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RESEARCH ARTICLE / ARAŞTIRMA MAKALESİ

The Impact of News Related Covid-19 on Exchange Rate Volatility: A New Evidence From Generalized Autoregressive Score Model

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Abstract

The COVID-19 pandemic causes serious problems for the economy. When considering the significant impact the COVID-19 pandemic had on capital flows and global trade, it can be stated that the outbreak of this virus has caused sharp fluctuations in exchange rate markets. From this point of view, this study examines the effect of the news regarding the COVID-19 pandemic on exchange rate volatility for 12 emerging and developed countries that were most affected by the outbreak. The data covers the period between January 1, 2019 and August 31, 2022. For this purpose, we use the Generalized Autoregressive Score (GAS) model with student-t distribution, which is a new approach to measure the volatility of a financial series and to obtain the volatility clustering and fat-tail properties of a financial series. The findings of this study show that panic and fake news about the COVID-19 pandemic has increased the volatilites of exchange rates, while media hype news decreases the volatilities. These results indicate that the negative and speculative news regarding COVID-19 adversely affects exchange rate volatility through increasing the uncertainty of financial markets.

Keywords

Exchange Rate Volatility, COVID-19, Generalized Autoregressive Score Model, Expected Shortfall, Tail Effect

Jel Codes: F31, G15, C58, C22

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1. Introduction

Modeling the volatility of a financial time series is essential for investors, economists, and policymakers. Exchange rate volatility has been measured by the GARCH family models in many studies (Thorlie et al., 2014; Abdullah et al., 2017; Ogutu et al., 2018; Peng et al., 2021). The GARCH family models assume that the conditional distribution does not change over time (Makatiane and Kalebe, 2018). However, the Generalized Autoregressive Score (GAS) model proposed by Creal et al. (2013) allows for the predictions of the time-varying parameters. The GAS model is a score-based model and is more flexible than other models (Harvey and Sucarrat, 2014; Troster et al., 2019). This model utilizes full likelihood information of the parameters (Ardia et al., 2016). It is also more robust than the heavy-tailed distributions (Troster et al., 2019).

The impact of the news on the exchange rate volatility has become an increasingly important issue in late years. The Efficient Market Hypothesis (EMH) by Fama (1970) states that asset prices accurately represent all available information and are thus merely a response to new pieces of information which influence investors' perceptions about the future economic situation and cash flows. Contrary to other financial markets, foreign exchange rate markets are rather ideal to test EMH because they are always open. This property allows the sudden responses of exchange rate changes reported on the news to be researched. The empirical and theoretical literature has concentrated on how economic or political news impacts the movements in exchange markets (Laakkonen, 2007; Omrane and Savaşe, 2017; Li et.al., 2019). Many studies are available in the literature which focused on how news effects exchange rates (Andersen et. al., 2003, 2007; Pearce and Solakoglu, 2007, Laakkonen, Birz and Lott, 2013, Caporale et. al. 2018, Jabeen et al., 2020). The consensus states that the information reported on social media platforms exhibits an important effect on the exchange market dynamic, particularly during periods of economic and political uncertainty.

The factors affecting exchange rate volatility vary depending on the theoretical framework. These factors include: relative income and money supply in the flexible price monetary model (Frankel, 1976), the real interest rate in the sticky-price monetary model (Dornbusch, 1976), and trade balance in the portfolio balance model (Branson, 1977, 1981, 1983). In addition, expectations regarding the central bank's behavior can also cause fluctuations in exchange rates (Balduzzi et. al., 2001). In terms of investor psychology, the most crucial factor influencing exchange rate volatility is the "surprising" news about uncertainty (De Long et. al., 1990, Campell et. al., 1993).

The COVID-19 pandemic has caused increases in worries and uncertainty and has thus generated pressure in the financial markets and exchange rates (Segal and Gerstel, 2020). Due to uncertainty and worry, the currencies of both developing countries and the countries which export energy have depreciated against reserve currencies, which are the dollar, euro, and yen. By contrast, the dollar has shown a little change against the euro and yen. The main reasons for the fragility from exchange rate volatility are the debt stock issued in foreign currency exceeding the foreign exchange reserve and dependence on the commodity. Coordinated policy responses, such as swap lines, to be implemented against the negative economic effects of the COVID-19 pandemic can help fragile economies with excessive currency volatility.

In the present study, we contribute to the literature in several ways. Firstly, we examine the response of the exchange rate market to the news about the COVID-19 pandemic in the twelve emerging and developed countries which have had the highest number of cases. Secondly, we apply the newly developed Generalized Autoregressive Score (GAS) model to obtain the marginal distributions of the exchange rates. Although GARCH-type models are commonly used in modeling financial series due to their ability to define volatility clustering property, the GAS model utilizes the full density rather than the first and higher moments of a financial series. By this means, an effective choice can be provided by optimizing the time-varying parameters of the model. The GAS model enables additional flexibility in selecting the scaling matrix, which ensures a way to update the time-varying parameters. Because this model comprises the GARCH family models, it makes it possible to obtain the volatility clustering of exchange rate returns.

2. Literature Review

The fluctuations of exchange rates have been a crucial issue in macroeconomy since the collapse of the Bretton Woods System. In this way, many studies in the literature have analyzed the volatility of exchange rates, both on developing and developed countries, through different approaches. Mandelbrot (1963) and Fama (1965) stated that because exchange rates generally have such characteristics as clustered volatility, conditional heteroscedasticity, and asymmetry, that they do not exhibit normal distribution. The study also indicates that price changes are characterized by volatility periods and the uncoditional distributions of them are typically fat-tailed or leptokurtic. As such, many studies have shown that price changes are non-normal distributions, such as the scaled t, the lognormal, or the stable Paretian (Mandelbrot, 1963; Praetz, 1972, Clark, 1973; Blattberg and Gonedes, 1974). Similar analyses for changes in exchange rates are performed by Rogalski and Vinso (1978), McFarland et al. (1982), and Hsieh (1988). These studies indicate that unconditional distributions of exchange rates change across different days of the week.

