Dynamic equicorrelation analysis of financial contagion: Evidence from Latin America markets

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Abstract

In this research, we employ the multivariate autoregressive moving average-generalized autoregressive conditionally heteroscedastic-dynamic equicorrelation (ARMA-GARCH-DECO) model to identify contagion among Latin American financial markets during financial turmoil period. We analyze the dynamic conditional correlations among 18 American Depositary Receipts (ADR), 8 Exchange Traded Funds (ETF) and 6 Foreign Exchange Rates (Forex). Our sample includes daily closing prices from April 1, 2014 to January 29, 2021, for Argentina, Brazil, Chile, Colombia, Mexico, and Peru. Results find long-run properties in the volatility of most instruments including those belonging to defensive super sector implying that defensive super sector and basic materials are the most impacted sectors during the last financial crises. We present evidence that in times of economic disruption like in the midst of the COVID-19 pandemic, those financial assets do not act as safe harbor investments since they are relatively more correlated during period of financial crises than in normal periods. Our findings have policy implications and are of interest to practitioners who look a better understanding of the dynamics of spillovers among the behavior of emerging financial assets.

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Keywords: Dynamic equicorrelation model, American Depositary Receipts, Exchange Traded Funds, Foreign Exchange Rates, ARMA-GARCH, Latin American markets.

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1. Introduction

Understanding the volatility dynamics of Latin America financial instruments has received considerable attention following the dramatic Brazilian economic downturn in 2014. Latin America's main market, Brazil saw a dramatic change when it faced the worst recessions in its history from mid-2014 onward. The problem gradually got worse as the financial situation carries on with its downward spiral, worsened by commodity price shock and political turmoil. This situation has renewed interest in examining the evolution of connectedness among emerging markets and developed economies. Understanding the time-varying connectedness across these markets has several important implications for asset allocations, risk management, policy recommendations and implementation.

Several studies using the dynamic conditional correlation- generalized autoregressive conditional heteroscedasticity (DCC-GARCH) and provide empirical evidence that US stock volatility and weakening credit market conditions induce financial contagion to the Latin America [1, 2]. Similar methodologies have been used to detect potential contagion among emerging markets. They show that Latin America markets are mostly net volatility receivers [3, 4]. Moreover, studies using different methodologies found the interdependence of Latin American assets and call for international portfolio diversification [5, 6]. As this literature indicates, the dynamics of volatility spillover among Latin America markets is an interesting research topic, therefore, it calls for further studies using different approaches and a broader set of datasets. The DCC framework for correlations is a useful modeling tool, however when the number of test assets becomes large the estimation can become unreliable and even breakdown completely.

The aim of this study is to provide a more comprehensive analysis of static and temporal volatility spillover among Latin America financial instruments including American Depositary Receipts (ADR), Exchange Traded Funds (ETF) and Foreign Exchange Rates (Forex). We contribute to the existing literature by integrating an ARMA-GARCH-DECO specification with Ling and McAleer [7] and Engle and Kelly [8] frameworks to examine conditional spillover among the underlying assets. The Dynamic Equicorrelation (DECO) class of correlation models is aimed to overcome some of computational difficulties of DCC. Regarding ARMA-GARCH, we specifically utilize an ARMA(1,1)-GARCH(1,1) specification on returns series to extract the conditional volatility, fat tail, serial correlation, leverage effects, and heteroscedasticity issues. As Danielsson [9] pointed it out, financial series may be propelled by the presence of volatility clusters and fat tails. Volatility clustering is the observation that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." tendency of large changes in prices of financial assets to cluster together [10, 11] while "fat tail" refers to probability distributions with a relatively high probability of extreme outcomes. Those tendencies can be captured using a GARCH framework. To account for structural variation, we divide our sample into three subsamples, i.e. the Brazilian economic crisis period (pre-2017 subsample), the calm period (between 2017 to 2019 subsample) and covi-19 recession period (post-2019 subsample).

Consistent with previous research, our results support low level of correlation among the assets under study indicating relatively no interconnectedness among the assets. During the financial turmoil periods, the equicorrelation coefficient among variables is relatively higher compared to calm period. In addition, we found long-run volatility properties among the markets.

The remainder of this article is structured as follows. In section 2 we present previous literature relevant for volatility spillover in Latin America markets. The empirical methodology and the dataset are presented in section 3 and 4, respectively. The obtained empirical results are discussed in section 5. The final Section 5 concludes the analysis.

2. Literature review

Since the 2008 global financial crisis, an emerging strand of literature employing different datasets and various econometric frameworks focuses on the connectedness dynamics among emerging markets assets such as American depository receipt (ADR), Exchange traded fund (ETF) and Foreign exchange rate (Forex). Hwang [2] employs DCC-GARCH model to analyze the transmission of the 2008 US financial crisis to four Latin American stock markets. The sample covers daily stock returns from 2006 to 2010 related to specific markets, namely, Merval (Argentina), Bovespa (Brazil), Bolsa de Santiago (Chile) and Bolsa Mexicana de Valores (Mexico). He found evidence of financial contagion by showing that pair-wise conditional correlations are relatively higher and more volatile during the period of crisis. In other words, empirical findings show that stock markets in Argentina, Brazil, and Mexico are heavily affected by the 2008 US financial. Gamba-Santamaria, et al. [3] constructs volatility spillover indexes using a DCC-GARCH framework to model the multivariate relationships between US stock markets and four Latin American financial assets. Their results show that Brazil is a net volatility transmitter for most of the sample period, while Chile, Colombia and Mexico are net receivers. The total spillover index is substantially higher between the third quarter of 2008 and the second quarter of 2012, and shock transmission from the US to Latin America substantially increased around the bankruptcy of Lehman Brothers.

Multivariate DCC-GARCH model has also been employed by Rodriguez-Nieto and Mollick [1] to identify contagion from the USA to the largest developed and emerging markets in the Americas (Argentina, Brazil, Canada, Chile, Colombia, Mexico, and Peru) during the US financial crisis. Their sample considers daily closing prices from January 1, 2002 to December 31, 2015 and includes changes in the general economy’s credit risk represented by the TED spread, and changes in the US market volatility represented by the CBOE Volatility Index (VIX). Results suggest that increases in VIX have a negative intertemporal and contemporaneous relationship with most of the stock returns, and these relationships increase significantly during the US financial crisis. Moreover, they also find evidence of significant increases in contemporaneous conditional correlations between changes in the TED spread and stock returns. Increases in conditional correlations during the financial crisis are associated with financial contagion from the USA to the Americas. Those findings illustrate that during periods of financial distress, US stock volatility and weakening credit market conditions could promote financial contagion to the Americas. In their article, Marçal, et al. [4] used DCC-GARCH model to investigate the existence of contagion among countries on the basis of an analysis of returns for stock indices over the period 1994 to 2003. Results show that contagion spread from the Asian crisis to Latin America, but not in the opposite direction. A possible explanation for Latin America's vulnerability to financial crises lies in the weakness of its economic fundamentals during the period.

Esqueda, et al. [5] employ GARCH-M model to examine the effects of the U.S. investor sentiment on American depository receipts (ADR) premiums by using daily prices from 1995 to 2009. The volatility index (VIX) is used as a proxy for investor expectations about the stock market while liquidity, transaction costs, and domestic and U.S. stock exchange returns are controlled. They find that deviations from the law of one price in ADRs can be partially explained by the lag of the smoothed volatility index. Those findings have important implications for portfolio diversification on emerging markets as investment managers can improve hedging strategies by incorporating known values of the volatility index. In the other hand, Costa Correa, et al. [6] use VAR-MGARCH multivaried skewness models, with diagonal VECH representation to detect and measure the phenomenon of interdependence of ADR indices on the main Latin American capital markets (Brazil, Argentina, Chile and Mexico) and developed (United States, Japan, United Kingdom and France) given the 2008 financial crisis scope. They found that the ADR indices presented greater interdependence with the developed countries, compared to the analyzed Latin American equity markets.

In his research paper, Diamandis [12] uses weekly observations for the period January 1988–July 2006 and examines long-run relationships between four Latin America stock markets and a mature stock market that of the US via the autoregressive and moving average representations of a VAR model. The main finding of the analysis suggests that there are significant common permanent components driving the examined stock markets in the long run. Moreover, results also indicate that those five equity markets are partially integrated implying small long-run benefits from international portfolio diversification since the stock prices adjust very slowly to these common trends. Extending this framework, Esqueda and Jackson [13] analyze the behavior of 74 American depository receipts (ADR) and exchange rate returns from Argentina, Brazil, Chile, and Mexico by employing seemingly unrelated regressions (SUR) and multivariate regression models (MVRM) during the period May 1994 to May 2009. Results show that ADR prices are determined primarily by the underlying stock, exchange rates, host country index as well as U.S. stock market. Moreover, monitoring the underlying stock and local and host country stock indexes, they find that ADRs generate significant negative abnormal returns during currency crises, due to conversion exposure. Those findings confirm the predominance of the American stock exchanges in terms of ADR price discovery and market integration.

The advantage of our research in comparison with the above studies is the use of ARMA-GARCH-DECO specification to test spillover effect among Latin American financial instruments, while prior studies mostly have recourse to multivariate GARCH models to discover US markets contagion to emerging markets.

3. Methodology

Fama [14] suggested that the empirical distribution of stock returns characteristically exhibits a more peaked central part and fatter tail parts compared to the normal distribution assumed by financial theories. Besides those two properties, nonlinear dependence can explain the relationship between multivariate financial data. For example, a non-linear dependence among different assets can be discerned during a financial crisis, where many assets are likely to move together in the same direction depending on certain market conditions [15-17]. To study those tendencies, let's consider r_t returns series for the t = 1, . . ., T assets.

Conditional Variance

We define the conditional covariance matrix of all return series as $E_{t-1}[r_t r_t'] = H_t$. We can further decompose H_t into the following:

$$H_t = D_t R_t D_t \tag{1}$$

where $D_t = diag(\sigma_{i,t})$. Here, $\sigma_{i,t}$ is the conditional volatility of return series *i* and is the *i*th diagonal entry of H_t. Finally, R_t is the conditional correlation matrix for the return series. The Autoregressive Moving Average Model−Generalized Autoregressive Conditional

Heteroscedasticity−Dynamic Equicorrelation (ARMA-GARCH-DECO) model a la Engle and Kelly [8] puts specific parametric assumptions on the evolution of D_t and R_t separately.

