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Comparing COVID-19 with the GFC: A shockwave analysis of currency markets

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ABSTRACT

I analyze the shockwave effect of the COVID-19 pandemic on currency markets, with a comparison to the global financial crisis (GFC), employing Kapetanios m-break unit root test, investigations of standalone risk measures—downside variance, upside risk, volatility skewness, Gaussian Value at Risk (VaR), historical VaR, modified VaR—and Diebold–Yilmaz volatility spillover analysis. Standalone risk analysis shows that the turmoil in the initial months of COVID-19 was not as severe as that in the GFC. However, examination of co-movements and volatility spillovers illustrates a different scenario. According to the results of the static connectedness measure of Diebold–Yilmaz, the shockwave of the COVID-19 pandemic in the total volatility spillover is about eight times greater than that of the GFC. Among standalone risk measures, the results closest to this finding are obtained from volatility skewness analysis. Additionally, of six foreign exchange rates, the Brazilian real and Turkish lira are the currencies experiencing the greatest increase in received volatility during the GFC and the COVID-19 pandemic, respectively. These findings suggest the severe effect of crises on emerging financial markets.

1. Introduction

Foreign exchange markets are related to trade and transactions of products and services denominated in a foreign currency. Unexpected changes in the cash flows of these operations can hurt one of the counterparties. Since many financial institutions conduct their operations globally, unexpected events and movements in global markets can affect their profitability (Saunders and Cornett, 2011).

Today, most transactions in international markets are hedged against economic exposures through currency derivatives. Any method utilized in hedging strategies should incorporate currency change expectations, since currency changes will eventually cause cash flow fluctuations. The fluctuations in exchange rates can be modeled through various models, such as standard deviation, EWMA, GARCH, and FIGARCH. Based on the projections, financial institutions can create economic capital that can compensate for their losses. One of the models to gauge the extent of exposure is the value at risk (VaR). Especially for international investments, the value calculated in a VaR model should be accompanied by corresponding risk parameters, such as political risk and economic risk (fiscal irresponsibility and monetary instability). Although some of these risk factors are relatively easy to measure and predict, others can be hard to foresee and take precautions against. For example, financial contagion, which has been seen in different crises so far, such as the Asian crisis (1997) and the European sovereign debt crisis (2010–2012), is quite risky but not highly predictable. Financial contagion arises once a financial institution's distress jeopardizes other institutions' health and the financial system. As seen during the

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global financial crisis (GFC) in 2008–2009, the local and global obligations of some banks and insurance companies sparked defaults and ultimately induced a credit crunch in the market (Feinstein, 2017). Kumar and Persaud (2002) put forward three reasons for financial contagion. According to the authors, a devaluated currency can trigger speculative attacks in the reforming equilibrium exchange rate due to the reduced trade competitiveness of other countries. Another reason for contagion can be common external shocks attributed to plummeting commodity prices, as seen in the Latin American debt crisis during the 1980s. The last parameter is related to changes in investors' risk preferences. While some investors are considered risk takers, others can be risk averse or risk neutral. A rapid change in investors' risk appetite can cause significant fluctuations in asset prices. A switch in investors' risk preferences, such as a shift from risk taking to risk aversion, can bring about a collapse in the risky assets' value. The driving force behind this reaction can involve the working area of behavioral finance; hence, I do not elaborate on this discussion here. The shock transmission across markets and countries seen during the GFC was not the only example of financial contagion. To a certain extent, the characteristics of financial contagion can be seen in other market crashes as well, such as Black Monday (1987), the European Exchange Rate Mechanism crisis (1992), the Asian crisis (1997), and the dotcom bubble (2000).

Recently, global markets have been exposed to another version of the contagion phenomenon: the novel coronavirus of 2019 (COVID-19). Although speculation remains on this disease's origin, and conspiracy theories about its inception, such as via bioweapons and laboratory accidents, keep the media and public quite busy, the response of the global economy and financial indexes has been rapid and harsh. This paper aims to contribute to the literature by comparing the shockwave effects of the GFC and the COVID-19 pandemic. The GFC and its spread through financial and economic linkages are thoroughly examined in the literature (Mihaljek, 2009; Acharya and Schnabl, 2010; Coudert et al., 2011; Gunay and Georgievski, 2018). In the propagation of the crisis, the direction of volatility transmission was from the United States to developed and emerging countries, and trade links and capital flows were the main conduits of its spread. However, the GFC's directional framework might not apply to the COVID-19 crisis when the origin of the breakout and type of transmission mechanism are taken into account. Considering this fact, in this study, based on the work of Diebold and Yilmaz (2012), I allow volatilities to be transmitted between emerging and developed economies simultaneously, unlike the study of Otranto (2015), which has a constraint in the flow of volatility and its direction. Second, I compare the crises through a shockwave analysis. The literature indicates that above-trend volatility destabilizes the economy by affecting cash flows and required rate of returns. Minsky (1982) discusses a similar effect for low volatility levels. Therefore, the extent of volatility and its timing is important for policy responses and to cope with future disturbances. In most cases, the inception of volatilities occurs in shockwaves, and predictability, regarding their duration and extent, increases when the causes and driving forces are defined. Therefore, the initial period of market volatility is vital with regard to quantifying its severity and for determining strategies. To that end, in this study, I examine the first three months of both crises, the GFC and the COVID-19 pandemic. Unlike COVID-19, the effects of the GFC were greater and more severe in economies that utilize instruments of structured finance and have high debt ratios, as seen in European Union (EU) countries. However, the recent financial turmoil due to the COVID-19 pandemic has displayed a different image in both its origin and causes. This time, the crisis is not due to structural reasons, since the turbulence is due to social distancing, lockdowns, and healthcare-oriented measures. Since health is common ground for all human beings—and beyond the market structure, financial linkages, or economic model utilized—almost all countries responded to the pandemic with strict emergency measures. None of the economies has been immune to the impact of contagion and the similarity in the driving force of market turbulences allows us to investigate reasons that led to the differing reactions of various markets.

The GFC was a good lesson for the integration of economies and financial systems. It was learned that abusive loan practices and deregulations can be disastrous for an economy, and the financial turmoil can be transmitted through cross-market linkages. Therefore, even though the adequacy of policy responses was not in question in domestic economies, the propagation of the crisis shifted it to a different dimension through contagion effects. Unfortunately, the lessons taken from the GFC and corresponding regulations for a safer economy were not sufficient to prevent the shockwave of COVID-19 in the currency market, since no country has been immune to the negative influence of this type of contagion. Of all these lessons, such as stress tests, new oversight bodies, disclosure rules, and capital adequacy arrangements, maybe the most important experience that applies to this pandemic as well as to the GFC is the relation between illiquidity and bankruptcy. Hence, since the beginning of the current crisis, a series of extraordinary actions have been taken by various governments. Because liquidity injection is an inevitable action to be taken when considering the nature of the pandemic, in regard to this outbreak, this study is not discussing the transparency of the economic systems, reckless lending or lack of regulations, as the pandemic hurt economies mainly due to the lockdowns and social distancing procedures. On the other hand, responses to the pandemic could distort market equilibrium rates in currency markets, when the impact of nationalism- and protectionism-oriented actions taken by governments is considered. For example, US government tariffs are still in effect and negotiations are suspended due to the pandemic. However, as the US and Chinese economies lead global economic growth, escalation of the current problems would not serve either side. For instance, through simulation studies, Li et al. (2018) show that the imposition of tariffs would hurt both the United States and China, while China seems to lose more due to the United States' stronger bargaining power. Based on the lessons of the GFC, an overregulated American economy, trade wars, and the impact of COVID-19 could exacerbate the unprecedented fall in world trade. Therefore, instead of acting alone by ignoring the global equilibrium of the financial system, if countries take the facts into account and work together, the crisis and its risks can be mitigated more rapidly and a strong rebound can become possible. As Blinder (2015) states, a sharp recession can be accompanied by a rapid V-shaped recovery.