An alternative approach is the ARCH (Autoregressive Conditional Heteroskedasticity) model framework of Engle (1982). Engle (1982) points out that the unconditional distribution will be symmetric and leptokurtic if the conditional distribution is normal. Following this study, Milhoj (1987), Hsieh (1988), and Diebold and Nerlove (1989) applied ARCH models to exchange rates. Bollerslev (1986) proposed the GARCH (Generalized Autoregressive Conditiona Heteroskedasticity) model. This model is the extended-ARCH model and is a function of the lagged shocks and conditional variance. The ARCH and GARCH models assume that the effect of the negative and positive shocks on conditional variance is symmetric. However, it is often observed that the downside fluctuations lead to a higher volatility than the upside fluctuations, which shows that the volatility responds asymmetrically to the shocks. Thus, the alternative GARCH family of models, such as EGARCH (Nelson, 1991), TARCH (Zakoian, 1994), and GJR-GARCH (Glosten, Jaganna, and Runkle, 1993), were developed. Bollerslev (2010) also provides a reference guide to the ARCH models, with 100 variants and GARCH model extentions. Many studies apply these models to different financial series such as stock markets (Alberg et al., 2008; Lim and Sek, 2013; Lin, 2018), exchange rates (Rapach and Strauss, 2008; Barunik et al., 2016; Abdullah et al., 2017; Donkor et al., 2022), cryptocurrencies (Chu et al., 2017; Cerqueti et al., 2020; Arı, 2022). Rapach and Strauss (2008) analyzed the volatility of the currencies of Canada, Denmark, Germany, Japan, Norway, Switzerland, and the UK by using the GARCH model for the years 1980 to 2015. This studied revealed that the parameter estimates for these exchange rates generally change across the subsamples, defined by structural breaks in the GARCH(1,1). Abdullah et al. (2017) investigated the daily exchange rate volatility in Bangladesh during the period of 2008 to 2015. They used alternative GARCH family models under both normal and Student-t distribuiton assumptions. They concluded that the currency of Bangladesh has a fat-tail and skewed distribution, which means that GARCH(1,1) with Student-t distribution performs better than the normal distribution. Donkor et al. (2022) examined the oil price volatility and exchange rate volatility of oil-dependent economies with the GARCH and EGARCH models before and after the Global Financial Crisis. Chu et al. (2017) applied various GARCH models to seven cryptocurrencies and concluded that the IGARCH and GJR-GARCH models show perform better at predicting the volatility of cryptocurrencies. Arı (2022) examined the volatility of Bitcoin/USD by using discrete and continuous-time GARCH models and found that the continuous-time GARCH model is better than the discrete-time GARCH model in terms of predicting volatility.

Many studies are available in the literature which focus on how the news affects exchange rates (Andersen et. al., 2003, 2007; Pearce and Solakoglu, 2007, Laakkonen, 2007; Birz and Lott, 2013, Caporale et. al. 2018; Jabeen et al., 2020). The study of Andersen et al. (2003) indicated that exchange rates respond very quickly to US macroeconomic news. Similarly, Andersen et al. (2007) researched the effects of US macroeconomic news on the US, German, and British bond, stock, and exchange rates. They concluded that macroeconomic news creates conditional mean jumps and that bond markets are most strongly affected by macroeconomic news. Pearce and Solakoglu (2007) examined the impact of macroeconomic news on the dollar-Mark and dollar-Yen exchange rates. They used high-frequency data and concluded that the impact of the news depends on the state of the economy, although this effect was found to be linear and symmetric. Laakkonen (2007) analyzed the effect of European and US macroeconomic news on USD/EUR volatility by using Flexible Fourier Form. This study revealed that macroeconomic news enhances USD/EUR volatility and that bad news has a greater effect on it. Caporale et. al. (2018) explored the impact of macroeconomic news on exchange rates *vis-a-vis* the Euor and the US of the currencies of emerging countries, including Turkey, Thailand, Indonesia, South Africa, Korea, Hungary, Czech Republic, Mexico, and Poland. They used VAR-GARCH(1,1) and revealed that foreign news during crisis periods significantly affects spillovers between macroeconomic news and exchange rates. Jabeen et al. (2020) examined the impact of macroeconomic news on PKR/USD exchage rate volatility by employing the GARCH model in Pakistan. They indicated that both domestic and foreign macroeconomic news has a significant effect on the PKR/USD exchange rate. They also stated that PKR/USD exchage rate volatility instantly adjusts to the news.

In contrast to the GARCH family models, the Generalized Autoregressive Score (GAS) model lets the conditional distribution change over time. This model with time-varying parameters is a score-based model and is more suited to heavy-tailed distributions than other models. The GAS model, which is a score-based technique, was first proposed by Creal et al. (2011, 2013) and Harvey (2013). This model is a new approach to model volatility of financial time series. Harvey and Luati (2014) analyzed data with a thick-tail structure by using the GAS model and pointed out that the GAS model with skew distribution is more effective in modeling the thick-tail structure, and so it provides advantages for the estimation of financial risks. Makatjane et al. (2017) applied the GAS model to stock returns. They stated that heavy tail in returns and risk measurements can be modeled with the GAS model. Blasques et al. (2019) indicated that the GAS model provides more consistent results in estimating risk measurement. Among the empirical studies, Erer and Erer (2018) estimated the volatility of the BIST 100 and Dow Jones Indexes by using the GAS model to obtain time-varying dynamic conditional variance. Babatunde et al. (2020) used the GAS model with its variants for estimating the volatility of the US/Naira, Pound sterling/Naira and Euro/Naira exchange rates, with GAS-T, EGAS-T, and EGAS-SKT being selected as the best model, respectively. Lazar and Xue (2020) compared the GARCH model with the GAS model by employing intraday data the S&P 500, Dow Jones Industrial Average, Nikkei 225, and FTSE 100. They found that the GAS model shows a higher performance for the benchmark models across all indices than the GARCH model. Xu and Lien (2020) investigated the impact of the US-China trade war on the daily exchange rates of CNY (China), JPY (Japan), KRW (South Korea), ZAR (South Africa), EUR (Germany and Netherlands), SGD (Singapore), and AUD (Australia) by using the GAS model. They expressed that the GAS model is an effective tool in modeling exchange rate volatilty. Jeribi and Ghorbel (2021) used the GAS model to forecast and model the risk of stock market indices, cryptocurrencies, and gold returns. They concluded that GAS-ts (student) and GAS-sts (skewed student) outperform for gold, cryptocurrencies, and developed and emerging stock market indices.