Each individual return series' conditional variance is displayed as a standard GARCH process. The main advantage of ARCH models is that they can generate accurate models to predict the volatility of financial time series. Conditional variance individual return series can be written as:

$$\mathrm{E}_{t-1}[r_{i,t}^2] = \sigma_{i,t}^2 \tag{2}$$

Following Engle [18], we use ARMA model to fit the mean and GARCH model to fit the variance. In other words, we utilized the ARMA (1,1)-GARCH (1,1) models because of their simplicity and reliability. They are given by:

$$Y_t = \mu_i + \varphi_i Y_{i,t-1} + \varepsilon_{i,t} + \theta_i \varepsilon_{i,t-1} \tag{3}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \tag{4}$$

where a given individual return series Y_t is decomposed into a conditional mean (μ_i) containing one lag in both AR and MA terms and a conditional variance (ε_t); φ (phi) and θ (theta) are coefficients to estimate. α (alpha) and β (beta) are also model coefficients and are all positive; the constant σ^2 is the unconditional variance of ε_t. We also assume that $\alpha_i + \beta i < 1$ and $\sigma_{it}^2 = \omega_i / (1 - \alpha_i - \beta_i)$. Those are positivity constraint and condition for existence of the fourth moment of the GARCH [7].

Cai, et al. [19] and Bollerslev [20] suggest replacing the conditional normal distribution with the conditional Student's t-distribution in order to capture leptokurtosis form of the returns. It takes the following form:

$$f(\varepsilon_t) = \frac{\Gamma\left[\frac{1+v}{2}\right]}{\sqrt{v\pi}\,\Gamma\left(\frac{v}{2}\right)}\left[1 + \frac{\varepsilon_t^2}{v}\right]^{-\frac{1+v}{2}} \tag{5}$$

where v is the degree of freedom of the t-distribution.

Importantly, the volatility residual vector $\varepsilon_t = [\varepsilon_{1,t} \ldots, \varepsilon_{N,t}]$ of our ARMA-GARCH-DECO model will have the same correlation structure as the original return series. We now turn to modeling this correlation structure.

Conditional Correlation

The ARMA-GARCH-DECO model assume a specific parametric form for conditional correlation matrix R_t. More specifically, on a given day the model assumes that all pairwise correlations are identical. Kang, et al. [21] suggest that the correlation matrix R_t is an equicorrelation matrix and evolves as:

$$R_t = (1 - \rho_t) I_N + \rho_t J_N \tag{6}$$

$$\rho_t = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{7}$$

$$q_{ij,t} = \bar{\rho}_{i,j} + \alpha_{DECO}\left(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \bar{\rho}_{i,j}\right) + \beta_{DECO}\left(q_{i,j,t-1} - \bar{\rho}_{i,j}\right) \tag{8}$$

where $\bar{\rho}_{i,j}$ is the unconditional correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t-1}$; J_N is the n×n matrix of ones, and I_N s the n-dimensional identity matrix. This process allows us to represent the degree of co-movement of a group of financial instruments with a single time-varying correlation coefficient. By modeling the univariate return series as individual ARMA-GARCH processes, and their standardized residual series as a DECO process, we form the complete ARMA-GARCH-DECO specification.

Estimation

We estimate the parameters of our ARMA-GARCH-DECO model system using sequential quadratic programming technique in *OxMetrics 6.20* software. In order to implement this method, we assume the stacked return series $r_t = [r_{1,t}, \ldots, r_{N,t}]$ and conditional covariance H_t followed a Student t-distribution density as explained above. It can be shown that this function can be decomposed into a volatility component and a correlation component, which naturally leads to a two-step estimation procedure [22]. First, we estimate univariate ARMA-GARCH models to each return series. Next, we use the stacked residuals $\varepsilon_t = [\varepsilon_{1,t} \ldots, \varepsilon_{N,t}]' = D_t^{-1} r_t$, to estimate the correlation parameters α_{DECO} and β_{DECO} by maximizing the following function:

$$L_c(\alpha_{DECO}, \beta_{DECO}) = \frac{1}{T}\sum_t (log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t - \varepsilon_t' \varepsilon_t') \tag{9}$$

As is similar with the univariate ARMA-GARCH process, the single correlation ρ_t will be stable and mean-reverting so long as $\alpha_{DECO}>0$, $\beta_{DECO}>0$, $\alpha_{DECO}+\beta_{DECO}<1$. The standard restrictions and properties of the univariate ARMA-GARCH models that are used to model each individual return series' volatilities also naturally still hold. Moreover, those estimated parameters may reveal to be consistent estimates in the event that the true correlations evolve as a DCC system, but with much less computational overhead [19].

4. Data

The sample used in this paper is composed of 3 financial instruments including American Depositary Receipt (ADR), Exchange Traded Fund (ETF) and Foreign Exchange Rate (Forex). Data related to ADR are retrieved from J.P. Morgan's ADR website using filtering criteria such as NYSE as EXCHANGE; Latin America as REGION; and Argentina, Brazil, Chile, Colombia, Mexico and Peru as COUNTRY. 71 relevant ADRs were identified. Out of which 18 are selected based on trading history and market cap. ETF and Forex samples relating to the above-mentioned countries have been selected from Yahoo finance based on data availability. All ETFs except ECH are either listed on the NYSE Arca or the NASDAQ Global Market Composite (NASDAQGM). Table 1 details the financial instruments, as well as industry and related country considered in this paper. With a market capitalization of more than US $43 billion, the Brazilian corporation Ambev is the largest company considered in this study. FMX from Mexico has the second largest market capitalization, of US $14.9 billion, making the Beverages/Brewers the most prominent industry under study. Argentina's TGS having a market cap of US $658 million is the smallest company while Consumer Defensive remains the most representative sector in this paper.

In addition, our study considers daily data from Yahoo finance for the period starting from April 1, 2014 through January 29, 2021. The choice of this period is based on the devastating impact on the economy of two major crises which are the Brazilian crisis and coronavirus pandemic. This period was further divided into three sub-periods: Brazilian economic crisis (April 1, 2014 − December 30, 2016), calm period (January 3, 2017 − December 31, 2019) and COVID-19 recession (January 2, 2020 − January 29, 2021). From mid-2014 onward, Brazil which is largely dependent on the export of commodities, experienced one of the most intense and prolonged recessions in its economic history charectized by a dramatic drop of GDP score and high unemployment rate [23, 24]. COVID-19 recession, also known as the Great Lockdown [25] is the worst global economic crisis since the Great Depression of the 1930s which has triggered a recession in many economies and regions [25, 26]. The situation is taking a heavy toll on emerging stock markets and commodities markets to the point that even safer instruments, such as gold returns, turn negative [27, 28]. The sub-sample period named "calm period" considered data between the two above-mentioned crises. Daily returns are computed as 100 times the first difference in the log of the price level P of the financial instrument at time t and time t-1. That is, $r_t = (\log P_t - \log P_{t-1}) \times 100$. Figure 1 plots the daily returns for each financial instrument over the full sample period. These plots reveal that all markets except CLP/USD and COP/USD fell substantially around the global stock market crash beginning on 20 February 2020.

[Table 1 about here]

5. Empirical Results

Table 2 described the sample size and summary statistics of our variables. Latin American financial instruments except TGS, ARGT and SID have negative daily mean returns during the full sample period. The average returns range from −0.0014 (ARS/USD) to 0.0004 (TGS). Standard deviations range from 0.0083 (MXN/USD) to 0.4002 (COP/USD). In other words, COP/USD following by CLP/USD, SID and CIG are more significantly volatile than any other instrument. Skewness describing the asymmetry of the normal distribution shows that all instruments except SID and CLP/USD have negative (left skewness) value, indicating a greater probability to generate negative return outcomes. Kurtosis coefficient measuring the peakedness of the distribution imply that all variables have leptokurtic distribution (positive excess kurtosis) and shows evidence of fat tails in all markets. In addition, the Jarque-Bera test strongly rejects the normality of returns series. The means are mostly negative during the Brazilian economic crisis. The mean returns range from − 0.0016 (CIG) to 0.0019 (TGS). COP/USD, CLP/USD, SID and CIG having respectively a standard deviation of 0.6299, 0.3606 and 0.0499 are the most volatile instruments while MXN/USD is the safest one. In addition, all variables are positively skewed and have positive excess kurtosis while the Jarque-Bera test strongly rejects the normality confirming that the distribution has fatter tails.

As expected, the average value of financial instruments ranging from -0.0017 (ARS/USD) and 0.0009 (ELP) are more likely positive during the calm period. Higher standard deviation scores 0.0384 (STGS), 0.035 (SID) and 0.0304 (CIG) makes those variable the most volatile instruments while MXN/USD and EPU are the less volatile one during this period. Moreover, variables mostly have a long-left tail and positive excess kurtosis while the test of Jarque-Bera strongly rejects the normality distribution assumption. On the other hand, during the COVID-19 lock-down period, the mean return of financial instruments is mostly negative and range from -0.0042 (YPF) and 0.0017 (SID). ARS/USD with a standard deviation of 0.0020 is the safest instrument while SID having a standard deviation of 0.0547 appears to be the most volatile among variables. Additionally, returns are mostly negatively skewed while their kurtosis values are greater than 3 (leptokurtic distributions), which means that the probability of extreme return is very high. The Jarque-Bera statistic for residual normality shows that the returns of those instruments are under a non-normal distribution assumption.

[Table 2 about here]

Table 3 illustrates the use of Augmented Dickey-Fuller (ADF) test to evaluate whether our series have unit root or not. This test indicates that the return of the instruments under study all reject the null hypothesis of a unit root at 1% level of significance, meaning that the return series are stationary according to the ADF. Based on our model specification, we use one lag value of both the AR and MA parameters to select the models. But the Lagrange Multiplier (LM) test returns serial correlation problem in more about one-third of the markets. This study also used the ARCH-LM process to test the ARCH effect and eliminate heteroscedasticity in the volatility of the data; the test illustrates that the GARCH (1,1) models can be applied in the returns. It showed that all instruments except BRL-USD, TV and EWW are now free of heteroscedasticity problems with insignificant values starting from 0.0024 to 2.3555. In other words, the test results suggest no autoregressive conditional heteroscedasticity for each sample in the GARCH-ARMA models.

[Table 3 about here]

In Table 4(a), we estimate ARMA-GARCH-DECO models for the overall sample. The sample mean of squared residuals was used to start recursion. The positivity constraint for the GARCH (1,1) and the condition for existence of the fourth moment of the GARCH are both observed in instruments belonging to defensive super sector (ABEV, CBD, CIG, ELP, CCU, ENIA, FMX, IBA, KOF, TV), financial services and basic materials sectors (TEO, SID, TIMB, BVN, BSAC, CIB), ETF (EWZ, FBZ, ECH, CXG, EWW, EPU) and forex (BRL/USD, PEN/USD). Those constraints are given by alpha > 0, alpha/(1 – beta)≥ 0 and alpha + beta < 1 as proposed by Doornik, et al. [22] and Ling and McAleer [7]. The coefficient α(alpha) captures the influence of new shocks on volatility while the parameter β(beta), measures persistence of volatility shocks. Results show that the volatility persistence of those assets is not very long in this period, and there is a certain degree of "volatility clustering phenomenon”. In the other hand, the constraint of stationarity is observed in assets coming from exchanged traded fund (ARGT, ICOL) and foreign exchange rate (CLP/USD, COP/USD, MXN/USD). However, the condition for existence of the fourth moment of the GARCH is not observed. That constraint is over 1, meaning that there is a long-lasting volatility in those markets. Other results show that the positivity constraint for the GARCH (1,1) and the condition for existence of the fourth moment of the GARCH are not observed in ARS/USD. This constraint equals 2.35067>1. Dynamic Equicorrelation Model coefficients are all statistically significant. Rho having a score of 0.2778 show the level of correlation among the assets under study. Alpha (DECO) measures the short-run volatility impact while Beta (DECO) rate the long-run volatility effect. The results show that the model captures the long-run volatility impact among the markets with a score close to 1 (0.9104).