The structural differences between the GFC and COVID-19 crises motivated me to compare these two financial crises. Considering the economic integration of countries and the flow of funds in international markets, I believe that the critical variable in measuring tension would be the exchange rates. The currency rates effectively and rapidly incorporate tension in the market and are important not only for domestic supply and demand but also for foreign trade. Fluctuations in the value of home currencies directly impact the economic stability in advanced and emerging economies and are the fundamental reason for today's trade wars. Therefore, I utilize six

currencies that are evenly selected from advanced and emerging economies and employ various tests to examine spillover effects.

2. Literature review

The GFC and the COVID-19 pandemic are mainly analyzed in regard to volatility spillovers and financial contagion phenomena. Even before the COVID-19 pandemic, there was a great deal of interest in contagious effects in the finance literature (Antonakakis et al., 2020, 2018a, 2018b, 2018c; Baele, 2005; Gabauer and Gupta, 2018, 2020; Hong, 2001; Inagaki, 2007; Mukherjee nath and Mishra, 2010; Ng, 2000; Tamakoshi and Hamori, 2016). In one study, Mondria and Quintana-Domeque (2013) test financial contagion in Asian and Latin American markets through alterations in international investors' attention allocation. To that end, they employ data from news stories in the *Financial Times*. The results show the presence of an attention reallocation structure of financial contagion. Hasman and Samartín (2008) analyze the provision of contingent credit lines, which is a mechanism to avoid the spread of a financial crisis. Frexedas and Vayá (2005) employ spatial econometrics to account for the financial contagion experienced in Thailand, Russia, and Brazil. According to their findings, conventional moneylenders are the most persistent channels of contagion in these markets. Dasgupta (2004) explores financial contagion and its influence in the banking sector by modeling contagion as an equilibrium phenomenon. Empirical findings show that the potential contagion risk makes banks unwilling to insure one another against liquidity turbulence, and there is a positive likelihood of contagious bank failures in the unique equilibrium of the economy. Park and Song (2001) explore the presence of financial contagion through correlation analysis during the Asian crisis. The authors state that the Asian crisis did not trigger a crisis in South Korea, while the impact on Taiwan was non-negligible because of issues in rolling over short-term loans to Korean corporations.

Missio and Watzka (2011) analyze whether contagion effects were present during the European sovereign debt crisis, through dynamic conditional correlation (DCC) analysis. Their results indicate the existence of a contagion phenomenon, which appears to have emerged with rating announcements. Van Rijckeghem and Weder (1999) account for financial contagion through shifts in bank lending by employing panel data analysis. Their results for 30 emerging market economies illustrate that common bank lenders are a more robust predictor of contagion than similarities between major economic indicators. Caporale et al. (2009) utilize a minority game approach and employ simulation studies to test contagion phenomena under different scenarios. Their approach sheds light on parameters that can identify contagion effects in the early stages of a financial crisis. To account for contagion effects in the European stock market and distinguish them from interdependence effects during the GFC, Candelon and Tokpavi (2016) propose a kernel-based nonparametric inferential procedure. In addition, Durante et al. (2013) offer a new approach by expanding the study by Durante and Jaworski (2010) to test spatial contagion in financial markets. Based on a comparison between threshold copulas, the model is applied to the links between the Greek stock market and other European equity markets. Elliott et al. (2014) investigate the impact of defaults and failures on further breakdowns in financial markets. The authors show that integration and diversification have different levels of influence on the extent of cascades. Acemoglu et al. (2015) state that, when the extent of connection in financial networks increases, the soundness of financial stability improves. Asongu (2011) examines the influence of political risks on financial contagion in developing economies. According to the results, African stock markets display strong financial linkages, and political risks can play an essential role in the transmission mechanism of market turbulence. Corsetti et al. (2001) develop a new method to test financial contagion. Their results demonstrate that current methods for testing contagion phenomena have drawbacks in terms of the assumption of the variance of country-specific shocks. Salgado et al. (2000) employ a panel probit model to analyze three financial crises from the 1990s to determine the determinants of contagion effects. Their results illustrate that statistically significant parameters in the propagation of crises are a common creditor and reserve adequacy.

The literature on COVID-19 grows very fast. In one study, Zhang et al. (2020) examine systemic and country-specific risks in the global economy. The authors also discuss the potential risks of policy interventions and economic measures implemented during the crisis. Akhtaruzzaman et al. (2020) investigate the financial contagion during the COVID-19 pandemic. The results indicate that stock returns display a significant increment in conditional correlations during the pandemic, and the rise in conditional correlations is significantly higher in financial firms. Bahaj and Reis (2020) examine the swap lines during the pandemic. They find that swap lines have a statistically significant influence on CIP deviations in the auction period. Gunay (2020) studies the effect of the pandemic on stock markets and analyze the conditional correlations in stock index returns of six countries through the DCC-FIGARCH model. Among the countries analyzed, the highest correlations are observed between China and Turkey. While the DCC weakens between 2005 and 2019, following the pandemic, these two stock markets display a 20 % rise in dynamic correlations. Albuquerque et al. (2020) analyze the influence of ratings of environmental and social policies on stock return variability during the pandemic. The results show that high ratings in environmental and social policies lower the stock return volatility in the first quarter of 2020. Utz et al. (2020) discuss the macroeconomic influences of the coronavirus outbreak. The authors state that the pandemic has mainly taken the form of a global recession because of social distancing and job losses. Lahmiri and Bekiros (2020) show that the coronavirus pandemic has caused a shift in the information-sharing network among the financial markets. Haroon and Rizvi (2020) survey public information arrivals' effect during the pandemic on stock markets. Authors find a significant relationship between news outlet and equity market volatility. Corbet et al. (2020a) find some evidence of flight to quality in their analysis, which employs stock markets, gold, and Bitcoin. Liu et al. (2020) calculate the abnormal returns to investigate the coronavirus pandemic's effect on different industries. The results demonstrate positive abnormal returns for pharmaceutical manufacturing, software, and information technology (IT) services. Yarovaya et al. (2020) examine the contagion phenomenon and discuss COVID-19 in a contagion-oriented framework. Goodell (2020) analyses the economic and social influence of COVID-19 in various markets and institutions. Gunay et al. (2020b) investigate the sectoral effect of COVID-19 and the Black Summer bushfires on the Australian stock market. The results show that, while the bushfires had a limited influence on only large firms in the consumer staples and industrials sectors, COVID-19 seems to have affected the real

estate and energy sectors as well. In another sectoral analysis, [Corbet et al. \(2020b\)](#) examine the turmoil in energy-focused corporations' stock returns during the COVID-19 pandemic and the West Texas Intermediate oil futures negative price event of April 20, 2020. The volatility spillover analysis results exhibit significant volatility transmission from oil prices to the energy and coal markets. [Salisu and Akanni \(2020\)](#) introduce a global fear index and illustrate its utilization in stock return predictions in Organisation for Economic Co-operation and Development data. The results show that consideration of an asymmetry effect and of macroeconomic factors improves the performance of the index in forecasting equity market returns. To explore the relation between the Japanese stock market and the yen (JPY), [Narayan et al. \(2020\)](#) employ various econometric analyses and find that the yen's depreciation has led to higher stock returns in the period of the pandemic. Their results show significant differences with the pre-pandemic period. [Dutta et al. \(2020\)](#) state that gold has been a safe haven asset for crude oil markets in the chaotic environment of the COVID-19 pandemic.