3. Data

To analyze the effects of COVID-19-related news on exchange rate volatility in emerging and developed countries, we compared the US Dollar to the following currencies between January 1, 2019 and August 31, 2020: Turkish Lira (TL), Russian Ruble (RUB), Brazilian Real (BRL), India Rupee (INR), South African Rand (ZAR), Mexican Peso (MXN), Japanese Yen (JPY), Euro (EUR), British Pound (GBP), Swiss Franc (CHF), China Renminbi (CNY), and Canada Dollar (CAD). These countries were chosen because they were the countries with the highest number of cases. The daily exchange rate data was obtained from the website "investing.com." We computed the daily returns by using the formula $R_{i,t} = log\ (P_{i,t} / P_{i,t-1})$,, where $P_{i,t}$ is the closing prices of the exchange rate in day t for i country.

We used four indices in our comparison: the coronavirus panic index, the coronavirus media hype index, the coronavirus fake news index, and the coronavirus worldwide sentiment index, and COVID-19-related news. These variables were obtained using the RavenPack analytics tool, which provides real-time analytics related to the COVID-19 outbreak. RavenPack also incorporates such global news outlets as *The Wallstreet Journal* and *Dow Jones News* (Smales, 2014; Dai et.al., 2015; Ho et.al., 2017; Blitz et.al., 2019; Rognone et.al., 2020; Cepoi, 2020). Detailed information about the variables is shown in Table 1 below.

Table 1
The Data and Source

Variables	Description	Source
Exchange Rate Return (EX)	Daily returns are computed as $R_{i,t} = log\ (P_{i,t} / P_{i,t-1})$, where $P_{i,t}$ is close prices of the excgange rate in day t for i country	investing.com
Coronavirus Panic Index (PANIC)	This index measures the level of news chatter indicating 'panic' or 'hysteria' and 'coronavirus'. It takes values between 0 and 100.	https://coronavirus.ravenpack.com/
Coronavirus Media Hype Index (MEDIAHYPE)	This index measures the percentage of news talking about the coronavirus. It takes values between 0 and 100.	https://coronavirus.ravenpack.com/

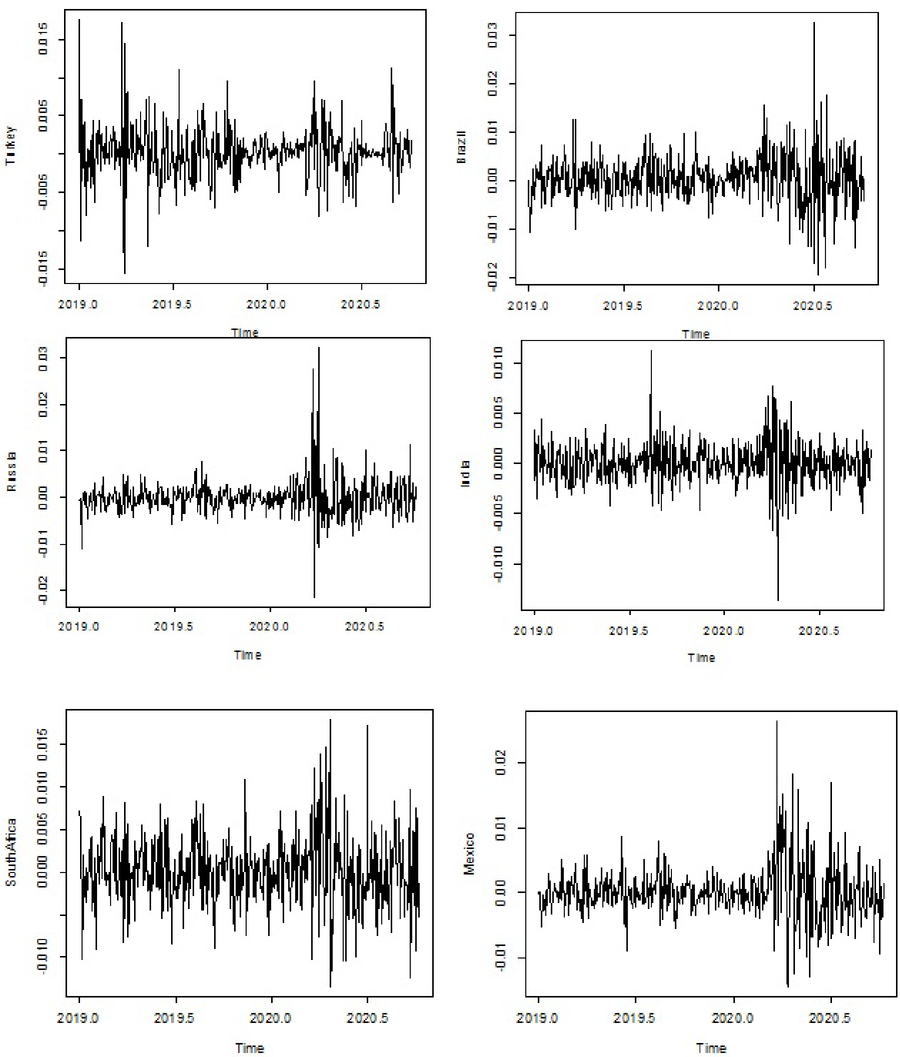
Coronavirus Fake News Index (FAKENEWS)	This index measures the level of media chatter about the coronavirus that makes reference to misinformation or fake news alongside COVID-19. It takes values between 0 and 100.	https://coronavirus.ravenpack.com/
Coronavirus Worldwide Sentiment Index (SENTIMENT)	This index measures the level of sentiment across all entities mentio thee the alongsnedide the coronavirus. It takes values between -100 and 100.	https://coronavirus.ravenpack.com/

In Figure 1, Panel A and Panel B indicate the exchange rate returns for emerging countries and for developed countries, respectively. As displayed in Figure 1, the clusters were observed in the return series at certain intervals. Therefore, the volatility fluctuates at certain intervals. This event is called volatility clustering, which means that the small changes follow small fluctuations and that the large changes follow large fluctuations.