[Table 4a about here]

Table 4(b) presents the estimation of ARMA-GARCH-DECO models for the Brazilian crisis period. Results show that when θ (theta) coefficient is negative, φ(phi) is positive, and in reverse. The stationarity condition is that this factor be less than the unit in absolute value. Furthermore, the positivity constraint for the GARCH (1,1) and the condition for existence of the fourth moment of the GARCH are both observed in assets derived from communication services and energy sectors (TEO, TGS, YPF, TIMB), defensive super sector (ABEV, CBD, CIG, ELP, CCU, ENIA, FMX, IBA, KOF, TV), financial services and basic materials (BSAC, CIB, BVN), Exchange-traded fund (ARGT, EWZ, FBZ, ECH, ICOL) and forex (BRL/USD). This shows that Telecom Services and utilities industries have the most volatile assets during this period. In addition, the coefficient α(alpha) and β(beta) are positive as well as statistically significant for those returns (except for TEO, TGS, CIB and TV) implying that economic shocks especially those of external do have long standing effects on those markets. Similarly, the positivity constraint for the GARCH (1,1) is observed in ETF (CXG, EWW, EPU) and forex (ARS/USD, CLP/USD). However, the condition for existence of the fourth moment of the GARCH is not observed. That constraint is over 1. For returns such as CXG, EWW and EPU, value of β is close to 1, indicating that old shocks tend to persist, instead of dying out quickly. Other results show that the positivity constraint for the GARCH (1,1) is not observed while the condition for existence of the fourth moment of the GARCH is observed in PEN/USD. That constraint is equals 0.942848 and should be < 1. Its negative and statistically significant β implies that economic shocks don't have any effects on this exchange rate volatility. Figure 2 plots the conditional variance. The plot seems to indicate that the volatility increases as time passes for most of the assets which is confirmed in Figure 3 drawing the conditional correlation during that crisis period. During the Brazilian crisis period, the equicorrelation coefficient among variables, with a score of 0.3160, is higher than that of the overall sample. It supports the predictions of Hwang [2] stating that the total spillover is substantially higher in period of financial turmoil. Beta (DECO) summarizes the long-run volatility impact among the markets with a score close to 1. Alpha (DECO) measuring the short-term volatility effect is low but statistically not significant.

[Table 4b. about here]

Table 4(c) presents the results of ARMA-GARCH-DECO estimations during the calm period. The positivity constraint for the GARCH (1,1) and the condition for existence of the fourth moment of the GARCH are both observed for assets related to defensive super sector (ABEV, CBD, ELP, SID, CCU, ENIA, FMX, IBA, KOF, TV), communication and financial services (TIMB, BSAC), exchange-traded funds (EWZ, FBZ, ECH, CXG, ICOL, EWW, EPU) and foreign exchange rate (BRL/USD, CLP/USD, MXN/USD, PEN/USD). Results also show that financial instruments emanating from energy and telecommunication-related sectors (TEO, TGS, YPF, CIG), Exchange traded fund (ARGT) and Forex (ARS/USD) observed the positivity constraint for the GARCH (1,1) is but denied the condition for existence of the fourth moment. Moreover, their positive coefficient α from the fitted model capturing the influence of new shocks on volatility is statistically significant. Moreover, we find the condition for existence of the fourth moment of the GARCH is observed in CIB but the positivity constraint for the GARCH (1,1) is not. That constraint is over 1. Additionally, Figure 4 plotting the conditional variance indicate a relatively stable price as low volatility is observed during that period. Figure 5 draws the conditional correlation during that crisis period. It can be seen that the constraints described above are satisfied for all possible realizations of the past information and for all linear combinations of the variables. Results for Dynamic equicorrelation model are also reported. Rho with a statistically significant score of 0.2450 shows that the assets ADRs, ETFs and Forex are less correlated with the market movements during calm period than during period of financial turmoil. Moreover, we also find that long-run volatility impact of Beta(DECO) (0.8962) is lower than that of other sub-periods, meaning that volatility is less persistent compared to other periods.

[Table 4c. about here]

We ran ARMA-GARCH-DECO estimations for the period, we named “COVID-19 recession period”. Table 4(d) presents the results of those estimations. Volatility persistence is observed in our data during that period as shown by the existence of the positivity constraint and the fourth moment of the GARCH in assets related to defensive super sector (ABEV, CCU and IBA, ENIA, CBD), communication and financial services (TEO, TV, BSAC,), exchange-traded funds (ARGT, ECH) and Foreign exchange rate (ARS/USD, BRL/USD COP/USD). This implies that covid-19 shocks have long standing effects on many industries such as department stores, telecom services, banks, food and beverage. However, we only observed the positivity constraint for the GARCH (1,1) in assets returns of different sectors such as energy and telecommunication services (TGS, YPF, TIMB, CIB), utilities and basic materials

(CIG, ELP, SID, FMX, KOF, BVN), ET funds (EWZ, CXG, ICOL, EWW, EPU) and forex (MXN/USD, PEN/USD). The condition for existence of the fourth moment of the GARCH is not observed in the above-mentioned financial returns. High value of β indicates that old shocks tend to persist. Figure 5 indicates a relatively high volatility during the stock market crash period in all markets while Figure 6 translates how highly correlated are those markets during that period. Dynamic Equicorrelation Model with a significant degrees of freedom (10.5937) is also reported. Coefficient rho (0.3032) shows a relatively high level of correlation among financial assets compared to the calm period. Beta (DECO) (0.8906) measuring the long-run volatility effect confirming the long impacts of the novel coronavirus pandemic on those financial instruments.

[Table 4d. about here]

Table 1: Categories of financial instruments and related countries

Related-country	Type	Symbol	Name	Sector	Industry	Market cap (million USD)
Argentina	ADR	TEO	Telecom Argentina	Communication Services	Telecom Services	1428
		TGS	Transportadora de Gas del Sur S.A.	Energy	Oil & Gas Midstream	658
		YPF	YPF Sociedad Anónima	Energy	Oil & Gas Integrated	2659
	ETF	*ARGT* [1]	*Global X MSCI Argentina ETF*			
	Forex	*ARS/USD*	*Argentine Peso to US Dollar Exchange Rate*			
Brazil	ADR	ABEV	Ambev S.A.	Consumer Defensive	Beverages—Brewers	43690
		CBD	Companhia Brasileira de Distribuição	Consumer Cyclical	Department Stores	3723
		CIG	Companhia Energética de Minas Gerais	Utilities	Utilities—Diversified	2544
		ELP	Companhia Paranaense de Energia - COPEL	Utilities	Utilities—Diversified	1539
		SID	Companhia Siderúrgica Nacional	Basic Materials	Steel	7711
		TIMB	TIM S.A.	Communication Services	Telecom Services	5917
	ETF	*EWZ* [1]	*iShares MSCI Brazil ETF*			
		FBZ [2]	*First Trust Brazil AlphaDEX Fund*			
	Forex	*BRL/USD*	*Brazilian Real to US Dollar Exchange Rate*			
Chile	ADR	BSAC	Banco Santander-Chile	Financials Services	Banks—Regional	9534
		CCU	Compañía Cervecerías Unidas S.A.	Consumer Defensive	Beverages—Brewers	3025
		ENIA	Enel Américas S.A.	Utilities	Utilities—Regulated Electric	11435
	ETF	*ECH* [3]	*iShares MSCI Chile*			
	Forex	*CLP/USD*	*Chilean Peso to US Dollar Exchange Rate*			
Colombia	ADR	CIB	BanColombia S.A.	Financial Services	Banks—Regional	4367
	ETF	*CXG* [1]	*Global X MSCI Colombia ETF*			
		ICOL [1]	*iShares MSCI Colombia ETF*			
	Forex	*COP/USD*	*Colombian Peso to US Dollar Exchange Rate*			
Mexico	ADR	FMX	Fomento Económico Mexicano	Consumer Defensive	Beverages—Brewers	14898
		IBA	Industrias Bachoco	Consumer Defensive	Farm Products	2058
		KOF	Coca-Cola FEMSA	Consumer Defensive	Beverages—Non-Alcoholic	2322
		TV	Grupo Televisa	Communication Services	Broadcasting	4341
	ETF	*EWW* [1]	*iShares MSCI Mexico ETF*			
	Forex	*MXN/USD*	*Mexican Peso to US Dollar Exchange Rate*			
Peru	ADR	BVN	Compañía de Minas Buenaventura S.A.A.	Basic Materials	Other Precious Metals & Mining	2550
	ETF	*EPU* [1]	*iShares MSCI Peru ETF*			
	Forex	*PEN/USD*	*Peruvian Nuevo Sol to US Dollar Exchange Rate*			

Note: American depositary receipts (ADR) are all listed on the New York Stock exchange (NYSE). ETF means Exchange-traded fund.
[1]: Listed on the NYSE Arca; [2]: Listed on the NASDAQ Global Market Composite (NASDAQGM); [3]: Listed on the Better Alternative Trading System (BATS)

Source: Yahoo finance (https://finance.yahoo.com/) and J.P Morgan (https://adr.com/dr/drdirectory/drUniverse)