3. Methodology: total volatility spillover index

[Diebold and Yilmaz \(2012\)](#) analyze return and volatility spillovers based on a vector autoregressive (VAR) model and focus on variance decompositions. Unlike the model of [Diebold and Yilmaz \(2009\)](#), the model does not need to rely on the Cholesky factor identification of the VAR. Loosely speaking, for each asset i in the model, the authors add the share of its forecast error variance that links to the shocks to asset j ($j \neq i$) and then sum this quantity across all $i = 1, \dots, N$. Consider a covariance stationary N -variable p th-order VAR model such as

$$x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t \quad (1)$$

The moving average demonstration of the model can be written as

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (2)$$

where $A_i = \Phi_1 A_{i-1} + \Phi_2 x_{i-2} + \dots + \Phi_p A_{i-p}$. The moving average coefficients are vital components of the system. To inspect system shocks, [Diebold and Yilmaz \(2012\)](#) use generalized variance decompositions that allow for the assessment of the fraction of the H -step-ahead error variance in predicting x_i due to shocks x_j . The H -step-ahead generalized forecast error variance decomposition, $\theta_{ij}^g(H)$, is calculated as

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A' e_i)} \quad H = 1, 2, \dots, \quad (3)$$

where Σ is the variance matrix for the error vector ε , σ_{jj} is the standard deviation of the error term for the j th equation, A_h is the h -step moving average coefficient matrix, and e_i is the selection vector, with one as the i th element and zero otherwise. The term $\sum_{j=1}^N \theta_{ij}^g(H)$ can be different from one. In this framework, the total volatility spillover index can be written as

$$S^g(H) = \frac{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \theta_{ij}^g(H)} \times 100 \quad (4)$$

where, $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \theta_{ij}^g(H) = N$

4. Empirical analysis

4.1. Data

In empirical section of the study, I investigate the shockwave effects of the COVID-19 pandemic and the GFC on the following six exchange rates: the US dollar/euro (USD/EUR), US dollar/British pound sterling (USD/GBP), US dollar/Japanese yen (USD/JPY), US dollar/Chinese yuan (USD/CNY), US dollar/Brazilian real (USD/BRL), and US dollar/Turkish lira (USD/TRY). Historical exchange rates are obtained from the Thomson Reuters Eikon database. In the determination of the variables, the reasoning is twofold. First, I seek evidence from both developed and emerging markets. Second, related to the map of the pandemic, there are differences in case numbers and the effectiveness of policies in coping with the outbreak. Regarding the first point, I utilize the USD/EUR, USD/GBP, and USD/JPY exchange rates for advanced economies' currencies, and USD/CNY, USD/BRL, and USD/TRY for emerging countries.

The steps taken by governments in developed countries reveal differences, including in their pandemic measures. The responses

and success and failure stories also vary greatly among the selected countries. The measures employed against the crisis enable this analysis to incorporate a policy factor, in tandem with the extent of economic development. For example, the United Kingdom has been criticized for being late in its response to the pandemic, since it was possibly distracted by Brexit. On the other hand, even at the peak of the outbreak, Japan appeared to be a success story. The Japanese government lifted the national state of emergency and has instead focused on clusters of cases, rather than implementing countrywide testing. The extent of exposition differs across EU countries, with each country's reaction being more self-protective, as in putting their needs ahead of that of the wider European community. As for emerging economies, I also select countries that differ in their reactions to and performance against the pandemic. Inevitably, I start with China, since the pandemic originated in the Chinese city of Wuhan. The second and third emerging countries, Turkey and Brazil, differ significantly in their management of the crisis. As discussed in [The Economist \(2020\)](#), Turkey portrays a relative success in coping with the pandemic, even though it is a neighbor of Iran, from which early-case transmissions are associated. Turkey kept its primary workforce ready by ordering only the young and elderly to stay at home and imposed curfews during the weekends and holidays. However, the Brazilian government avoided such steps, and the country has recorded the second-highest number of COVID-19 cases in the world as of June. Another criterion in selecting emerging market currencies, namely, those of Turkey and Brazil, was to utilize countries from the Fragile Five. Even though Turkey has been a success story in its management of the pandemic, its currency has displayed wild volatility and steep depreciation in 2020. The imposition of the central bank's low interest rate policy to stimulate economic growth left the country at risk against attacks on the Turkish lira. On the other hand, the record low international reserves, high current account deficit, and ratio of external debt to the gross domestic product (GDP) has increased the lira's vulnerability and limited the country's options to mitigate the coronavirus' impact. The current status of Turkey's economy demonstrates that not many options are left to support the lira. In addition, Turkey is highly dependent on tourism income in its balance of payments, and expectations in tourism statistics have been disrupted by the pandemic, which, in turn, has increased the weakness of the economy against foreign shocks ([Chadwick, 2019](#)). Similarly, the Brazilian economy is sensitive to changes in market dynamics, especially in oil prices. According to Thomson Reuters Eikon statistics, Brazil is the fifth highest non-OPEC oil-producing country as of June 2020, with an average growth rate in crude oil exports of -16.6 % between March 31 and June 30, 2020. In addition, Brazil has the highest ratios of general gross government debt to the GDP (75.79 %) and of current account deficit to the GDP (-2.7 %) compared to Russia, India, and China; of these economies, the International Monetary Fund's June 2020 projections expect Brazil to undergo the greatest contraction in GDP growth (-9.1 % [IMF, 2020](#)). These statistics indicate that the Brazilian real is also considerably fragile, as discussed for the Turkish lira.

4.2. Results

In empirical section of the study, I employ various tests for the pre-crisis and crisis periods: the [Kapetanios \(2005\)](#) m-break unit-root test, downside variance, upside risk, volatility skewness, Gaussian VaR, historical VaR, modified VaR, and Diebold and Yilmaz's (2012) volatility spillover analysis through the R packages of [Gabauer \(2020\)](#) and [Peterson et al. \(2020\)](#). Each period consists of three months. Accordingly, to split the data into two subsections, I select two reference dates: Lehman Brothers' bankruptcy (September 15, 2008) and the Chinese government's official notification to the World Health Organization of atypical cases of pneumonia (December 31, 2019).

Table 1
Descriptive Statistics for the GFC.

		USD/EUR	USD/GBP	USD/JPY	USD/CNY	USD/BRL	USD/TRY	
GFC Period	Pre-Crisis	Mean	0.0013	0.0013	0.0000	-0.0004	0.0013	-0.0002
		Std. Dev.	0.0064	0.0058	0.0065	0.0076	0.0075	0.0087
		Skewness	0.3915	-0.4310	-0.1722	-0.1640	0.2883	-0.0957
		Kurtosis	3.7242	4.6495	2.9890	3.3933	4.8797	3.5402
		Jarque-Bera	3.0807	9.3812	0.3217	0.7104	10.4700	0.8895
		Probability	0.2143	0.0092	0.8514	0.7010	0.0053	0.6410
	Crisis	Mean	0.0006	0.0024	-0.0027	0.0000	0.0046	0.0035
		Std. Dev.	0.0137	0.0142	0.0156	0.0236	0.0326	0.0246
		Skewness	-0.4802	0.0411	0.2416	-0.2528	-0.2077	0.1576
		Kurtosis	2.7332	2.7360	4.6482	2.6215	2.3423	6.3628
		Jarque-Bera	2.6912	0.2071	7.9901	1.0804	1.6391	30.896
		Probability	0.2604	0.9016	0.0184	0.5826	0.4406	0.0000
	Pre-Crisis	Mean	-0.0004	-0.0011	0.0001	-0.0004	-0.0006	0.0008
		Std. Dev.	0.0027	0.0059	0.0028	0.0020	0.0066	0.0060
Skewness		0.0552	-1.0311	0.2244	-0.8655	0.1906	0.9400	
Kurtosis		2.8835	5.1113	3.5895	5.2182	3.6767	6.6932	
Jarque-Bera		0.0654	22.138	1.3955	20.121	1.5331	43.650	
Probability		0.9678	0.0000	0.4977	0.0000	0.4646	0.0000	
COVID-19 Pandemic	Mean	0.0002	0.0010	-0.0002	0.0003	0.0041	0.0016	
	Std. Dev.	0.0063	0.0103	0.0090	0.0037	0.0122	0.0063	
	Skewness	0.7316	0.2519	0.4269	0.4570	0.3428	-0.0769	
	Kurtosis	5.9450	5.6767	6.2152	4.5134	4.9109	4.8998	
	Jarque-Bera	27.486	18.855	28.128	7.9448	10.476	9.2336	
	Probability	0.0000	0.0001	0.0000	0.0188	0.0053	0.0099	