Table 2
Descriptive Statistics

Panel A: Emerging Countries						
	Turkey	**Brazil**	**Russia**	**India**	**South Africa**	**Mexico**
Mean	0.000324	0.000329	0.000063	0.000048	0.000151	0.000102
Median	0.000162	0.000128	-0.00004	0.000016	-0.000052	-0.00020
Maximum	0.017487	0.032468	0.032146	0.011238	0.017865	0.026346
Minimum	-0.01553	-0.01948	-0.02135	-0.01355	-0.013430	-0.01439
Std. Dev.	0.003428	0.005251	0.003924	0.002218	0.004297	0.004159
Skewness	0.377519	0.309240	1.912243	-0.06994	0.315692	1.076220
Kurtosis	7.742547	7.150010	20.54262	7.681101	4.451596	9.244128
Jarque-Bera	417.0349	318.3589	5829.531	396.6087	45.312810	788.8336
Probability	0.0000	0.0000	0.0000	0.0000	0.000000	0.0000
Observations	434	434	434	434	434	434
Panel B: Developed Countries						
	China	**Japan**	**Switzerland**	**Euro**	**England**	**Canada**
Mean	-0.000002	-0.000038	-0.000085	0.000036	-0.000046	-0.000024
Median	0.000000	0.000052	0.000043	0.000077	0.000050	0.000002
Maximum	0.006861	0.011414	0.009047	0.006282	0.018491	0.007416
Minimum	-0.003259	-0.009453	-0.008471	-0.011458	-0.012619	-0.006595
Std. Dev.	0.001141	0.002037	0.001775	0.001765	0.002700	0.001887
Skewness	0.904666	-0.114598	-0.113232	-0.431316	0.326839	0.395249
Kurtosis	7.667542	8.325000	5.996055	7.464838	9.314131	6.338149
Jarque-Bera	453.161700	513.714200	163.249700	373.943600	728.677800	212.806900
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	434	434	434	434	434	434

Panel A: Emerging Countries



Panel B: Developed Countries

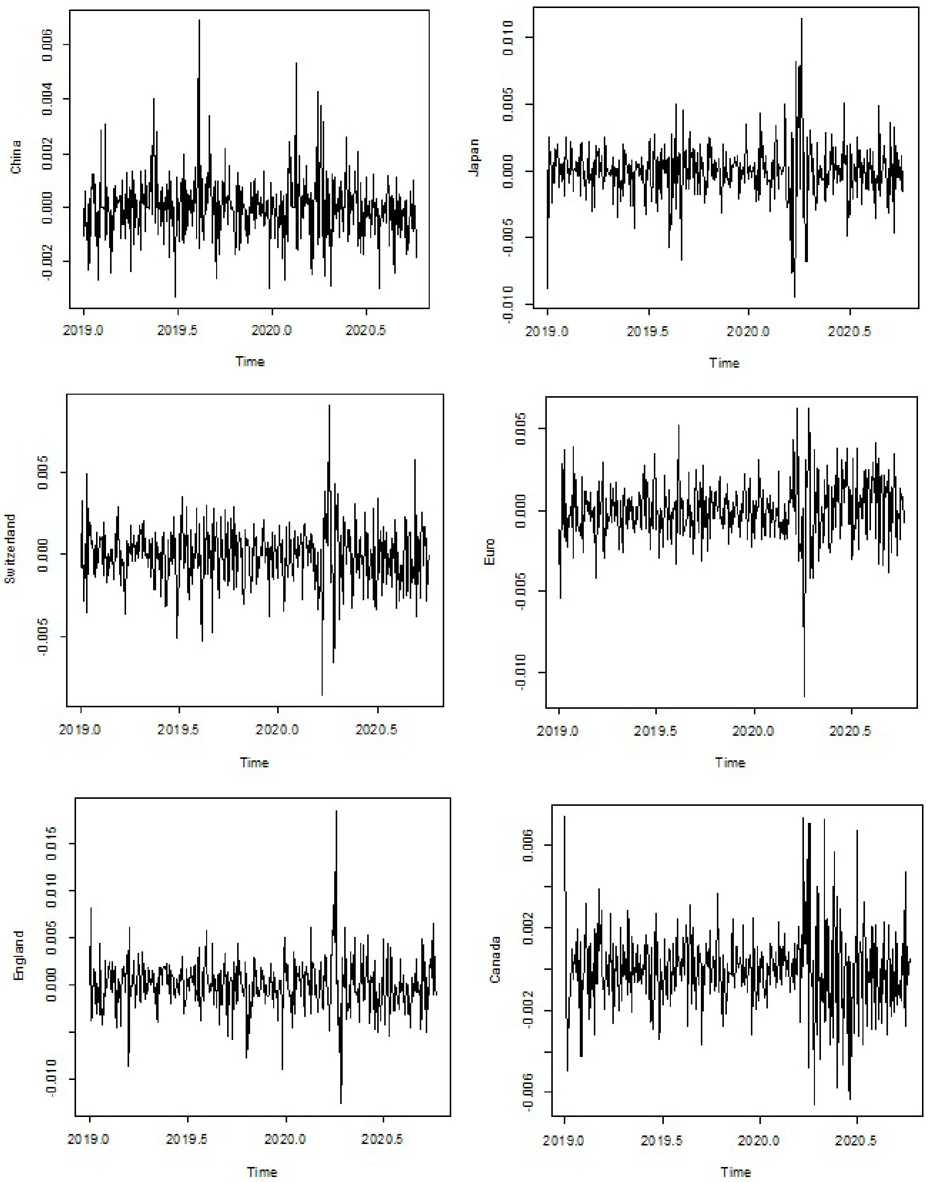


Figure 1. Exchange Rates Return Series

Table 2 indicates the descriptive statistics regarding the exchange rate returns for emerging and developed economies. During the investigated period, the returns had a positive mean in emerging countries, while the returns for developed countries exhibited a negative mean. The kurtosis values were considerably higher than “,” representing the critical value for normal distribution. Therefore, the return series have fat tails. Also, the returns are not normally distributed based on the JB test statistics and instead follow the leptokurtic distribution.