Table 2: Sample Size and summary statistics of ADR, ETF and Forex

	Argentina					Brazil								
	ADR			ETF	Forex	ADR						ETF		Forex
	TEO	TGS	YPF	ARGT	ARS/USD	ABEV	CBD	CIG	ELP	SID	TIMB	EWZ	FBZ	BRL/USD
Panel A. Full sample period – April 1, 2014 through January 29, 2021														
Mean	-0.0006	0.0004	-0.0012	0.0002	-0.0014	-0.0006	-0.0007	-0.0006	-0.0001	0.0001	-0.0004	-0.0002	-0.0003	-0.0005
Std. Dev	0.0274	0.0343	0.0332	0.0188	0.0125	0.0226	0.0268	0.0363	0.0303	0.0449	0.0256	0.0250	0.0246	0.0114
Skewness	-1.7138	-3.9116	-1.9456	-2.4482	-11.3777	-0.5819	-0.2398	-0.5498	-0.5154	0.1720	-0.4391	-1.1867	-1.3397	-0.1604
Kurtosis	32.9269	81.5757	28.4679	36.6783	241.6670	10.8147	6.9621	8.5060	7.3039	8.2190	7.6202	16.6543	21.0915	6.8109
Jarque-Bera	65066.0	447125.7	47596.9	83052.6	4121778.0	4476.3	1142.2	2260.6	1404.5	1961.7	1586.0	13773.2	23985.0	1048.8
Probability	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Observations	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721
Panel B. Brazilian economic crisis period – April 1, 2014 through December 30, 2016														
Mean	-0.0001	0.0019	-0.0009	0.0002	-0.0010	-0.0006	-0.0014	-0.0016	-0.0006	-0.0004	-0.0011	-0.0004	-0.0005	-0.0005
Std. Dev	0.0214	0.0265	0.0267	0.0148	0.0132	0.0188	0.0263	0.0379	0.0315	0.0499	0.0263	0.0230	0.0212	0.0116
Skewness	0.4188	0.3982	0.0776	0.0683	-17.7293	-0.0149	-0.2168	-0.2924	-0.1565	0.6698	0.0102	0.0291	0.4584	-0.0744
Kurtosis	5.9770	5.5801	4.9344	4.2889	408.3457	3.4884	4.3648	6.3481	4.5229	7.9099	4.6803	3.5627	7.4937	4.6543
Jarque-Bera	276.9	211.1	109.1	48.7	4794413.0	6.9	59.4	334.5	70.0	750.1	81.8	9.3	609.1	79.9
Probability	.000	.000	.000	.000	.000	.031	.000	.000	.000	.000	.000	.01	.000	.000
Observations	695	695	695	695	695	695	695	695	695	695	695	695	695	695
Panel C. Calm period – January 3, 2017 through December 31, 2019														
Mean	-0.0006	-0.0003	-0.0005	0.0002	-0.0017	-0.0001	0.0004	0.0005	0.0009	0.0001	0.0006	0.0005	0.0003	-0.0003
Std. Dev	0.0286	0.0384	0.0283	0.0185	0.0140	0.0182	0.0234	0.0304	0.0244	0.0350	0.0199	0.0191	0.0193	0.0100
Skewness	-3.6131	-6.4493	-4.0571	-4.6145	-4.9306	-0.5439	-0.5893	-0.5620	-0.4988	-0.1196	-0.6394	-1.1773	-1.4754	-0.6461
Kurtosis	57.1972	114.9421	64.4213	71.8779	58.2121	7.2623	10.7914	12.5405	8.0263	4.7556	8.9959	13.1289	14.1092	11.3468
Jarque-Bera	93921.8	398909.9	120590.1	151721.7	98825.0	607.9	1950.8	2899.3	825.0	98.6	1180.8	3397.3	4150.8	2241.2
Probability	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Observations	754	754	754	754	754	754	754	754	754	754	754	754	754	754
Panel D. COVID-19 recession period – January 2, 2020 through January 29, 2021														
Mean	-0.0021	-0.0013	-0.0042	0.0003	-0.0013	-0.0019	-0.0017	-0.0011	-0.0013	0.0017	-0.0017	-0.0012	-0.0013	-0.0011
Std. Dev	0.0362	0.0396	0.0543	0.0270	0.0020	0.0375	0.0356	0.0460	0.0401	0.0547	0.0360	0.0399	0.0407	0.0141
Skewness	0.0970	-0.0028	-1.1395	-1.1408	-0.6089	-0.5485	0.1068	-0.7884	-0.8143	-0.6311	-0.6137	-1.4397	-1.5528	0.2702
Kurtosis	4.6813	6.1627	11.2783	9.5265	8.6933	7.2704	5.3860	6.8100	7.4809	7.5047	6.6637	13.2140	14.4269	5.0031
Jarque-Bera	32.5	113.4	835.5	541.7	384.2	220.3	65.0	192.7	257.6	248.0	169.2	1276.3	1589.1	48.8
Probability	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Observations	272	272	272	272	272	272	272	272	272	272	272	272	272	272

Source: Authors' own computations

Table 2 (cont.): Sample Size and summary statistics of ADR, ETF and Forex

	Chile					Colombia				Mexico						Peru		
	ADR			ETF	Forex	ADR	ETF		Forex	ADR				ETF	Forex	ADR	ETF	Forex
	BSAC	CCU	ENIA	ECH	CLP/USD	CIB	CXG	ICOL	COP/USD	FMX	IBA	KOF	TV	EWW	MXN/USD	BVN	EPU	PEN/USD
Panel A. Full sample period – April 1, 2014 through January 29, 2021																		
Mean	-0.0001	-0.0002	-0.0001	-0.0002	-0.0002	-0.0003	-0.0005	-0.0005	-0.0005	-0.0002	0.0000	-0.0005	-0.0009	-0.0003	-0.0003	-0.0001	0.0000	-0.0002
Std. Dev	0.0186	0.0158	0.0188	0.0154	0.2291	0.0234	0.0176	0.0177	0.4002	0.0172	0.0185	0.0168	0.0242	0.0165	0.0083	0.0323	0.0135	0.0129
Skewness	-0.5055	-0.2563	-0.3123	-0.9924	0.0105	-0.5788	-1.4579	-1.4387	-0.0161	-0.4341	-0.4569	-0.4722	-0.3562	-1.2158	-1.0403	-0.2863	-0.9942	0.2189
Kurtosis	25.3772	7.5924	16.3225	20.0256	430.4871	24.9393	22.3150	20.6261	124.3696	12.1556	9.5079	6.1608	11.5820	13.7684	11.7211	10.5301	16.6289	16.6145
Jarque-Bera	35980.6	1531.2	12756	21069	13104353	34611.8	27362	22872	1056305.0	6065.1	3096.9	780.3	5317.7	8739.1	5764.3	4089.5	13603	13305.2
Probability	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Observations	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721	1721
Panel B. Brazilian economic crisis period – April 1, 2014 through December 30, 2016																		
Mean	-0.0001	-0.0001	0.0000	-0.0003	-0.0002	-0.0006	-0.0010	-0.0010	-0.0009	-0.0003	0.0002	-0.0007	-0.0007	-0.0005	-0.0006	-0.0002	0.0000	-0.0003
Std. Dev	0.0143	0.0157	0.0155	0.0119	0.3606	0.0197	0.0168	0.0177	0.6299	0.0154	0.0168	0.0158	0.0170	0.0137	0.0078	0.0370	0.0132	0.0131
Skewness	-0.0339	0.0238	0.3364	-0.0257	0.0074	0.0495	-0.1282	-0.2750	-0.0084	-0.3428	0.0051	-0.1550	-0.1189	-0.7964	-1.6058	0.0702	0.7961	-0.0724
Kurtosis	3.9977	6.9083	4.3924	4.3860	174.1797	4.3722	5.0157	5.4694	50.2648	4.3305	4.1331	4.7336	5.4726	8.5426	20.8082	4.5088	9.2644	4.0380
Jarque-Bera	29.0	442.4	69.3	55.7	848551.2	54.8	119.6	185.4	64691.8	64.9	37.2	89.8	178.7	963.1	9482.3	66.5	1209.8	31.8
Probability	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Observations	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695	695
Panel C. Calm period – January 3, 2017 through December 31, 2019																		
Mean	0.0001	-0.0001	0.0004	-0.0002	-0.0001	0.0005	0.0001	0.0001	-0.0002	0.0003	0.0001	-0.0001	-0.0008	0.0000	0.0001	0.0004	0.0002	0.0001
Std. Dev	0.0144	0.0124	0.0159	0.0127	0.0093	0.0160	0.0111	0.0108	0.0100	0.0138	0.0169	0.0144	0.0195	0.0131	0.0070	0.0204	0.0092	0.0129
Skewness	0.9098	-0.3496	-0.5258	0.9095	0.4146	0.0634	-0.2100	-0.1619	-0.6169	-0.0471	-0.1289	-0.0684	-0.0926	-0.4623	-0.2905	-0.1415	-0.3010	-0.0975
Kurtosis	14.4176	6.3477	9.7499	14.4533	7.9581	4.1937	4.1792	4.2420	4.7571	4.3358	4.8018	4.3409	5.5365	5.6703	4.2083	5.1166	4.3990	23.5539
Jarque-Bera	4199.6	367.4	1466.1	4225.1	793.9	45.3	49.2	51.8	144.8	56.3	104.1	57.1	203.2	250.9	56.5	143.3	72.9	13273.6
Probability	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Observations	754	754	754	754	754	754	754	754	754	754	754	754	754	754	754	754	754	754
Panel D. COVID-19 recession period – January 2, 2020 through January 29, 2021																		
Mean	-0.0005	-0.0005	-0.0014	-0.0004	-0.0001	-0.0016	-0.0011	-0.0011	-0.0004	-0.0012	-0.0009	-0.0012	-0.0016	-0.0004	-0.0005	-0.0015	-0.0003	-0.0005
Std. Dev	0.0332	0.0231	0.0305	0.0265	0.0090	0.0420	0.0300	0.0292	0.0112	0.0271	0.0255	0.0242	0.0440	0.0275	0.0122	0.0442	0.0217	0.0126
Skewness	-0.7367	-0.3667	-0.2760	-1.5026	-0.3062	-0.5698	-1.7273	-1.7818	-1.5379	-0.4351	-0.9472	-0.7976	-0.2950	-1.2453	-0.8340	-0.7036	-1.8843	2.0354
Kurtosis	14.1660	5.4122	12.2267	12.0369	3.7086	14.3743	15.3398	15.4838	11.1347	10.3594	11.9586	5.3733	5.8753	8.9999	5.8821	12.7030	12.0138	33.7369
Jarque-Bera	1437.6	72.0	968.3	1027.9	9.9	1481.0	1861.0	1910.2	857.2	622.4	950.2	92.7	97.6	478.3	125.7	1089.4	1081.8	10895.0
Probability	.000	.000	.000	.000	.007	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Observations	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272	272

