-19 on the exchange rates, using global data on the spread of the pandemic. Clearly, future research on the impact of the recent pandemic on other aspects of the financial and economic activity would be of great interest.

For instance, to further investigate the impact of Covid-19 on the dynamics of exchange rates, future research using data on extending the model to include other currencies, such as the Japanese Yen, the Canadian and Australian dollars, could be done. Also, taking into consideration the fact that the second wave of the recent Covid-19 pandemic is still in progress, further research using an extended dataset to account for the second and any upcoming waves would be relevant. Finally, additional variables of interest could be added to the model, such as the number of successful vaccinations, and so on.

DATA AVAILABILITY STATEMENT
Data available on request from the authors. Data sources for further reading: https://www.histdata.com/download-free-forex-data/; https://finance.yahoo.com/; https://github.com/CSSEGISandData/COVID-19

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ENDNOTES
1 The results of the Phillips–Perron unit root test are available upon request by the authors.

2 Note, that the results for the actual Covid-19 era were similar, and are available upon request by the authors.

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