4. Methodology

The fluctuations in the asset prices, such as stock prices, bond returns, and exchange rates, are of importance for portfolio investors, policymakers, and central banks because they are the essential indicators of financial instability and financial risk. As such, the so-called risk must be correctly measured. The generalized autoregressive conditional volatility models are frequently used to measure risk in the literature because many financial series have the fat-tails and leptokurtic distribution. There are various techniques to measure conditional volatility. Some of these techniques suppose that the distributions used to estimate the parameters have not changed based on previous and new information, which leads the parameters to be fixed over time. They are called parameter-based models, as defined by Cox (1981). The most well-known of these models are the stochastic volatility (SV) model (Shephard, 2005) and the stochastic density model (Bauwens and Hautsch, 2006; Koopman et.al., 2008). However, the financial time series with high frequencies needs to organize the possibilities based on new information. Therefore, the parameters can change over time. These models are called observation-based models, as defined by Cox (1981). In this approach, the time variation of the parameters is accrued by allowing the parameters to be a function of both the lagged dependent variables and the lagged explanatory variables. Some of these models are: the GARCH models (Engle, 1982; Bollerslev, 1986; Engle and Bollerslev, 1986), the Autoregressive Conditional Duration and Intensity (ACD and ACI, respectively) models (Engle and Russell, 1998) and Russell, 2001), and the Dynamic Conditional Correlation (DCC) model (Engle, 2002). Recently, the GAS model has been proposed by Creal et.al. (2013) and Harvey (2013) to measure downside risk.

GARCH models with variants are adept at measuring smooth fluctuations in the volatility of financial returns. However, these models may fail in the case of financial crisis or turmoil, when the level of volatility may change suddenly. The GAS model allows for the updating of the time-varying parameter quickly when the data is informative (Blasques et al., 2019). The GAS model provides time variation in the parameters based on the score of the conditional density function. This model is a new approach to the observation-based models, with the extended versions of the model considering asymmetry, long memory, and complex dynamics. The GAS model allows the parameters to change over time. Depending on the score, it utilizes from the absolute density structure rather than the first and higher moments. It estimates the parameters based on the lagged values of the response variable and explanatory variables.

The GAS model has Nx1 vectors. In the relevant equation, y_t denotes the dependent variable of interest, f_t is the time-varying parameter vector, x_t is a vector of the exogenous variables, and θ is a vector of static parameters. It is defined as $Y_t = \{y_1,\ldots,y_t\}$, $F_t=\{f_1,\ldots,f_t\}$ and $X_t=\{x_1,\ldots,x_t\}$. The available information set at time t consists of $\{f_t, F_t\}$ where $\{Y_{t-1}, F_{t-1}$ l, $X_t\}$, for t= 1, …, n.

It is assumed that y_t is generated by the observation density

$y_t \; p(y_t \,|\, f_t, F_t$ (1)

Furthermore, it is assumed that the mechanism of updating the time-varying parameter f_t is given by the familiar autoregressive updating equation.

$$f_{t+1} = \kappa + \sum_{i=1}^{p} A_i s_{t-i+1} + \sum_{j=1}^{q} B_j \, f_{t-j+1} \qquad (2)$$

where K is the matrix of constant values, A and B are the coefficient matrix for the appropriate dimensions for i=1, …, p and j=1, …, q,

$s_t = s_t(y_t, f_t, F_t; \theta).$

$F_t = \{Y_{t-1}, F_{t-1}l, X_t\}$

where t ad θ are the vector of the static parameters. Unknown coefficients are given with θ. Accordingly, $\kappa=\kappa(\theta)$, $A_i=A_i\,(\theta)$ and $B_j=B_j\,(\theta)$ and i=1,2,…,p and j=1,2,…,q.

The model estimation is made based on the observation density function in equation (1). The time-varying parameter (f_t) is given as follows for t+1 period when y_t observation occurs.

$$s_t = S_t . \nabla_t, \nabla_t = \frac{\partial lnp(y_t | f_t, F_t; \theta)}{\partial f_t}$$

$$S_t = S(t, f_t, F_t; \theta)$$

$$\kappa \equiv (\kappa_\mu, \kappa_\emptyset, \kappa_v) A \equiv diag(a_\mu, a_\emptyset, a_v) \wedge B \equiv diag(b_\mu, b_\emptyset, b_v) \qquad (3)$$

where s_t is a scale matrix function. Equation (3) is a positive definite. f_t is employed intuitively in the scoring in the GAS model. The scores are determined based on not only the first and second moments but also the total density function. Equations (2)-(3) define the GAS (p,q) model (Creal, Koopman, and Lucas, 2013). This model is estimated with the maximum likelihood approach.

5. Empirical Results

The return series must be nonlinear in the GAS model. We applied Teraesvirta's neural network test, White neural network, Keenan's one-degree, and Tsay's tests to determine whether these series have a nonlinear structure. In these tests, the null hypothesis indicates the linearity in the mean. According to the results in Table 3, the null hypothesis is statistically rejected for all returns. Therefore, they have a nonlinear structure on average.