Source: Authors' own computations

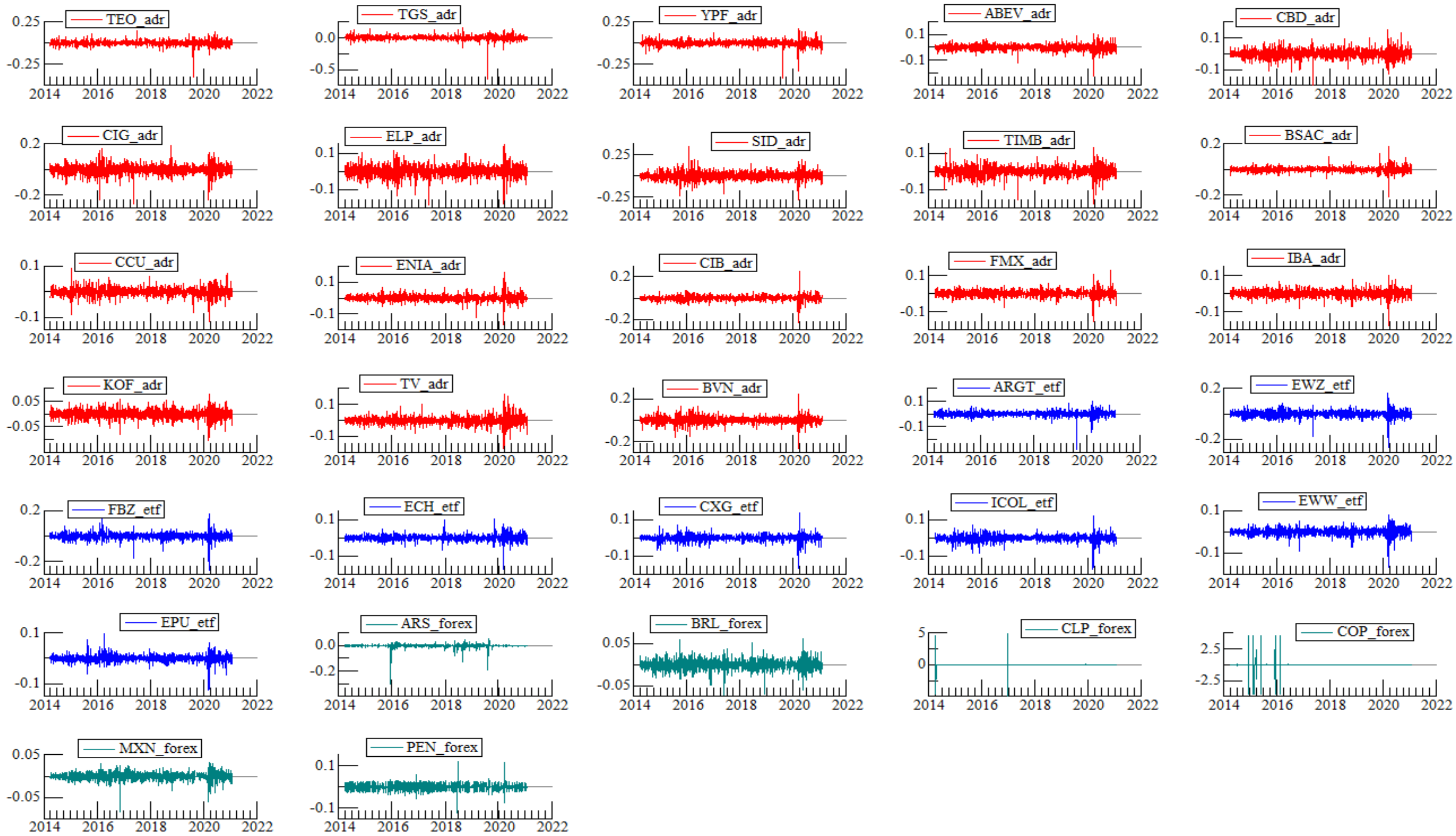

Fig. 1 Daily returns of ADR, ETF and Forex (April 1, 2014-January 29, 2021). All returns are the first differences of natural logarithms of the instrument closing price.

Source: Authors' own computations

Table 3. Summary Statistics of Unit Root, LM, and ARMA-LM tests for ADR, ETF and Forex

ADR/ ETF/Forex	ADF	ARMA	AIC	LM	ARCH-LM	GARCH	AIC	ARCH-LM
TEO	-22.7009***	(1,1)	-4.3565	3.6775	7.6583**	(1,1)	-4.5632	0.5204
TGS	-17.6838***	(1,1)	-3.9071	1.6352	0.4679	(1,1)	-4.1385	0.7217
YPF	-13.7109***	(1,1)	-3.9716	3.9602	73.4609***	(1,1)	-4.3020	2.3555
ARGT	-12.4962***	(1,1)	-5.1049	4.9841*	15.9462***	(1,1)	-5.3538	0.0888
ARS/USD	-10.1020***	(1,1)	-5.9305	1.8942	2.4684	(1,1)	-6.7150	0.0341
ABEV	-17.8151***	(1,1)	-4.7477	3.0643	100.7680***	(1,1)	-4.9467	0.4308
CBD	-17.6900***	(1,1)	-4.3966	4.9946*	80.6383***	(1,1)	-4.4895	0.9629
CIG	-14.9660***	(1,1)	-3.7955	1.0493	113.8730***	(1,1)	-3.9752	0.3140
ELP	-13.0503***	(1,1)	-4.1587	0.5219	157.5476***	(1,1)	-4.3359	0.7157
SID	-42.6480***	(1,1)	-3.3670	2.8888	77.7574***	(1,1)	-3.5381	1.5426
TIMB	-10.4940***	(1,1)	-4.4915	1.5255	107.2668***	(1,1)	-4.6209	0.3706
EWZ	-12.9064***	(1,1)	-4.5663	7.1450**	453.2187***	(1,1)	-4.8390	0.0280
FBZ	-11.7363***	(1,1)	-4.5868	3.0096	296.9472***	(1,1)	-4.8609	0.3253
BRL/USD	-46.8240***	(1,1)	-6.1293	0.8109	66.0424***	(1,1)	-6.2426	6.3509**
BSAC	-24.5172***	(1,1)	-5.1538	6.5253**	284.0638***	(1,1)	-5.4820	0.4868
CCU	-19.5804***	(1,1)	-5.4543	3.9750	60.2379***	(1,1)	-5.5985	1.2801
ENIA	-15.0977***	(1,1)	-5.1071	6.8630**	303.7472***	(1,1)	-5.3538	0.4182
ECH	-14.8008***	(1,1)	-5.5070	25.5288***	392.8134***	(1,1)	-5.8371	1.4728
CLP-USD	-17.4017***	(1,1)	-0.7686	1.0417	0.0035	(1,1)	-4.2205	0.0024
CIB	-11.2218***	(1,1)	-4.6824	2.7944	328.5083***	(1,1)	-5.0838	1.3534
CXG	-13.7790***	(1,1)	-5.2719	2.8293	371.8041***	(1,1)	-5.7093	0.2858
ICOL	-13.6408***	(1,1)	-5.2569	5.6125*	292.4970***	(1,1)	-5.6227	0.1640
COP/USD	-15.0608***	(1,1)	0.3163	23.7637***	0.0090	(1,1)	0.0749	0.0107
FMX	-11.9802***	(1,1)	-5.2901	6.6209**	156.8076***	(1,1)	-5.4836	1.6338
IBA	-44.7490***	(1,1)	-5.1454	0.8246	74.0269***	(1,1)	-5.2596	1.5404
KOF	-43.4363***	(1,1)	-5.3292	0.4167	164.6531***	(1,1)	-5.4697	0.0639
TV	-14.4197***	(1,1)	-4.6033	15.9266***	191.4253***	(1,1)	-4.9286	7.3836**
EWW	-9.3558***	(1,1)	-5.3721	2.7377	298.6913***	(1,1)	-5.7241	5.2137*
MXN/USD	-40.6380***	(1,1)	-6.7360	0.0551	63.57915***	(1,1)	-6.9865	1.0562
BVN	-14.3690***	(1,1)	-4.0316	6.8448**	186.2673***	(1,1)	-4.2952	0.6160
EPU	-9.9301***	(1,1)	-5.7813	8.3776**	359.2711***	(1,1)	-6.1554	1.1079
PEN/USD	-14.5425***	(1,1)	-6.1755	1.4365	10.1496***	(1,1)	-6.1895	0.0662

ADF: t-statistic for the Augmented Dickey-Fuller test with a constant and trend at the level. ARMA: Autoregressive Moving Average model order, AIC: Akaike information criterion; LM: Breusch–Godfrey serial correlation test.; ARCH-LM: Engle's LM test for ARCH (autoregressive conditional heteroscedasticity) effects; GARCH: Generalized Autoregressive Conditional Heteroscedasticity model order.

Source: Authors' own computations

Table 4(a): Summary Statistics of multivariate ARMA-GARCH-DECO Model (full sample period)

Univariate ARMA(1,1)-GARCH(1,1) model					
Variable	**Phi**	**Theta**	**Alpha**	**Beta**	**Log-likelihood**
TEO	-0.6491	0.6517	0.2703 **	0.6481 ***	3931.464
TGS	-0.8416***	0.8843***	0.6375 *	0.3292 *	3567.478
YPF	0.6923**	-0.6583**	0.3357 **	0.6042 ***	3706.574
ARGT	0.1278	-0.1314	0.2190 **	0.7354 ***	4612.321
ARS/USD	-0.0387	0.4097***	0.5339 ***	0.8004 ***	5778.262
ABEV	-0.2685	0.2065	0.0687 ***	0.9068 ***	4260.189
CBD	0.2567	-0.2288	0.0528 ***	0.9252 ***	3865.867
CIG	-0.0184	-0.0156	0.0969 ***	0.8858 ***	3426.879
ELP	0.6268***	-0.6522***	0.1122 ***	0.8432 ***	3734.978
SID	-0.8779***	0.8681***	0.0679 ***	0.9224 ***	3045.515
TIMB	0.3152	-0.3280	0.1230	0.8164 ***	3982.088
EWZ	-0.1672	0.1152	0.1571 **	0.7895 ***	4169.843
FBZ	-0.4597***	0.4307**	0.0765 ***	0.8753 ***	4187.242
BRL/USD	-0.0290	-0.0917	0.1438 ***	0.8126 ***	5378.258
BSAC	0.8417***	-0.8521***	0.1140 ***	0.8532 ***	4723.211
CCU	0.4677***	-0.4408***	0.1135 ***	0.8417 ***	4823.432
ENIA	0.3804	-0.3348	0.1250 ***	0.7847 ***	4610.949
ECH	-0.1021	0.1941	0.1392 ***	0.8222 ***	5028.977
CLP/USD	0.8827*	0.7144***	1.3981 *	0.6827 ***	2830.915
CIB	0.4490***	-0.3859**	0.1488 ***	0.7972 ***	4379.662
CXG	0.4958***	-0.3623***	0.1355 ***	0.8459 ***	4916.030
ICOL	0.5384**	-0.4622*	0.1326 ***	0.8532 ***	4843.758
COP/USD	0.4242***	-0.9913***	5.1722 ***	0.1010 **	2529.601
FMX	-0.7093***	0.6941***	0.1138 ***	0.8349 ***	4724.320
IBA	0.5074***	-0.5895***	0.1378 ***	0.7338 ***	4531.781
KOF	-0.9059***	0.9150***	0.1034 ***	0.8301 ***	4711.304
TV	0.0349	0.0200	0.0515 ***	0.9356 ***	4243.701
EWW	0.0334	-0.0083	0.1618 ***	0.8050 ***	4931.001
MXN/USD	0.1413	-0.1854	0.1535 ***	0.8292 ***	6016.907
BVN	0.2322	-0.2852	0.0712 **	0.9120 ***	3702.189
EPU	0.5585	-0.4943	0.1529 ***	0.8030 ***	5300.997
PEN/USD	0.0309	-0.6281***	0.0361 **	0.8145 ***	5331.934

Dynamic Equicorrelation Model	
Rho	0.2778 ***
Alpha (DECO)	0.0410 ***
Beta (DECO)	0.9104 ***
Df	8.7555 ***
AIC	-174.6859
Log-likelihood	150513.227

Note: *, ** and *** are significance at 10, 5 and 1% levels. Df refers to degrees of freedom and AIC means Akaike information criterion.