As a preliminary analysis, I examine the descriptive statistics of the time series. The results are presented in Table 1. In the pre-crisis results for the GFC, the highest average returns are observed for the USD/EUR, USD/GBP, and USD/BRL exchange rates. Although the Turkish lira has a negative return average before the GFC, along with its depreciation against the American dollar, the Turkish lira presents the second-highest return average in the crisis period, after the Brazilian real. According to standard deviation statistics, while all the exchange rates display higher fluctuations in the crisis period, the biggest spike in the variability of the return series is seen for the USD/BRL exchange rate. Although the USD/TRY exhibits the most extraordinary fluctuations in the pre-crisis period, its variability takes second place in the crisis period. The Jarque–Bera test statistic indicates that exchange rates do not display a pattern in terms of a normal distribution: comparison between the pre-crisis and crisis periods shows that, while some of the variables shift from a normal to a skewed distribution, others exhibit the reverse movement. Only the USD/EUR and USD/CNY exchange rates show a Gaussian distribution both before and during the crisis. In contrast to the GFC, the average returns in the COVID-19 pandemic are relatively low in both periods. However, similar behavior is seen in the soaring standard deviations following the two reference events, although the increase during the COVID-19 pandemic is lower than that in the GFC. The average growth in standard deviations for the GFC is 2.88, compared to 2.01 for the COVID-19 pandemic. A similar situation is observed in the distributions of the return series. While some series display a normal distribution, others are skewed and have high kurtosis values, indicating deviations from normality. As seen in the skewness statistics, only the USD/TRY returns exhibit negative skewness during the COVID-19 pandemic. Accordingly, it can be stated that the frequency of positive returns is higher than that of losses in this period. Therefore, the findings regarding the shockwave of COVID-19 indicate that, as of yet, little of the tension and turmoil noted in the media regarding the spread of the pandemic has been

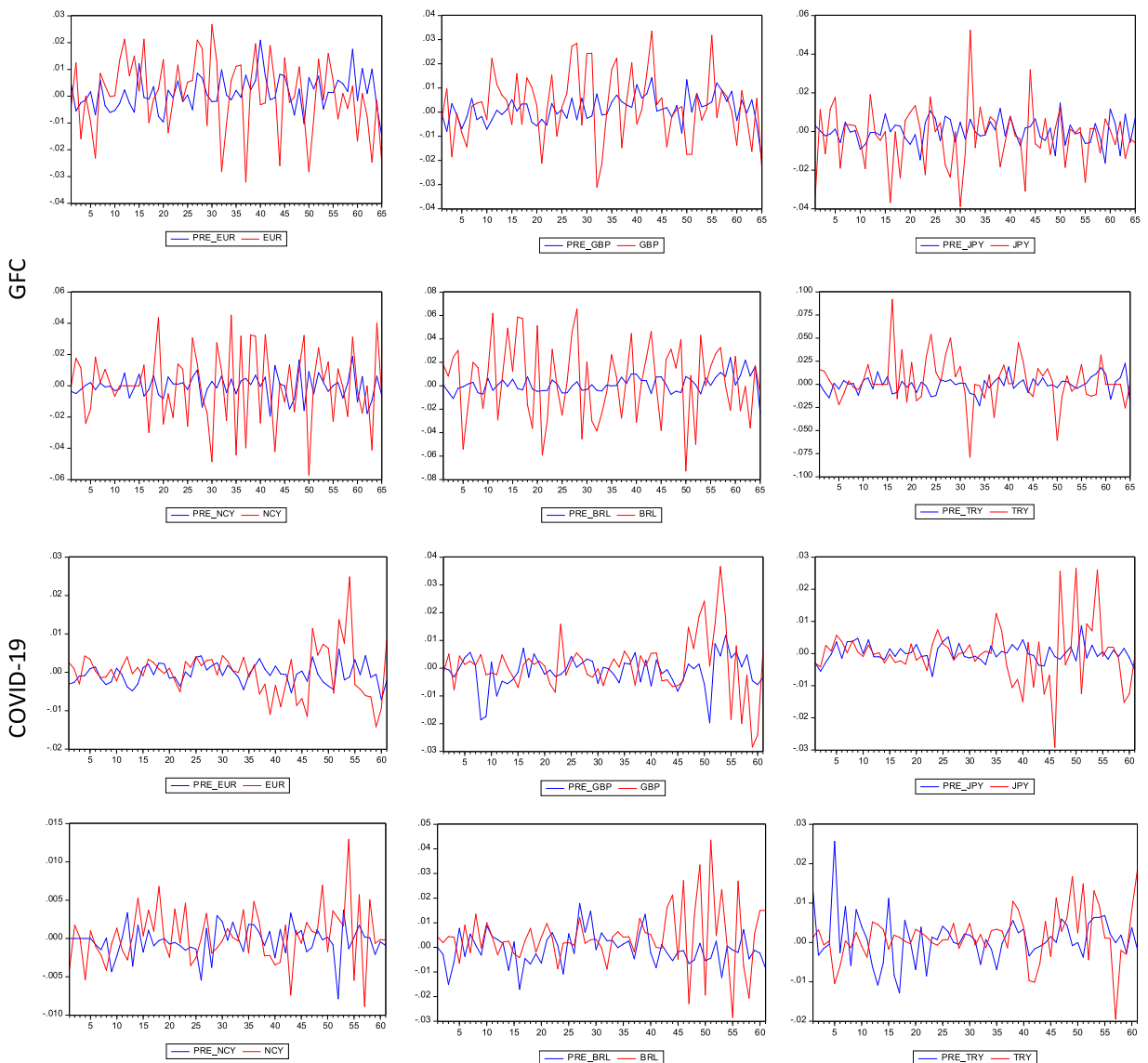


Fig. 1. Exchange rates during the GFC and COVID-19 outbreaks.

incorporated in the standalone behavior of exchange rates.

In Fig. 1, I present the return series for each variable. Blue and red denote the pre-crisis and crisis returns, respectively. Accordingly, it can be stated that, in alignment with the mean statistics given in Table 1 for both reference events, the returns in the crisis periods (in red) show greater fluctuations. However, these fluctuations are relatively small in the COVID-19 pandemic, and higher variability occurs around the latest observations. Unlike those for the other currencies, the USD/TRY exchange rate does not show much difference between the pre-crisis and crisis periods. While returns were highly volatile in the early days of the pre-crisis period, similar fluctuations occurred in the most recent days of the crisis. The pattern for USD/TRY differs from those for the other exchange rates. Another finding that merits attention involves the earlier fluctuations in USD/CNY returns. Since the pandemic originated in China, this finding is in line with expectations.

Following the analysis of descriptive statistics, in this stage, I implement Kapetanios' m-break unit-root test for the variables. In the model's configuration, I allow up to five breaks for all of the time series and select 95 % as the confidence level. Estimated test statistics and detected break dates are presented in Table 2. Since the data were already split into two categories for the GFC and the COVID-19 pandemic, based on the reference dates, by default, I do not expect to see a break on September 15, 2008, or December 31, 2019.

Financial time series tend to display a trend, and having a trend can generate changes in the mean and variance over time. As Brooks (2019) states, the use of non-stationary time series can lead to spurious regression and potentially questionable results. For nonstationary time series, shocks to the system will not gradually die away, and their persistence will be infinite. Considering these facts, I carry out the Kapetanios m-break unit-root test before proceeding. Proposed by Kapetanios (2005), this test is quite robust against structural breaks in a time series. The results in Table 2 indicate that the null hypothesis of a unit root against the alternative hypothesis of an unspecified number of structural breaks is rejected at the 95 % confidence level for all variables. This means that all the time series are stationary in their levels, $I(0)$.