Table 3
Nonlinearity Tests

Panel A: Emerging Countries						
	Turkey	**Brazil**	**Russia**	**India**	**South Africa**	**Mexico**
Teraesvirta	13.1706***	6.5271**	11.0113***	2.8074	2.3351	10.0333***
White	14.0385***	5.3599*	6.1370**	2.3023	1.2489	8.4507**
Keenan	8.0146***	0.0175	39.0821***	8.7562***	3.8286**	3.8792**
Tsay	2.3033***	1.9240***	4.5747***	1.6219	1.5785	9.7606***
Panel B: Developed Countries						
	China	**Japan**	**Switzerland**	**Euro**	**England**	**Canada**
Teraesvirta	2.0997	36.4707***	0.8908	7.2463**	1.7622	8.9470**
White	2.9547	27.2654***	0.9828	7.5460**	7.5369**	3.6926
Keenan	0.4006	0.0001	3.0154*	2.4754	0.0005	10.2366***
Tsay	0.5276	3.6577***	0.4136	1.7583**	3.6490***	0.0000

*Note: *, ** and *** indicate significance at 10%, 5% and 1%, respectively.*

The VaR (Value at Risk), which is a technique used to measure possible downside risks, is estimated based on the GAS model. The shocks and the extreme events leading to "tail risk" in financial markets designate and change the distributions of the financial series. The standard VaR model assumes that the data have a normal distribution. However, testing of stationary of tail, skewness, shape, and location, which are parameters for each univariate distribution, is an important process. Therefore, it is of vital importance to utilize methods such as the VaR, taking into account the distribution parameters in question (Gonzalez-Rivera et.al., 2004). In the case of the existence of tail risk, the expected shortfall is more affected by the risk in question than the realized shortfall risks. These techniques are called the Expected Shortfall (ES). Consequently, these methods that measure the shortfall risks are applied to test the consistency and effectiveness of the parameters from the GAS model. The obtained values from the VaR are an indicator regarding the model risk and risk levels. In other words, the shortfall risks provide an opportunity to evaluate the validity of models. Using the GAS model to measure the shortfall risks provides additional information about the tail risks. Additionally, shortfall risks enable us to evaluate the validity of GAS model and to information about tail risks.

The estimated VaR values for the exchange rate returns from the GAS model with Student-t distribution are exhibited in Table 4. The results indicate both the time-dependent parameters and the parameters regarding the distribution, which provides information about the fat tails. In the Table 4, the location, scale, and shape parameters define the univariate distribution. The "shape" value shows the shape of the distribution. If this value is higher than 3, it indicates the possible tail effect. The coefficients of kappa1, kappa 2 and kappa 3 refer to the elements of vector κ, i.e., κ_u (location), $\kappa_\emptyset$ (scale) and κ_v (shape), respectively. In addition, a_1, a_2 and a_3 show the estimates a_μ (location), $a_\emptyset$ (scale) and a_v (shape), b_1, b_2 and b_3 show the estimates b_μ (location), $b_\emptyset$ (scale) and b_v (shape), where $\emptyset$ is the scale parameter of the Student-t distribution.

To test the consistency and effectiveness of the estimators, the VaR values for exchange rate returns were calculated using the above-mentioned parameters. There is a difference between the realized and calculated risk levels because these values are impacted by the deviations, which leads the realized shortfalls to be higher than the calculated ones. This result indicates that the method is more effective against the extreme shocks.

Table 4

The Results of VaR and GAS Model

Panel A: Emerging Countries						
	Turkey	**Brazil**	**Russia**	**India**	**South Africa**	**Mexico**
Panic	0.0003***	0.0004	0.0018***	-0.0003*	0.0012**	0.0014***
	(0.00003)	(0.0006)	(0.0005)	(0.0002)	(0.0005)	(0.0004)
Mediahype	-0.000016	-0.00007	-0.0001***	0.000003	-0.0001***	-0.0001***
	(0.00007)	(0.00004)	(0.00003)	(0.00003)	(0.00004)	(0.00003)
Fakenews	-0.0005*	0.0018	0.0007	0.0010	0.0043*	0.0035*
	(0.0002)	(0.0028)	(0.0027)	(0.0008)	(0.0023)	(0.0020)
Sentiment	-0.000008	-0.00001	-0.000001	-0.00001	-0.000006	0.00002
	(0.00004)	(0.00004)	(0.00004)	(0.00003)	(0.00003)	(0.00005)
kappa1	0.0002**	0.00003**	-0.000037	0.000002	-0.00002	-0.00005
	(0.0001)	(0.00006)	(0.00009)	(0.00007)	(0.0001)	(0.00009)
kappa2	-1.1984***	-0.3945***	-4.1552***	-0.4471***	-1.5163***	-0.5977***
	(0.2379)	(0.0250)	(0.0863)	(0.0020)	(0.5025)	(0.1780)
kappa3	-0.0470***	-1.0589***	-1.1756***	-1.1756***	-1.1756***	-1.1756***
	(0.0148)	(0.2495)	(0.3018)	(0.2060)	(0.2438)	(0.2874)
a1	0.000001***	0.000001***	0.000001***	0.0000009***	0.000001**	0.000001***
	(0.0000003)	(0.0000003)	(0.0000002)	(0.0000001)	(0.0000004)	(0.0000002)
a2	0.5691***	0.3794***	0.3794***	0.1897***	0.3794***	0.5690***
	(0.0973)	(0.0904)	(0.0885)	(0.0503)	(0.1042)	(0.1191)
a3	0.1898***	0.9483***	1.8966***	1.5173***	0.1897***	0.1897***
	(0.0011)	(0.0029)	(0.0057)	(0.0069)	(0.0014)	(0.0002)
b1	0.5000***	0.8144***	0.5000***	0.5000***	0.5000***	0.5000***
	(0.0271)	(0.0057)	(0.0059)	(0.0040)	(0.0199)	(0.0075)
b2	0.8972***	0.9634***	0.9634***	0.9634***	0.8641***	0.9468***
	(0.0197)	(0.0017)	(0.0073)	(0.00003)	(0.0448)	(0.0154)
b3	0.9800***	0.5496***	0.5000***	0.5000***	0.5000***	0.5000***
	(0.0087)	(0.0385)	(0.0216)	(0.0451)	(0.0288)	(0.0171)
Location	0.0003	0.0002	0.00007	0.000005	-0.00004	-0.0001
Scale	0.000008	0.000020	0.00001	0.000003	0.00001	0.00001
Shape	7.9991	7.9999	8	8	8	7.9999
AIC	-3958.588	-3527.843	-3927.390	-4221.457	-3615.640	-3850.512
BIC	-3921.685	-3490.940	-3880.487	-4184.554	-3578.737	-3818.609
Q(5)	7.4306	7.1627	2.6074	10.5074	10.2749	5.7348
$Q^2(5)$	4.0617	4.9473	4.1733	1.8408	2.0449	4.5873
ARCH(5)	1.4497	1.1969	1.2225	0.4037	0.1324	0.2587
Panel B: Developed Countries						
	China	**Japan**	**Switzerland**	**Euro**	**England**	**Canada**
Panic	-0.000023***	0.0001	0.00008	-0.000152	0.00074**	0.00066**
	(0.000005)	(0.00017)	(0.00019)	(0.000212)	(0.00033)	(0.00027)
Mediahype	-0.000011	0.000006	-0.000014	0.000026	-0.00008***	-0.00009***
	(0.00001)	(0.00003)	(0.00002)	(0.00002)	(0.00002)	(0.00002)