Source: Authors' own computations

Table 4(b): Summary Statistics of multivariate ARMA-GARCH-DECO Model (Brazilian crisis period)

Univariate ARMA(1,1)-GARCH(1,1) model

Variable	Phi	Theta	Alpha	Beta	Log-likelihood
TEO	-0.7324***	0.7093***	0.0322	0.9623***	1703.454
TGS	0.3993**	-0.3440*	0.0932	0.8930***	1576.057
YPF	0.3079	-0.2230	0.1394**	0.7683***	1564.665
ARGT	0.2132	-0.1478	0.1047**	0.7430***	1957.155
ARS/USD	0.0883	0.4653***	2.0783	0.4693	2304.336
ABEV	0.8038***	-0.8408***	0.0654***	0.8901***	1794.200
CBD	0.2734	-0.1628	0.0674***	0.9269***	1583.107
CIG	-0.7810***	0.7968***	0.0991**	0.8658***	1336.572
ELP	-0.8315***	0.8093***	0.0948**	0.8552***	1446.866
SID	-0.0252	0.0833	0.0709***	0.9299***	1160.283
TIMB	-0.2252	0.2680	0.1527	0.6359***	1552.348
EWZ	0.0575	-0.0289	0.0764***	0.9024***	1665.106
FBZ	-0.3721	0.3849	0.0258**	0.9581***	1702.729
BRL/USD	0.4808**	-0.5500**	0.1069**	0.8583***	2140.096
BSAC	0.2465	-0.2270	0.0583***	0.9069***	1985.300
CCU	0.3076	-0.2364	0.1221**	0.8134***	1934.591
ENIA	0.0508	-0.0089	0.0798***	0.8791***	1934.690
ECH	-0.0179	0.1493	0.0969**	0.8088***	2119.831
CLP/USD	1.0822*	0.7481***	2.4055*	0.6620***	929.029
CIB	0.4629***	-0.3511***	0.0864	0.8789***	1790.916
CXG	0.3051***	-0.1184	0.1049***	0.8865***	1923.057
ICOL	0.1402	-0.0320	0.0385**	0.9470***	1841.995
COP-USD	nc	nc	nc	nc	nc
FMX	0.3083	-0.2684	0.0592**	0.7930***	1925.826
IBA	0.6691***	-0.7193***	0.1562***	0.6768***	1870.116
KOF	-0.8965***	0.9235***	0.1731***	0.3446***	1916.082
TV	-0.3800	0.4772	0.0120	0.9812***	1855.323
EWW	0.0957	0.0007	0.1430***	0.8367***	2060.331
MXN/USD	nc	nc	nc	nc	nc
BVN	0.3192**	-0.3794***	0.0505***	0.9311***	1335.331
EPU	0.0485	0.0837	0.1149***	0.8770***	2106.255
PEN/USD	0.0098	-0.6265***	0.0284***	-0.9985***	2148.409

Dynamic Equicorrelation Model

Rho	0.3160***
Alpha (DECO)	0.0117
Beta (DECO)	0.9868***
Df	9.4516***
AIC	-172.1865
Log-likelihood	60030.795

Note: *, ** and *** are significance at 10, 5 and 1% levels; nc means that the tests are not reported since there is no convergence (no improvement in line search) using numerical derivatives. Df refers to degrees of freedom and AIC means Akaike information criterion.

Source: Authors' own computations

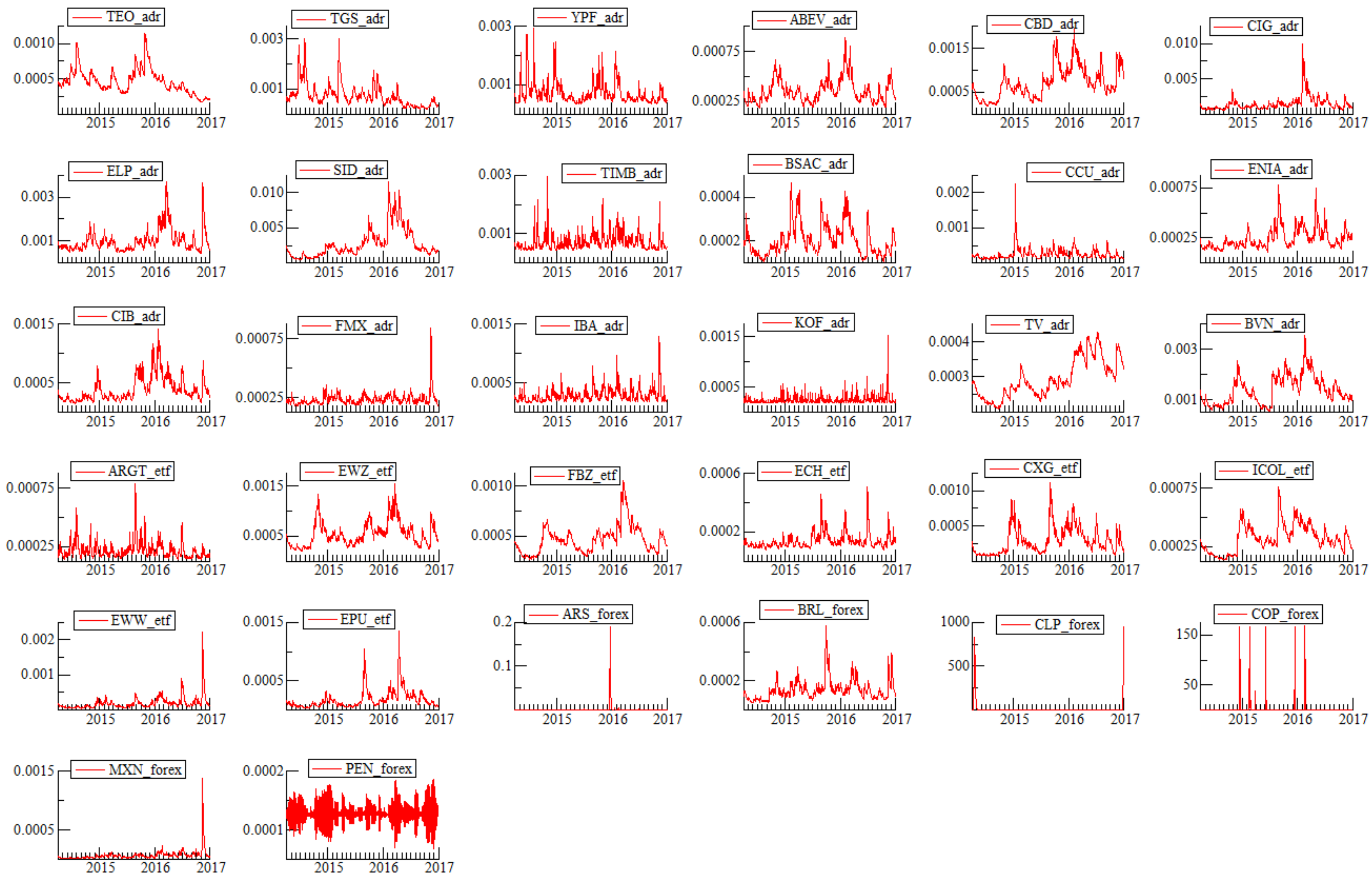

Fig 2. Conditional variance (Brazilian crisis period)

Source: Authors' own computations

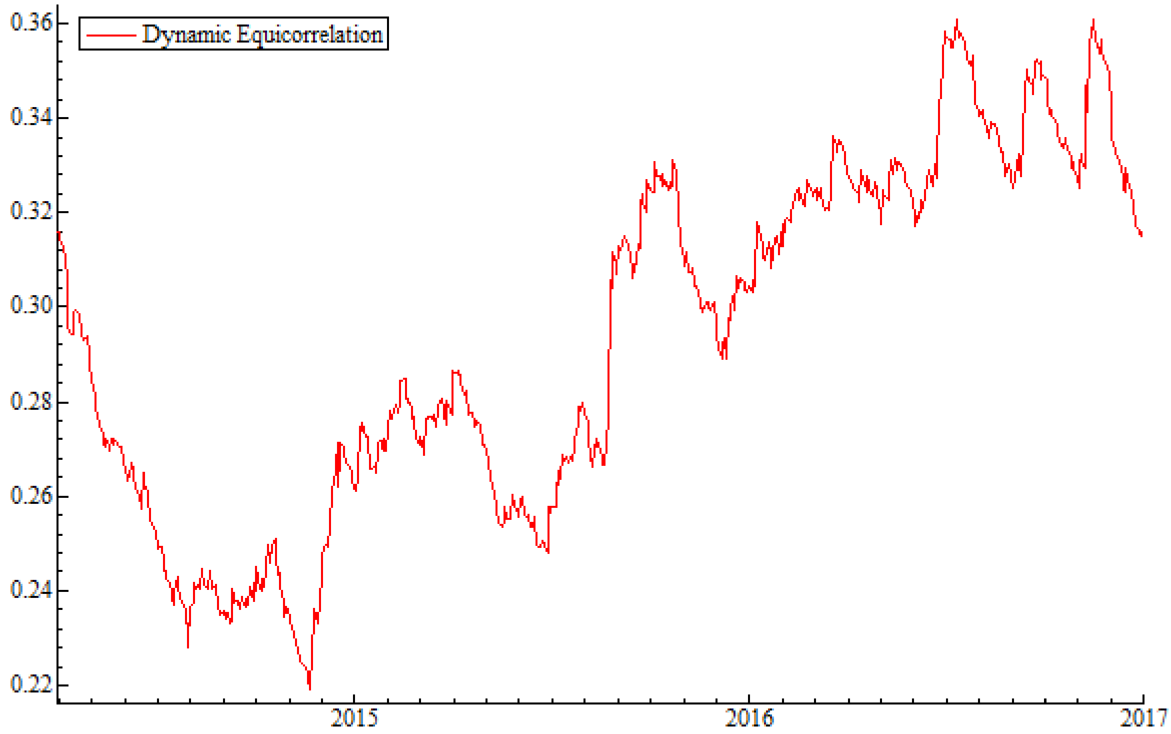

Fig 3. Conditional correlation (Brazilian crisis period)

Source: Authors' own computations

Table 4(c): Summary Statistics of multivariate ARMA-GARCH-DECO Model (calm period)