A VaR analysis measures the market risk of an asset or portfolio, and it can determine the maximum expected loss in an investment with a given probability, confidence level, and time horizon. As Carl and Peterson (2014) note, the Gaussian VaR assumes that asset returns follow a normal distribution; however, this might not be true for financial time series. Therefore, higher moments (skewness and kurtosis) should be considered for more accurate predictions. To that end, Favre and Galeano (2002) and Huisman et al. (1999) propose the Cornish–Fisher VaR, which incorporates fat tails and excess kurtosis in the model. As for the historical VaR, it assumes that the distribution of the logarithm of the return does not have a parametric form. The α quantile is calculated through the realized logarithmic returns without assuming normality (Alexander, 2008). The historical VaR is relatively easy to implement, since it does not require the estimation of covariance. Furthermore, since the past represents the immediate future in this method, fat tails are explained to the extent that they are present in historical observations (Jorion, 1997).

The results of the Gaussian VaR model exhibit two different patterns for the GFC and the COVID-19 pandemic (see Table 3). The pre-crisis and crisis periods indicate a jump in market risk following the default of Lehman Brothers. According to the Gaussian VaR, the risk rises by 2.04 times, on average, but it increases by 0.8 times for the COVID-19 pandemic. Thus, the mean deterioration or shockwave in the COVID-19 pandemic can be stated to be just 47 % that of the GFC in terms of standalone risk measures for exchange rates.

When I analyze the results country by country, it seems that the market risk in the USD/JPY returns shows a sharp increase. I carry out historical VaR analysis as the second method, to consider the real return distribution exhibited in the historical data. The results are

Table 2
Kapetanios m-Break Unit Root Test.

	USD/EUR	USD/GBP	USD/JPY	USD/CNY	USD/BRL	USD/TRY
GFC	-10.1387	-10.9577	-12.639	-12.0424	-8.7928	-9.5050
	21.07.2008	24.06.2008	30.06.2008	20.06.2008	10.07.2008	23.06.2008
	06.08.2008	08.07.2008	16.07.2008	02.07.2008	04.08.2008	03.07.2008
	18.08.2008	24.07.2008	31.07.2008	14.07.2008	18.08.2008	18.07.2008
	26.08.2008	14.08.2008	21.08.2008	24.07.2008	26.08.2008	04.08.2008
	03.09.2008	29.08.2008	04.09.2008	19.08.2008	03.09.2008	01.09.2008
	-10.6644	-9.0871	-13.1817	-10.0637	-10.4891	-9.8240
	22.09.2008	22.09.2008	29.09.2008	13.10.2008	22.09.2008	22.09.2008
	06.10.2008	17.10.2008	07.10.2008	22.10.2008	07.10.2008	24.10.2008
	27.10.2008	27.10.2008	27.10.2008	04.11.2008	22.10.2008	12.11.2008
COVID-19	05.11.2008	04.11.2008	06.11.2008	14.11.2008	12.11.2008	25.11.2008
	25.11.2008	12.11.2008	04.12.2008	26.11.2008	21.11.2008	04.12.2008
	-9.8722	-10.4469	-12.4263	-13.0981	-11.4253	-10.2086
	18.10.2019	09.10.2019	11.10.2019	14.10.2019	17.10.2019	15.10.2019
	01.11.2019	18.10.2019	01.11.2019	07.11.2019	05.11.2019	23.10.2019
	19.11.2019	01.11.2019	14.11.2019	19.11.2019	14.11.2019	31.10.2019
	03.12.2019	19.11.2019	28.11.2019	29.11.2019	27.11.2019	21.11.2019
	12.12.2019	12.12.2019	11.12.2019	18.12.2019	17.12.2019	13.12.2019
	-9.3099	-10.3509	-12.9484	-14.5716	-10.1124	-8.6158
	16.01.2020	31.01.2020	09.01.2020	20.01.2020	14.01.2020	09.01.2020
Crisis	03.02.2020	10.02.2020	06.02.2020	03.02.2020	24.01.2020	14.02.2020
	20.02.2020	02.03.2020	18.02.2020	26.02.2020	13.02.2020	27.02.2020
	09.03.2020	11.03.2020	09.03.2020	11.03.2020	09.03.2020	06.03.2020
	20.03.2020	19.03.2020	18.03.2020	19.03.2020	18.03.2020	20.03.2020

Table 3
VaR Analysis.

		GFC			COVID-19			GFC vs. COVID19
		Pre-crisis	Crisis	Change (%)	Pre-crisis	Crisis	Change (%)	
Gaussian VaR	USD/EUR	0.0092	0.0218	1.37	0.0048	0.0100	1.09	0.80
	USD/GBP	0.0082	0.0207	1.52	0.0106	0.0158	0.49	0.32
	USD/JPY	0.0105	0.0282	1.68	0.0045	0.0148	2.31	1.38
	USD/CNY	0.0128	0.0384	2.01	0.0037	0.0057	0.54	0.27
	USD/BRL	0.0109	0.0486	3.45	0.0113	0.0158	0.40	0.11
Historical VaR	USD/TRY	0.0145	0.0367	1.54	0.0089	0.0087	-0.03	-0.02
	USD/EUR	0.0075	0.0257	2.45	0.0045	0.0094	1.06	0.43
	USD/GBP	0.0071	0.0207	1.92	0.0101	0.0185	0.84	0.44
	USD/JPY	0.0120	0.0300	1.51	0.0039	0.0127	2.29	1.52
	USD/CNY	0.0147	0.0419	1.85	0.0038	0.0054	0.42	0.23
Modified VaR	USD/BRL	0.0071	0.0491	5.90	0.0108	0.0194	0.79	0.13
	USD/TRY	0.0143	0.0250	0.74	0.0083	0.0097	0.17	0.23
	USD/EUR	0.0084	0.0237	1.83	0.0047	0.0083	0.75	0.41
	USD/GBP	0.0087	0.0206	1.37	0.0120	0.0145	0.21	0.15
	USD/JPY	0.0108	0.0266	1.45	0.0043	0.0131	2.08	1.43
Modified VaR	USD/CNY	0.0130	0.0403	2.09	0.0041	0.0051	0.25	0.12
	USD/BRL	0.0100	0.0510	4.08	0.0109	0.0141	0.30	0.07
	USD/TRY	0.0146	0.0339	1.32	0.0068	0.0086	0.26	0.20

parallel to the previous findings. In this test, the GFC still exhibits a wild increase in the market risk of foreign exchange rates, compared with the COVID-19 pandemic. The growth in market risk in the COVID-19 pandemic is just 50 % that seen in the GFC. As discussed in terms of the descriptive statistics, some return series deviate from the normal distribution. Hence, I estimate the modified