Fakenews	0.000593***	-0.00096	-0.000073	-0.000119	0.000701**	0.00202*
	(0.000004)	(0.00073)	(0.00081)	(0.000921)	(0.00146)	(0.00114)
Sentiment	-0.000002	0.000002	-0.000006	0.000007	0.0000003	0.000001
	(0.000132)	(0.00003)	(0.00003)	(0.00003)	(0.00001)	(0.00004)
kappa1	-0.000008	0.000005	-0.000019	0.000005	0.000001	-0.000008
	(0.00004)	(0.00007)	(0.00007)	(0.00006)	(0.00008)	(0.00007)
kappa2	-0.2769***	-1.0947***	-1.3323***	-1.1190***	-0.8435***	-0.6813***
	(0.0894)	(0.2318)	(0.2094)	(0.2118)	(0.1098)	(0.1143)
kappa3	-1.1756***	-0.3194***	-0.2027***	-0.2027**	-0.5140***	-0.0859**
	(0.2394)	(0.0858)	(0.0676)	(0.09107)	(0.1354)	(0.0443)
a1	0.000001***	0.0000009***	0.000009***	0.0000009***	0.000001***	0.0000009***
	(0.0000001)	(0.0000001)	(0.0000001)	(0.0000001)	(0.0000002)	(0.0000001)
a2	0.5191***	0.1897***	0.1897***	0.1897***	0.1897***	0.1897***
	(0.0823)	(0.0532)	(0.0554)	(0.0556)	(0.0737)	(0.0448)
a3	0.1897***	0.1897***	2.8448***	5.50***	1.3276***	5.50***
	(0.0001)	(0.0007)	(0.0550)	(0.0212)	(0.0444)	(0.0925)
b1	0.8475***	0.5000***	0.5000***	0.5000***	0.5000***	0.5000***
	(0.0010)	(0.1341)	(0.1087)	(0.1160)	(0.1588)	(0.0167)
b2	0.9800***	0.9137***	0.8972***	0.9217***	0.9303***	0.9468***
	(0.1538)	(0.1837)	(0.1783)	(0.0093)	(0.0090)	(0.1537)
b3	0.5000***	0.8641***	0.9137***	0.9137***	0.7813***	0.9634***
	(0.0180)	(0.0022)	(0.0017)	(0.0010)	(0.0083)	(0.018)
Location	-0.00058	0.000011	-0.000039	0.0001	0.000002	-0.00001
Scale	0.0000009	0.000003	0.000002	0.000002	0.000005	0.000002
Shape	8	7.9999	8	7.9999	8	7.9999
AIC	-4607.303	-4337.469	-4396.160	-4420.956	-4081.629	-4324.200
BIC	-4570.401	-4300.566	-4359.257	-4384.053	-4044.726	-4337.297
Q(5)	16.6634	4.0528	4.4660	4.4701	3.5714	6.4443
$Q^2(5)$	6.0923	0.6840	14.2592	1.1690	6.6950	10.9774
ARCH(5)	0.6877	0.2822	2.0053	0.2523	1.3703	1.1261

*Note: *, ** and *** indicate significance at 10%, 5% and 1%, respectively. The values in paranthesis are standart deviations.*

Table 4 also shows the results regarding the impacts of the coronavirus panic index, the coronavirus media hype index, the coronavirus fake news index, and the coronavirus worldwide sentiment index on exchange rate returns in emerging and developed countries. As examined in Table 4, it is seen that the coronavirus panic index is statistically significant at a 5% level and has a positive effect on exchange rate volatility in Turkey, Russia, South Africa, Mexico, England, and Canada, while having a negative effect in China, but this effect is less than other countries. However, it does not have a significant and statistical effect on the exchange rate volatility of Brazil, Russia, India, Japan, and Switzerland. The coronavirus media hype index decreases the volatility in Russia, South Africa, Mexico, England, and Canada. The reason can be the positive news about the COVID-19 pandemic, such as vaccine studies, a decrease in the number of cases due to warming and the weather, and easing of the lockdown measures. The coronavirus fake news led the exchange rate volatility to increase only for China and England at a 5% significance level, which represents the speculative behaviors created by fake news in international markets. The coronavirus worldwide sentiment index does not have any significant impact on the exchange rate volatility for all studies countries.

Table 5
VaR Backtesting Results

	Test Type	α = 1%	α = 5%
Turkey	LR_{UC}	2.6323 (0.1047)	0.0000001 (0.9999)
	LR_{CC}	2.8398 (0.2441)	0.5321 (0.7663)
	DQ	7.8690 (0.3442)	1.5812 (0.9793)
Brazil	LR_{UC}	0.7827 (0.3763)	2.7509* (0.0971)
	LR_{CC}	0.8652 (0.6488)	4.3445 (0.1139)
	DQ	3.1683 (0.8690)	23.7463*** (0.0012)
Russia	LR_{UC}	0.0000001 (0.9999)	0.9768 (0.3229)
	LR_{CC}	0.0204 (0.9898)	1.1643 (0.5586)
	DQ	0.4912 (0.9994)	8.7753 (0.2691)
India	LR_{UC}	0.7827 (0.3763)	0.1984 (0.6559)
	LR_{CC}	0.8652 (0.6488)	1.3957 (0.4976)
	DQ	2.8248 (0.9007)	14.0167* (0.0588)
South Africa	LR_{UC}	2.6323 (0.1047)	0.7530 (0.3855)
	LR_{CC}	2.7567 (0.2519)	1.6618 (0.4356)
	DQ	3.1433 (0.8714)	4.7971 (0.6947)
Mexico	LR_{UC}	0.0000001 (0.9999)	0.1984 (0.6559)
	LR_{CC}	0.0204 (0.9898)	0.9731 (0.6147)
	DQ	0.9965 (0.9948)	6.6492 (0.4662)
China	LR_{UC}	0.0000001 (0.9999)	0.7530 (0.3855)
	LR_{CC}	0.0204 (0.9898)	1.4337 (0.4882)
	DQ	2.4657 (0.9296)	12.796* (0.0772)
Japan	LR_{UC}	0.0000001 (0.9999)	0.2253 (0.6350)
	LR_{CC}	0.0204 (0.9898)	0.5622 (0.7549)
	DQ	0.7688 (0.9977)	2.4203 (0.9329)