Univariate ARMA(1,1)-GARCH(1,1) model					
Variable	**Phi**	**Theta**	**Alpha**	**Beta**	**Log-likelihood**
TEO	-0.8685***	0.9000***	0.4610	0.4459	1721.751
TGS	-0.5406	0.6465	0.9808*	0.1405	1517.608
YPF	-0.5735***	0.6178**	0.5018*	0.2124	1716.452
ARGT	0.3851	-0.4492	0.3391	0.6303	2034.975
ARS-USD	-0.2187	0.6375***	0.9609**	0.4445***	2370.064
ABEV	-0.0219	-0.0412	0.0089	0.9822***	1959.488
CBD	-0.1664	0.2053	0.1303	0.2017	1770.387
CIG	-0.0048	-0.0654	0.0701	0.9256***	1598.772
ELP	0.2904	-0.3136	0.0816*	0.8407***	1745.993
SID	-0.1195	0.0474	0.0094	0.9834***	1465.927
TIMB	0.4428*	-0.4995**	0.0882	0.6804*	1896.450
EWZ	0.1864	-0.2417	0.2499	0.3577	1939.807
FBZ	0.5546**	-0.5725**	0.2950	0.0261	1932.067
BRL/USD	-0.2150	0.0272	0.1836*	0.6587***	2452.110
BSAC	0.4078	-0.4328	0.3585**	0.2137	2171.146
CCU	-0.0967	0.1169	0.0716*	0.7627***	2251.917
ENIA	-0.1162	0.1028	0.0673*	0.5793***	2063.351
ECH	-0.6769	0.7632*	0.1498**	0.7939***	2272.495
CLP/USD	-0.1122	-0.0652	0.1962***	0.6503***	2550.393
CIB	0.5994***	-0.5750***	0.1283**	-0.3216	2056.856
CXG	0.6675***	-0.5859***	0.0817**	0.8349***	2343.226
ICOL	0.6821***	-0.6145***	0.0707**	0.8907***	2359.578
COP/USD	nc	nc	nc	nc	nc
FMX	0.5601***	-0.6195***	0.0683**	0.8816***	2184.295
IBA	0.0551	-0.2197	0.0399	0.8445***	2023.665
KOF	-0.9790***	0.9897***	0.0484**	0.8910***	2140.843
TV	0.2632	-0.1877	0.0245*	0.9634***	1917.717
EWW	0.6953***	-0.7109***	0.1161***	0.8034***	2227.390
MXN/USD	0.4707	-0.5074	0.0993**	0.8450***	2703.962
BVN	nc	nc	nc	nc	nc
EPU	0.7841***	-0.7234***	0.0823***	0.7480***	2485.406
PEN/USD	0.0861	-0.6636***	0.0567	0.1323	2342.610

Dynamic Equicorrelation Model	
Rho	0.2450***
Alpha (DECO)	0.0284
Beta (DECO)	0.8962***
Df	10.5937***
AIC	-185.4022
Log-likelihood	70092.645

Note: *, ** and *** are significance at 10, 5 and 1% levels; nc means that the tests are not reported since there is no convergence (no improvement in line search) using numerical derivatives. Df refers to degrees of freedom and AIC means Akaike information criterion.

Source: Authors' own computations

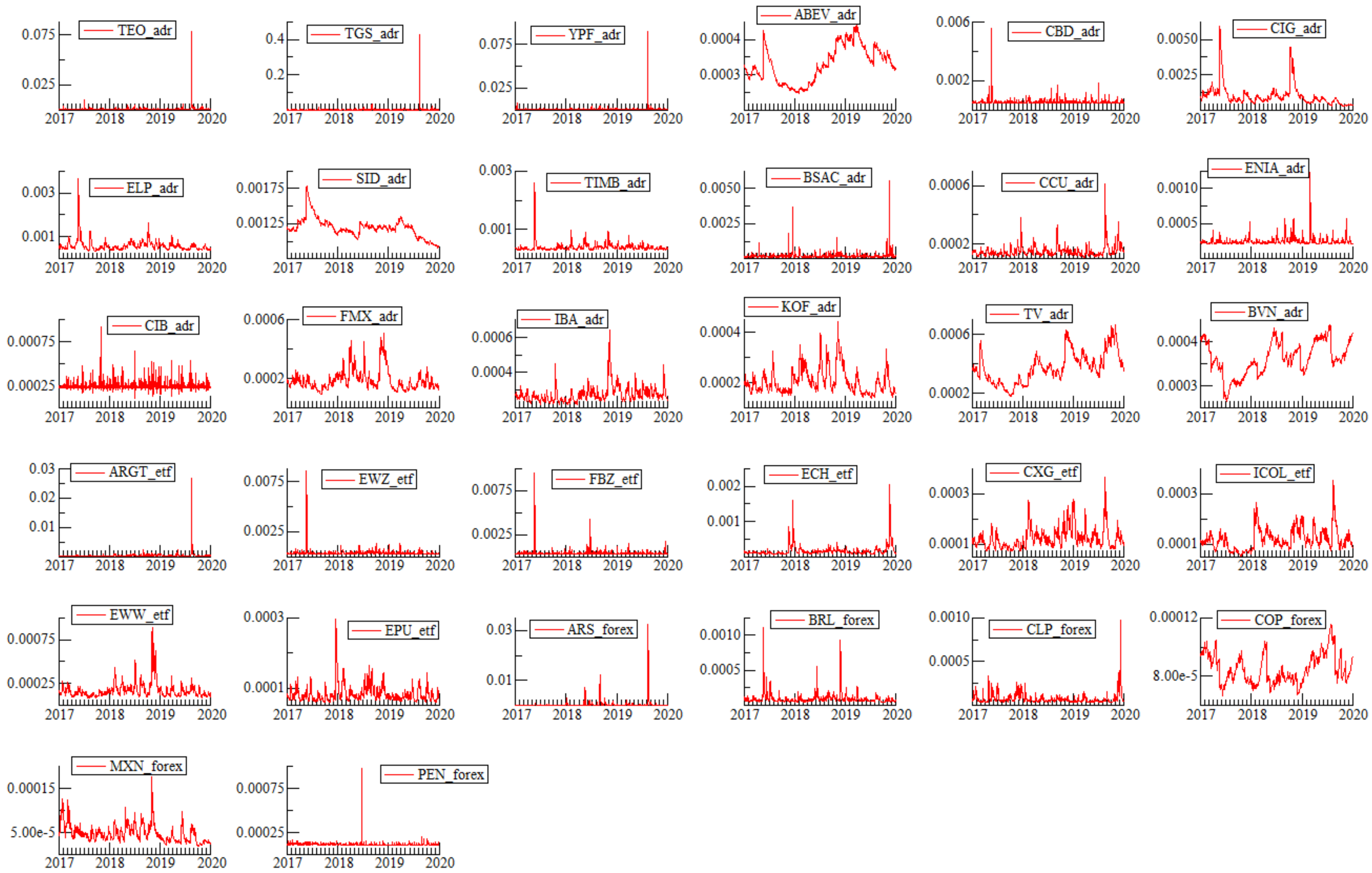

Fig 4. Conditional variance (calm period)

Source: Authors' own computations

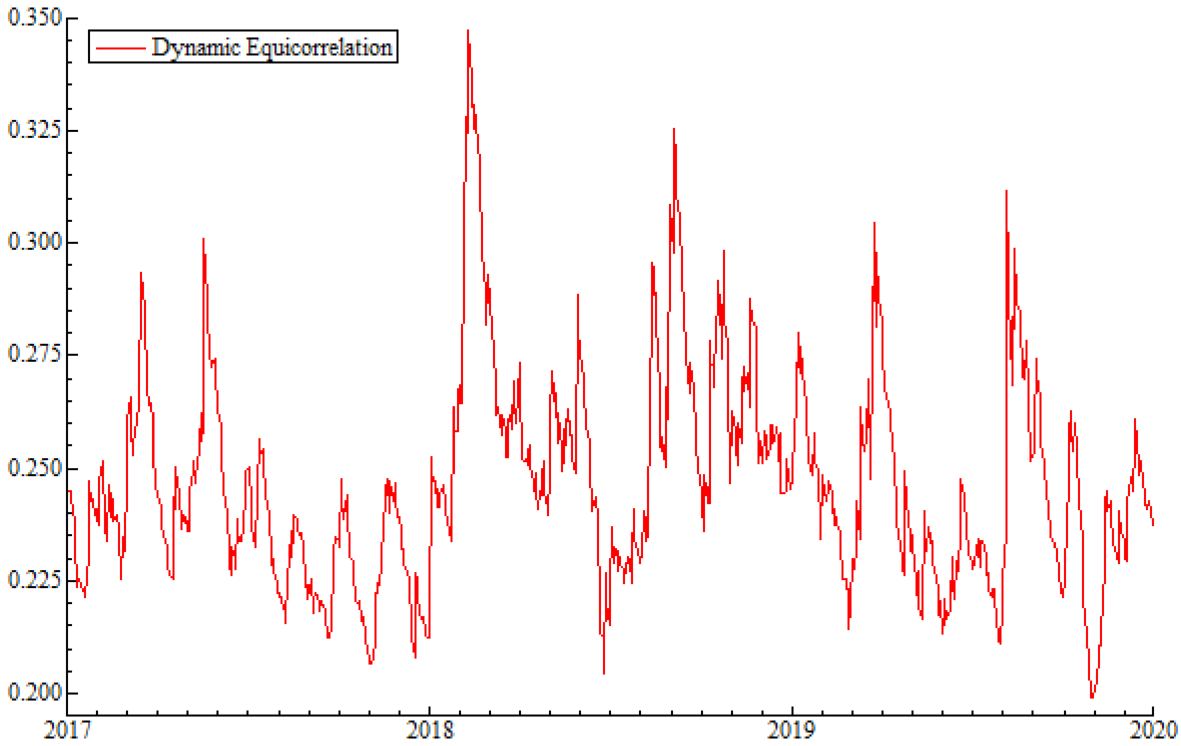

Fig 5. Conditional correlation (calm period)

Source: Authors' own computations

Table 4(d): Summary Statistics of multivariate ARMA-GARCH-DECO Model (COVID-19 recession period)

Univariate ARMA(1,1)-GARCH(1,1) model

Variable	Phi	Theta	Alpha	Beta	Log-likelihood
TEO	0.1985	-0.2363*	0.1574	0.7273 ***	530.631
TGS	0.2708	-0.3825	0.2552	0.7143 **	523.509
YPF	-0.3791	0.3105	0.4247 *	0.5637 ***	457.357
ARGT	-0.6425 ***	0.5426***	0.1874 *	0.7564 ***	642.046
ARS/USD	0.1577	-0.4166***	0.1201	0.5983 **	1322.303
ABEV	-0.5483 ***	0.4314**	0.1733 ***	0.7457 ***	533.089
CBD	-0.5367 ***	0.4134***	0.2193	0.3288	-164.080
CIG	-0.3156	0.2920	0.2360	0.7226 ***	497.919
ELP	0.3007	-0.3779*	0.2417 ***	0.7127 ***	549.641
SID	-0.3170	0.2282	0.3171	0.5998	443.088
TIMB	-0.0645	0.0034	0.2375 **	0.7478 ***	555.588
EWZ	-0.4654 **	0.3042	0.3640 ***	0.5870 ***	584.899
FBZ	-0.4851 **	0.3981**	0.3601 ***	0.5484 ***	587.643
BRL/USD	-0.0061	-0.0894	0.1704 **	0.7905 ***	793.596
BSAC	-0.7587 ***	0.6842***	0.3960 **	0.4085 *	590.566
CCU	-0.0739	0.0604	0.1883	0.7418 ***	652.918
ENIA	0.3405	-0.1996	0.2315 ***	0.7124 ***	633.365
ECH	-0.2398	0.2241	0.2394 ***	0.6389 ***	655.043
CLP/USD	nc	nc	nc	nc	nc
CIB	0.4328	-0.3528	0.4585	0.5532 ***	557.354
CXG	0.5350 **	-0.3310	0.4677	0.5446 ***	670.106
ICOL	0.6165 ***	-0.4835***	0.6144 *	0.4390 **	675.645
COP/USD	0.7147 ***	-0.6478***	0.1443	0.8282 **	872.060
FMX	-0.4706 **	0.3854**	0.3053 **	0.6491 ***	637.393
IBA	-0.6002 ***	0.5171***	0.2455 **	0.6756 ***	653.380
KOF	-0.5965 ***	0.4787***	0.3141 ***	0.6488 ***	670.205
TV	-0.5742 ***	0.5063***	0.1708 **	0.7577 ***	497.906
EWW	-0.5846 ***	0.4858***	0.2958 ***	0.6779 ***	658.955
MXN/USD	-0.4559 **	0.4028**	0.2499 **	0.7432 ***	855.085
BVN	0.4907 ***	-0.5809***	0.3050 ***	0.6338 ***	534.499
EPU	-0.5509 ***	0.4802***	0.3159 ***	0.6296 ***	732.553
PEN/USD	-0.6311 ***	0.1738	0.3064	0.7392 ***	866.887