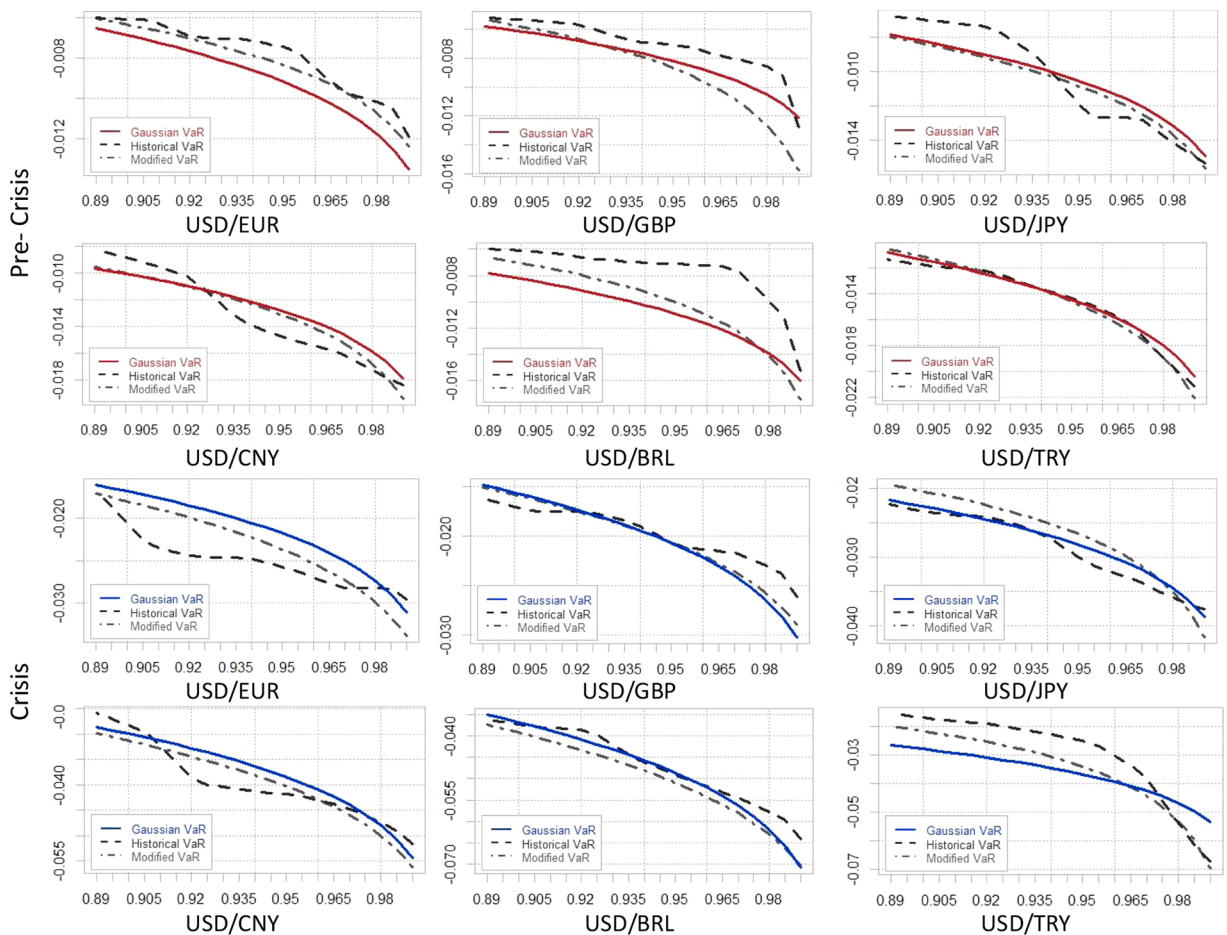


Fig. 2. VaR sensitivity to confidence levels in the GFC.

VaR (Cornish–Fisher VaR) as the last analysis, to take heavy tails and skewness into account. According to the results, even when the normality assumption is loosened and the likelihood of extreme events is accommodated in the model, the change in the market risk of the foreign exchange rates does not differ from previous findings. Moreover, the USD/JPY exchange rate still shows the highest fluctuations in the COVID-19 pandemic, unlike its mild behavior during the GFC. In Figs. 2 and 3, I present the sensitivity of VaR tests to changing confidence levels in the GFC and the COVID-19 pandemic, respectively.

Finally, to compare the characteristics of the pre-crisis and crisis periods for the GFC and the COVID-19 pandemic, I execute downside variance, upside risk, and volatility skewness analyses. Sortino and Van Der Meer (1991) state that standard deviation is not an accurate method for gauging the risk of financial instruments, since it does not determine what is at stake. Therefore, the authors recommend using downside variance as a robust risk measure. Although a long position in a stock or an option contract can induce a limited amount of loss, the overall risk can consist of different upside and downside variability weights. However, investors mostly worry about fluctuations and losses below minimum acceptable returns, that is, downside risk. According to the downside variance results in Table 4, in both the GFC and the COVID-19 pandemic, the downside risks increase compared with the pre-crisis period. However, the average shockwave expansion in the COVID-19 pandemic is still 47 % that in the GFC. Only the USD/JPY downside variance displays a larger rise in the COVID-19 pandemic than in the GFC. (Fig. 4 Table 4).

I compute the volatility skewness to determine the ratio of upside to downside variance. The results support the previous findings. A decline in volatility skewness indicates that the increase in downside variability is greater than for upside fluctuations. This situation can be interpreted as a deterioration or escalated turmoil in asset prices. However, since I am analyzing exchange rates and an increase in an exchange rate denotes a depreciation in the home currency, I note that an increase in volatility skewness shows that the magnitude of the loss or depreciation variability of the home currency is greater than the fluctuations in its appreciation. The results show that the escalation in the USD/GBP risk is 112 times worse than in the GFC. Similarly, the USD/CNY and USD/BRL exchange rates demonstrate soaring risk, with shockwaves approximately 19 and eight times greater, respectively, than in the GFC. This result shows that volatility skewness, which considers both sides of the corresponding risk, is quite successful in capturing market tension. Finally, I examine the upside fluctuations alone. Once I exclude the downside from the model, I see that the findings exhibit departures from the

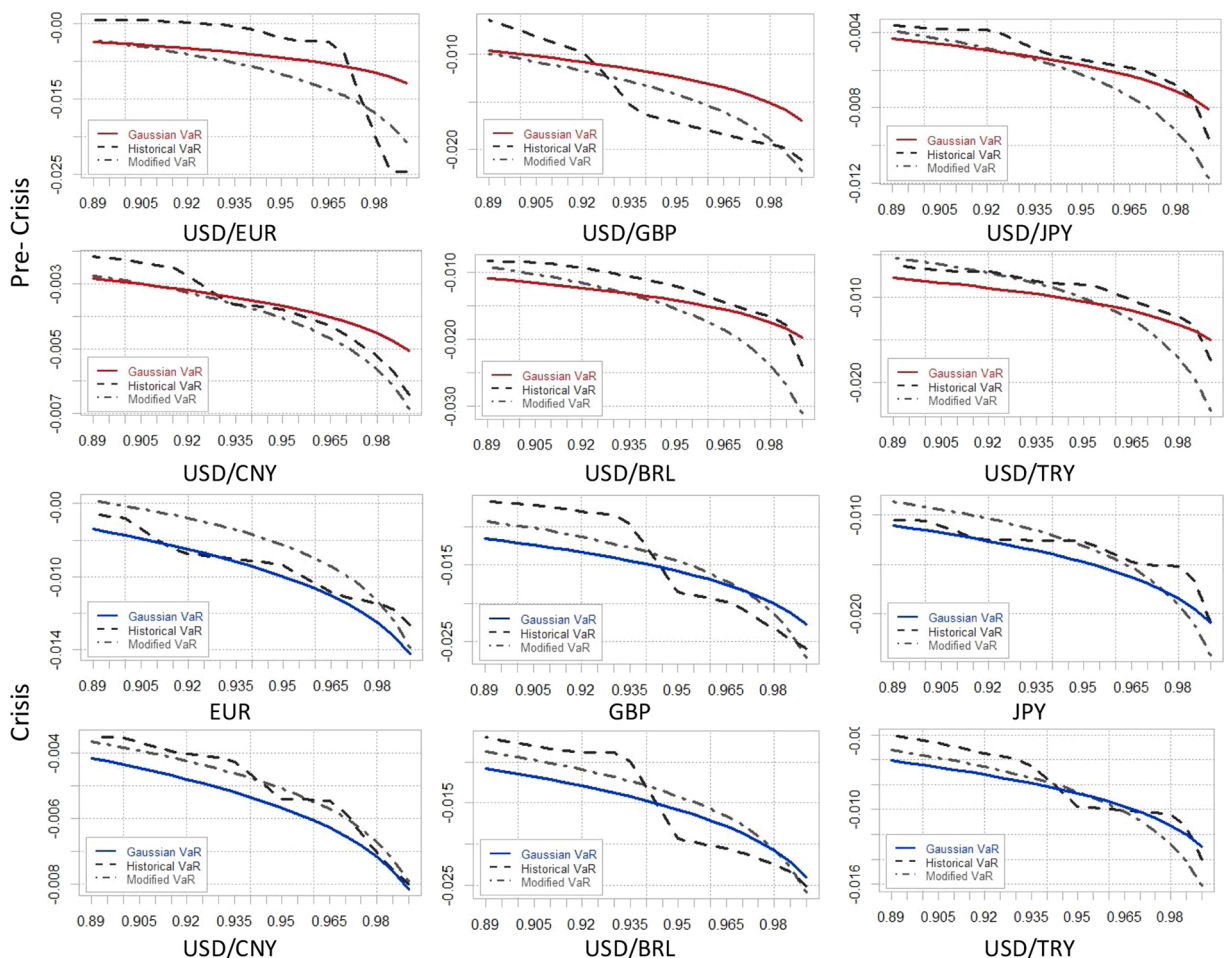


Fig. 3. VaR sensitivity to confidence levels in the COVID-19 pandemic.