Switzerland	LR_{UC}	0.7827 (0.3763)	0.1984 (0.6559)
	LR_{CC}	0.8652 (0.6488)	0.9731 (0.6147)
	DQ	3.1195 (0.8737)	10.5590 (0.1590)
Euro	LR_{UC}	2.0100 (0.1562)	0.9768 (0.3229)
	LR_{CC}	2.1672 (0.3660)	1.1543 (0.5586)
	DQ	0.9696 (0.9953)	1.0016 (0.9948)
England	LR_{UC}	0.0000001 (0.9999)	1.6258 (0.2036)
	LR_{CC}	0.0204 (0.9898)	3.0242 (0.2204)
	DQ	4.1783 (0.7590)	8.0227 (0.3305)
Canada	LR_{UC}	0.7827 (0.3763)	1.6258 (0.2036)
	LR_CC	0.8652 (0.6488)	3.0242 (0.2204)
	DQ	4.1440 (0.7427)	7.8225 (0.3484)

Note: The values in paranthesis are probabilities. $LR_{uc} = -2ln\{[(1-p)^{T_0}p^{T_1}]/[(1-\pi)^{T_0}\pi^{T_1}]\}p$ indicates the probability level, π indicates the percentage of violations, T_0 and T_1 are respectively the number of non-violations and violations in VaR. For large samples, the test statistics represents a chi-squared distribution. $LR_{CC} = 2\left(log\left(\hat{\pi}_{01}^{T01}(1-\hat{\pi}_{01})^{T00}\hat{\pi}_{11}^{T11}(1-\hat{\pi}_{11})^{T10}\right) - log\left(p^{T01+T11}(1-p)^{T01+T10}\right)\right)$, . $DQ = \frac{\Psi' z' z \Psi}{\alpha(1-\alpha)} \lim_{T\to\infty} \chi^2(2K+1)$. Z is the matrix of explanatory variables and $\Psi = (\delta, \beta_1, \cdots, \beta_K, \gamma_1, \cdots \gamma_K)'$ is the vector of 2K+1 parameters of the model.

The backtesting methods, which are the unconditional coverage test of Kupiec (1995) (LR_{UC}), the conditional coverage test of Christoffesen (1998) (LR_{CC}), and the Dynamic Quantile test of Engle and Manganelli (2004) (DQ), are used to test whether there is any statistical difference between the expected and realized deviations from the GAS model. The LR_{UC} test can be insufficient because of the jumps, bubbles, and excessive deviations. Therefore, the LR_{CC} test is more effective than the LR_{UC} test. However, both techniques can be biased due to the tail effects. The DQ test provides more effective results in the existence of tail effects. The results of backtesting based on the GAS model are given in Table 5. According to the results of the $LR_{UC,}$ the $LR_{CC,}$ and the DQ tests, the null hypothesis suggesting the difference between expected and realized shortfalls can be not rejected at a 5% level of significance for all returns. These findings are demonstrated in Table 5. There is not a statistically significant difference between what was realized and the deviations. This indicates the presence of tail effects and time dependence.

6. Conclusion and Discussion

Exchange rates act a crucial role in evaluating the financial position of a country. The deteriorating of exchange rates leads a country to move towards high inflation by affecting the purchasing power. Exchange rate fluctuations generally depend on the discounted value of the sum of observable and unobservable macroeconomic factors. Policy precautions carried out during the COVID-19 pandemic have deepened the adverse outlook of the macroeconomic factors in terms of the expected economic impacts of the pandemic. This leads exchange rate expectations to be relevant to the transmission of policy shocks due to the lockdown policies. During the uncertainty periods from the COVID-19 pandemic, some exchange rates (such as the euro) were observed to act as a safe haven, although the exchange rates in some countries (such as Turkey) were adversely affected by the pandemic as a consequence of the stringency policies.

This study analyzes the impacts of news regarding the COVID-19 pandemic on exchange rate volatility using the GAS model, which is a new approach based on the score of the conditional density function. In the study, the daily exchange rate returns for the countries with highest cases, which includes Turkey, Russia, Brazil, India, South Africa, Mexico, Japan, Europen Union, England, Switzerland, China, and Canada, were considered during the period between January 1, 2019 and August 31, 2020. News regarding the COVID-19 pandemic were classified into four indices: the coronavirus panic index, the coronavirus media hype index, the coronavirus fake news index, and the coronavirus worldwide sentiment index. Thanks to the GAS model with time-varying parameters, the effect of these so-called indices on exchange rate volatility can be evaluated for each period and the tail-effects can be taken into account.

The empirical results conclude that panic and fake news about the COVID-19 pandemic have lead to exchange rate volatility, while media hype reduced the volatility. The results highlight the view stated by Fang and Peress (2009) that the wideness of information dissemination impacts financial markets and exchange rates. In addition, the results reveal that an increase in the news stories regarding the COVID-19 pandemic has led to deteriorations in exchange rates. Thus, it can be stated that the negative and speculative news about the COVID-19 pandemic have increased uncertainty in financial markets, which adversely affected exchange rates.

The findings propose that proper communication channels should be more intensely used to diminish the effects of financial turmoil from the COVID-19 pandemic. To mitigate the negative results of the global pandemic, policymakers and the private sector should have an alternative plan against foreign currency risk, such as a strong reserve. Also, policymakers should develop appropriate policies and control mechanisms to effectively manage and minimize potential risk and negative effects from extreme currency risk.

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