Dynamic Equicorrelation Model

Rho	0.3032***
Alpha (DECO)	0.0123
Beta (DECO)	0.8906***
Df	9.8101***
AIC	-164.0796
Log-likelihood	22510.819

Note: *, ** and *** are significance at 10, 5 and 1% levels; nc means that the tests are not reported since there is no convergence (no improvement in line search) using numerical derivatives. Df refers to degrees of freedom and AIC means Akaike information criterion.

Source: Authors' own computations

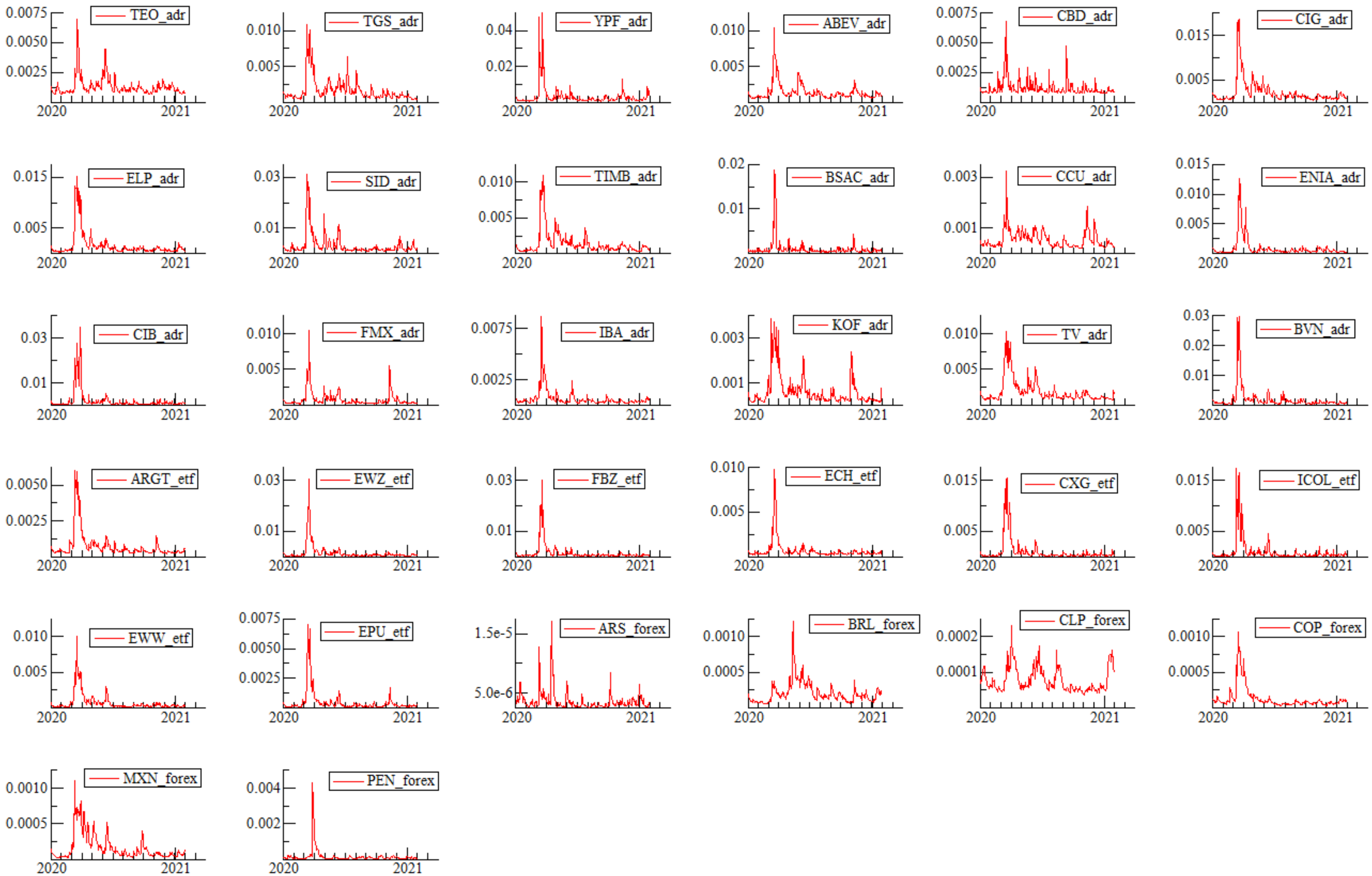

Fig 6. Conditional variance (COVID-19 recession period)

Source: Authors' own computations

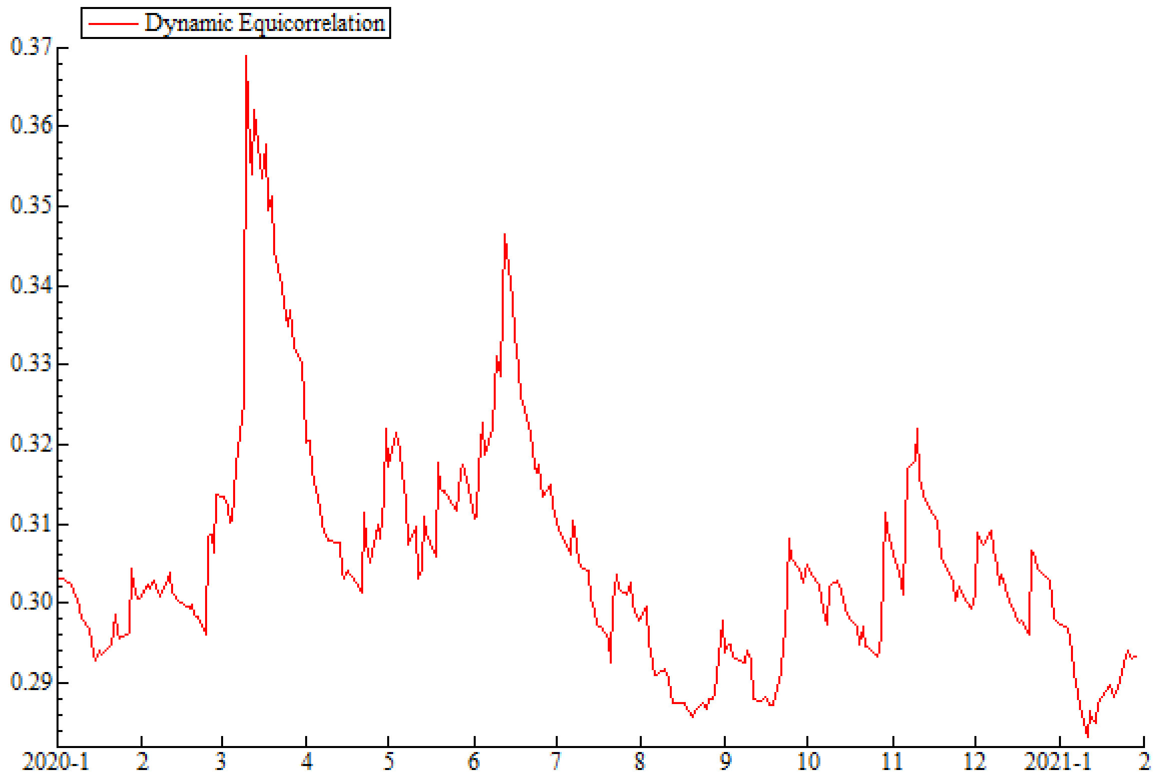

Fig 7. Conditional correlation (COVID-19 recession period)

Source: Authors' own computations

6. Conclusion

This paper uses ARMA-GARCH-DECO model to capture the impact of financial turmoil on 32 Latin American financial instruments including American depository receipt (ADR), Exchange-traded fund (ETF) and forex. For that purpose, we divided our sample into full sample, Brazilian crisis, calm period and COVID-19 recession period. In the overall sample, our model finds short-term properties in the volatility of most instruments including those belonging to defensive super sector. Moreover, statistically significant coefficients of the dynamic equicorrelation model show the presence of long-run volatility impact among the markets implying the predictability in the dispersion structure of returns. Defensive super sector and basic materials are the most impacted sectors during economic crises. The evidence presented here indicates that in times of economic disruption like in the midst of the COVID-19 pandemic, Latin American financial instruments do not act as safe harbor investments.

Other interesting finding is related to the correlation among markets. Results also show that financial assets are relatively more correlated during period of financial crises than in normal periods. This effect is particularly persistent during COVID-19 pandemic, lessening the benefits of international portfolio diversification for investors. Those results are of potential interest to various economic agents including international investors and policymakers who look a better understanding of the dynamics of spillovers among the behavior of emerging financial assets in order to build efficient risk hedging models or to implement appropriate policies to react to information transmission in periods of financial turmoil. This gives them the opportunity to build new diversification strategies in times of turbulence and design a better decision model that can protect them against the risk of contagion.

Although we have shown important contribution to the literature, it’s crucial to notice some limitations that future studies can consider. First, the paper only used data related to ADRs, ETF and Forex in 6 Latin American countries, meaning that our sample may not be representative of all markets instruments data related to that particular region. Future work can extend this framework by considering data from other institutions and markets. Second, we restricted our models in considering data and information during two recent crises. Subsequent research can enlarge the total observations by considering a longer period of time. Lastly, it appears that ARMA(1,1)−GARCH(1,1) models are too simple and may be inappropriate in correcting simultaneously serial correlation problems among series. other econometric methods other FI models like HYGARCH and FIEGARCH can be applied to these financial derivative instruments to determine other aspects of the long-memory and leverage effects phenomena. These limitations can provide future research avenues and can step on the contributions established by this paper regarding the effect of economic crisis on emerging markets instruments.

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