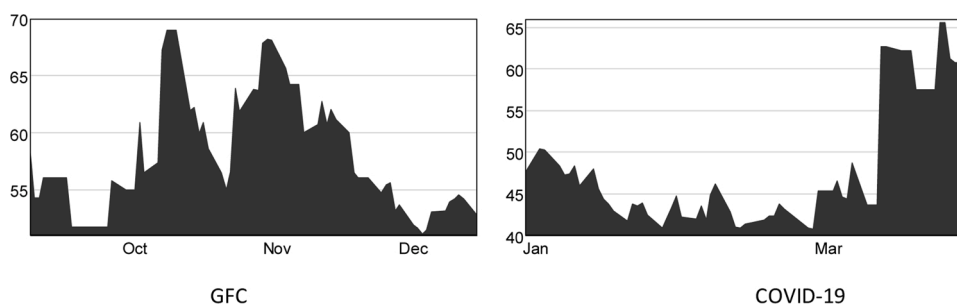


Fig. 4. Dynamic Connectedness – Total Volatility Spillover Index.

Table 4
Downside Risk Analysis.

		GFC			COVID-19			GFC vs. COVID19
		Pre-crisis	Crisis	Change (%)	Pre-crisis	Crisis	Change (%)	
Downside-Var.	EUR	0.4988	0.0100	-0.98	0.0021	0.0040	0.93	0.95
	GBP	0.0036	0.0086	1.41	0.0051	0.0066	0.28	0.20
	JPY	0.0046	0.0125	1.71	0.0018	0.0061	2.33	1.37
	CNY	0.0057	0.0172	2.02	0.0017	0.0023	0.31	0.15
	BRL	0.0043	0.0212	3.93	0.0048	0.0064	0.31	0.08
	TRY	0.0064	0.0151	1.36	0.0034	0.0037	0.07	0.05
Vol. Skewness	EUR	2.3152	0.8545	-0.63	0.6221	1.3643	1.19	1.89
	GBP	1.7096	1.7596	0.03	0.3349	1.432	3.28	111.9
	JPY	0.9392	0.5909	-0.37	1.354	1.1453	-0.15	0.42
	CNY	0.748	0.8578	0.15	0.4105	1.5707	2.83	19.26
	BRL	2.0622	1.3657	-0.34	0.8355	3.0562	2.66	7.87
	TRY	0.839	1.6799	1.00	2.0808	2.1207	0.02	0.02
Upside Risk	EUR	0.0054	0.0092	0.71	0.0017	0.0047	1.86	2.63
	GBP	0.0047	0.0114	1.44	0.0030	0.0079	1.65	1.15
	JPY	0.0045	0.0096	1.15	0.0021	0.0065	2.07	1.80
	CNY	0.0049	0.0159	2.24	0.0011	0.0028	1.55	0.69
	BRL	0.0062	0.0248	3.01	0.0044	0.0111	1.51	0.50
	TRY	0.0059	0.0196	2.34	0.0049	0.0054	0.08	0.04

previous analysis. The results indicate that, although both the GFC and the COVID-19 pandemic demonstrate deteriorations in the extent of risk exposure, the escalation in market tension for the USD/CNY, USD/BRL, and USD/TRY exchange rates in the COVID-19 pandemic is still less than that in the GFC.

In Table 5, I present the Diebold–Yilmaz static connectedness measures following the standalone risk analyses. This method, rather than investigation of the standalone behavior of exchange rates, will reveal the spillover effects in currency markets and the overall market response to shockwaves. In the model configuration, I use a 60-day rolling window. The VAR lag length and forecast horizon are selected to be four days and 10 days, respectively.. The results indicate that, for the pre-GFC period, the USD/BRL makes the greatest contribution to the other exchange rates' volatility. However, for the crisis period, the USD/JPY and USD/GBP exchange rates rank first and second in their contributions to the volatility of the other exchange rates. During the GFC, the descending order of the gross directional volatility spillovers to other exchange rates is USD/JPY, USD/GBP, USD/TRY, USD/EUR, USD/BRL, and USD/CNY. I examine the last column of Table 5 in both periods to inspect the gross directional volatility spillovers from other variables. According to the results, the volatility transmitted from other exchange rates to the USD/GBP exchange rate is the highest in both the pre-GFC and GFC periods. In contrast, although, in the pre-GFC period, the USD/BRL exchange rate exhibits the lowest volatility received from the other exchange rates, during the GFC, the USD/CNY exchange rate replaces the USD/BRL. However, the USD/BRL exchange rate displays the greatest increase in this statistic in the transition from the pre-crisis to the crisis period. To assess the percentage of the volatility forecast error variance caused by spillovers, I calculate the total spillover index value. The result is presented in the lower right of Table 5. Accordingly, 49 % of the volatility can be stated to be induced by spillovers in the pre-GFC period, and the GFC crisis did not cause a spike in this statistic. The shockwave effect of the GFC is quite limited, at 1.24 %.

To compare the shockwave effects of both crises, I carry out the Diebold–Yilmaz volatility spillover analysis for the COVID-19 pandemic as well. According to the findings, before the emergence of the pandemic in China and its global spread, the USD/GBP and USD/JPY exchange rates presented the greatest spillover to the other currencies. In contrast, in the pandemic period, the USD/BRL demonstrates the second-highest volatility spillover influence, after the USD/JPY variable. The USD/BRL exchange rate exhibits a dramatic rise in this impact along with the COVID-19 pandemic. The descending order of the gross directional volatility spillovers to other exchange rates during the pandemic is as follows: USD/JPY, USD/BRL, USD/GBP, USD/TRY, USD/EUR, and USD/CNY. As shown in Table 6, compared with the GFC period, in the COVID-19 pandemic, only the USD/BRL depicts a change in order, while the

Table 5
Diebold–Yilmaz Volatility Spillover Analysis for GFC.

		EUR	GBP	JPY	CNY	BRL	TRY	From
Pre-GFC	EUR	52.82	19.73	3.21	2.92	17.18	4.13	47.18
	GBP	11.54	39.84	10.21	4.26	24.19	9.96	60.16
	JPY	7.93	4.53	55.24	6.58	22.07	3.67	44.76
	CNY	9.24	6.39	5.15	43.03	29.43	6.77	56.97
	BRL	7.37	7.95	5.53	6.44	67.79	4.93	32.21
	TRY	3.05	3.06	11.34	8.97	28.37	45.21	54.79
	Directional to others	39.12	41.66	35.44	29.17	121.22	29.45	296.06
	Net Directional Connectedness	-8.06	-18.5	-9.32	-27.8	89.01	-25.33	49.34
	EUR	47.25	12.01	12.04	8.69	12.35	7.66	52.75
	GBP	11.59	40.41	23.86	9.43	6.01	8.71	59.59
During GFC	JPY	10.13	23.88	45.26	1.29	3.85	15.58	54.74
	CNY	3.37	8.5	3.73	64.88	9.35	10.17	35.12
	BRL	13.42	8.3	4.75	7.27	53.64	12.62	46.36
	TRY	8.38	11.71	21.01	4.09	9.76	45.05	54.95
	Directional to others	46.89	64.41	65.39	30.77	41.31	54.73	303.5
	Net Directional Connectedness	-5.85	4.82	10.66	-4.35	-5.05	-0.21	50.58

other variables remain the same. As for gross directional spillovers from the other currencies, the highest volatility transmission appears for the USD/CNY exchange rate before the pandemic period. However, following the pandemic, as seen in the GFC period as well, another emerging economy—Turkey—exhibits the highest increase (87 %) in gross directional spillovers from other currencies. Finally, to measure the impact of COVID-19 in the transmission of volatility in exchange markets, I evaluate the total spillover index statistic, in the lower right of [Table 6](#). Unlike in the GFC period, the shockwave effect of the pandemic is very high. In the total volatility spillover, the COVID-19 pandemic induces a rise of 10.44 %, which is 8.42 times higher than that seen in the GFC period.

The characteristics of these crises could be the reason for the large difference in the total volatility spillover index. The GFC can be evaluated under different phases. It emerged in the US mortgage market and, because of the evaporation of trust and panic, it triggered asset meltdowns and a liquidity crunch. In the following months and years, along with the deterioration in the real economy due to financial linkages and contagion effects, the liquidity crisis transmitted to European countries. However, the COVID-19 pandemic has displayed a different flow. This time, the panic has been accompanied by health concerns, and measures have induced sharp suspensions in economic activities, especially in the service sector. Because of the nature of the problem this time, economic fears have not been related to a specific country or financial system as in the case of the GFC. For example, the GFC was linked to mortgage-backed securities and structured financial instruments; hence, for any country that does not accommodate such a market, the harm was relatively low. On the other hand, since the crisis was induced by structural problems, such as a lack of regulations in certain instruments (e.g., credit derivatives) and markets, the recovery period was quite long. For example, as discussed by [Blinder \(2015\)](#), the US economy was not able to recover to its January 2008 peak payroll employment rate until May 2014. Besides, positive values in GDP growth are seen three quarters after the GFC's peak in the United States. However, in China, following a contraction of 6.8 % in the first quarter of 2020, in the second quarter the country exhibited 3.2 % growth, thanks to growth-inducing economic policies. This recovery rate is related to the fact that COVID-19 was not induced by structural problems in the Chinese economy or any other country's financial system. Since sharp lockdowns and social distancing measures during the outbreak have been experienced worldwide, the COVID-19 turbulence has been much more devastating, independent of the extent of countries' economic powers. The change in the total spillover index displays this finding by quantifying the difference.

Although the two crises have followed different paths and have different causes, both demonstrate that black swans are a fact of

Table 6
Diebold–Yilmaz Volatility Spillover Analysis for COVID-19.

		EUR	GBP	JPY	CNY	BRL	TRY	From
Pre-COVID-19	EUR	53.62	18.5	5.66	14.04	6.1	2.07	46.38
	GBP	5.59	52.42	16.92	5.93	7.46	11.68	47.58
	JPY	9.52	19.25	53.71	6.23	7.95	3.34	46.29
	CNY	11.82	15.05	27.34	29.85	4.07	11.87	70.15
	BRL	9.8	9.16	6.77	12.8	57.25	4.22	42.75
	TRY	7.2	7.24	7.25	5.95	4.98	67.39	32.61
	Directional to others	43.93	69.2	63.94	44.95	30.56	33.17	285.75
	Net Directional Connectedness	-2.44	21.62	17.64	-25.19	-12.19	0.56	47.63
	EUR	34.21	10.3	26.5	4.75	15.01	9.23	65.79
	GBP	9.68	24.58	27.84	1.82	27.23	8.84	75.42
During COVID-19	JPY	13.43	11.42	58.13	4.82	9.01	3.2	41.87
	CNY	7.35	7.07	8.42	52.08	11.68	13.4	47.92
	BRL	7.11	7.25	25.42	7.73	43.75	8.73	56.25
	TRY	2.49	13.09	24.4	9.63	11.56	38.84	61.16
	Directional to others	40.07	49.13	112.59	28.75	74.48	43.4	348.41
	Net Directional Connectedness	-25.72	-26.29	70.71	-19.17	18.23	-17.76	58.07

financial markets. While, today, signals of impending disaster before the GFC are clearly evident, the COVID-19 pandemic was a complete surprise and is a perfect example of the impact of the highly improbable. The existence of black swans shows that financial markets are riskier than noted by the propositions of conventional finance theory, which comprises modern portfolio theory, the random walk hypothesis, efficient market hypothesis, and the capital asset pricing model (Mandelbrot et al., 2005; Taleb, 2007). Therefore, it is clear that we need to adjust our risk measurement and forecast models accordingly to take into account the severe impact of unexpected events. This requires employing probability distributions with heavy tails and consideration of the skewness of returns. Corrections in the risk modeling can improve predictions for businesses and financial institutions, resulting in less harmful consequences, from liquidity to supply chain.

5. Conclusion

At the end of 2019, the world was confronted with one of the worst experiences in history, the COVID-19 pandemic. The pandemic not only affected the health of the public, but also hurt economies, especially in the service sector. Along with reduced expectations, financial markets were also negatively affected. This study has examined foreign exchange markets to quantify the shockwaves of the GFC and the COVID-19 pandemic. Econometric tests were conducted using various methods, including Kapetanios' m-break unit root test, downside variance, upside risk, volatility skewness, Gaussian VaR, historical VaR, modified VaR, and Diebold–Yilmaz volatility spillover analysis. Each test was executed for the pre-crisis and crisis periods.

The test results display two patterns. According to the analyses examining the change in risk in the standalone behavior of currencies, the COVID-19 shockwave has not been as bad as that of the GFC. In this group of methods (Gaussian VaR, historical VaR, modified VaR, and downside variance), only the USD/JPY exchange rate presents a different picture: a dramatic rise in risk in response to the shockwave of the COVID-19 pandemic. Except for this case, the deterioration in the currency market has not been as bad as it was in the GFC turmoil. However, the volatility skewness results demonstrate a different image, which is parallel to ongoing discussions in the media regarding the future of financial markets. Since the method distinguishes between upside and downside risks and utilizes their ratio, its values vary from those of other methods.

To examine the co-movement of the currencies, I also employed Diebold–Yilmaz volatility spillover analysis. The results of the method are quite similar to the findings for volatility skewness. In both crises, the USD/JPY exchange rate made the largest gross directional volatility spillover contribution to the other exchange rates. In contrast, the USD/GBP exchange rate appeared to receive the greatest volatility spillover from the others in both shockwaves. According to the static connectedness measure of Diebold–Yilmaz, the USD/BRL and USD/TRY exchange rates exhibit the greatest increases in gross directional volatility spillovers from other currencies in the GFC and the COVID-19 pandemic, respectively. Comparison of the GFC and COVID-19 shockwaves shows that the total volatility spillover in the COVID-19 period is 8.42 times higher than that in the GFC.

I find that the standalone behavior of currencies and the spillover of volatilities show a different picture. While some risk measures for standalone currencies display no deterioration, according to the volatility spillover analysis, the global currency market's response to COVID-19 has been more severe than in the case of the GFC. This result could be related to the characteristics of the two crises. While the GFC emerged in the United States, more specifically in the mortgage market, any country that did not accommodate mortgage-backed securities or credit derivatives was affected only to a limited extent by the crisis. The trade links of countries also mitigated the deterioration in economies. However, because of the COVID-19 pandemic, markets have faced global lockdowns and, regardless of their market structures and trade links, all countries have been faced with this grim reality.

Data sharing and data accessibility statement

The data that support the findings of this study are available from the author upon reasonable request.

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