Volatility Spillover Networks of Credit Risk: Evidence from ASW and CDS Spreads in Turkey and Brazil

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This study examines received and transmitted volatility spillovers of Credit Default Swap (CDS) and Asset-Swap Spread (ASW) for Brazil and Turkey. The empirical analysis is implemented using two country-based (stock markets and exchange rates) and two global (volatility index and global economic activity index) variables to account for the impact of integration into global markets. Empirical results suggest that both countries display distinctive features in their spillover networks. While exchange rates and the stock market figure prominently in Brazil as a source of spillovers, for Turkey, the primary element in spillovers appears to be credit risk indicators. Time-varying analysis results show that the European Debt Crisis of 2010–2011 and the global liquidity crunch of 2018–2019 are two critical periods in volatility spillovers that occurred toward credit risk indicators. Brazil displays more sensitivity to the developments of the pandemic than Turkey, likely due to its dependence on global economic activity and energy prices. Finally, for both countries, the leading variable in spillovers to credit risk indicators during financial turbulence episodes appears to be foreign exchange markets. This result highlights both economies' fragility and vulnerability to foreign exchange market-based shocks. Thus, we suggest effective and solid measures in this regard. Otherwise, those shocks could potentially induce a higher cost of financing in both economies due to the negative impacts on CDS and ASW spreads.

Keywords: Volatility Spillovers; Stock returns; Credit Risk; COVID-19; Country Studies.

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This paper examines volatility spillovers between global variables and financial markets in Brazil and Turkey. We focus on Brazil and Turkey because these countries have experienced several financial crises and there are several structural problems and vulnerabilities that are common to both economies. For example, in recent years, the Turkish lira depreciated substantially and Credit Default Swaps (CDS) have increased considerably. In addition, deterioration in the global supply chain due to the global COVID-19 pandemic led to increased vulnerability to external shocks in Turkey. Brazil is one of the countries most affected by the global pandemic, which also increased the vulnerability of the Brazilian economy.

The remainder of the paper is organized as follows: The next section elaborates on the impact of the COVID-19 outbreak on the Brazilian and Turkish economies, and Section 2 summarizes the relevant literature. The econometric methodology is presented in Section 3 and the empirical findings are presented in Section 4. We present robustness check results in Section 5 and Section 6 concludes the paper.

1. The impact of the COVID-19 Outbreak on Brazil and Turkey

The economic toll from the global COVID-19 pandemic has been high; the International Monetary Fund estimated significant contractions in global GDP in 2020—the deepest global recession since World War II. Particularly hard-hit have been global trade and financial markets, global value chains, tourism, and workers' remittances. The extent of the impact varies based on the characteristics of the countries. By way of comparison, the risk exposure in the current pandemic is higher than in the Global Financial Crisis of 2008. For advanced and emerging economies, the growth rates of 2020 were estimated at –6.6% and –1%, respectively (IMF 2020).

Although decreases in energy costs seem to create an advantage for oil-importing countries, the depreciation of local currencies limits this advantage. For example, Brent crude oil and natural gas prices declined by 47% and 11%, respectively, in the first half of 2020, yet the depreciation in the Turkish lira against the U.S. dollar (14%) and euro (12%) in the same period reduced possible advantages. Other emerging economies did not fare better as managing current account deficits became more difficult, particularly in light of declining tourism revenues and a sharp decrease in workers' remittances. The negative effect of the global pandemic on the Turkish economy is corroborated by several studies. For example, Nuno Fernandes (2020) investigated the effect of the pandemic under different scenarios. With a best-case scenario of 1.5 months of lockdown, the contraction in GDP was estimated to be 4.6% in Turkey. In the worst-case scenario, where the lockdown would take four months, the reduction in GDP was estimated to be 9.6% for Turkey. Warwick McKibbin and Rossen Fernando (2020) calculated the loss in GDP to be between 0.1% and 5.5% for Turkey under different scenarios.

Brazil is one of the hardest-hit countries by the global pandemic. As the 9th largest economy in the world, Brazil has aggressively countered the effects of the pandemic on the economy with some stress on the government's budget. Fernandes (2020) calculated that Brazil's GDP would shrink by 3.9% in 2020 under the best-case scenario of 1.5 months of lockdown. Under the worst-case scenario, the reduction in

GDP was estimated to be 8.8% in 2020, during which lockdown would take four months. McKibbin and Fernando (2020) put the range in 0.3%–8% of GDP for Brazil under different scenarios. Furthermore, the fiscal deficit increased at a record level and rose to $18.6 billion in April 2020, given the deterioration in public revenues and expenditures. Not only was the real sector in Brazil negatively affected by the global pandemic, but financial markets were also hard hit. Of emerging markets, Brazil’s stock market experienced the greatest total loss between January and April 2020, with the Bovespa falling more than 56% during the period. The Brazilian Real depreciated by 28% against the U.S. dollar during the same period. At the same time, the CDS spreads increased by 213% between January and April, reaching their highest value in April. Also, sharp declines in oil prices negatively affected the Brazilian economy as Brazil is among the top 10 oil-producing countries in the world.

As developing economies, Turkey and Brazil are classified as emerging markets in the list of leading indexing companies, such as S&P Global (2022) and MSCI (n.d.). While their dynamics of economic growth demonstrate some differences, they share vulnerabilities against particular market shocks as leading markets in their regions. For example, both countries were defined in the group of fragile five countries due to large external deficits, soaring inflation, and slowing economic growth by a research analyst at Morgan Stanley in 2013. Turkey's geographical location and history offer enormous economic development advantages. For instance, the Belt and Road Initiative between China and Turkey presents great potential for prosperity in the region and large-scale economic activity for Turkey. Likewise, Brazil is a major global economy with the largest GDP in its region and ranked eighth globally, according to the World Bank (n.d.). Among the country’s strengths are its potential in energy resources and agriculture. While both countries are considered crucial marketplaces for the global economy, they also manifest some distinctive risk factors based on their geographical locations. The credit risk indicators incorporate such factors, and the divergence of credit risk scores of the countries due to these elements can be monitored. This insight is affirmed by da Silva and Costa (2021), who report similarities between Turkey and Brazil and consider them intermediate global economic and policy powers. However, da Silva and Costa (2021) also emphasize the political factors that contribute to the dissimilarities between the two emerging economies as well as their risk levels. This study seeks to identify the linkages between credit risk indicators and selected market variables for these two countries. As market variables, we consider two domestic and two global factors. The domestic variables are equity and exchange markets, and for global variables, we utilize the Baltic Dry Index (BDI) as a proxy for global economic activity and the VIX index to represent global financial disturbances.

In examining the effects of global developments on financial markets in Brazil and Turkey, we use country-based variables, such as the stock and currency markets, and credit risk indicators, such as the CDS and ASW spreads. Although the Global Financial Crisis sparked a great deal of interest in CDS spreads both in academia and by the markets, they may not be the best indicator of credit risk. For example, Samet Gunay (2019) found that the ASW spread is a better early risk indicator than the CDS spread in accounting for sovereign risk. The ASW spread is a spread on the Libor interest rate to exchange fixed and floating interest rates in an interest-rate swap agreement. If correction procedures are not exercised, nominal-nominal ASW spreads would be more accurate due to the potential risks compared to discounted or premium bonds in asset swap contracts. As in CDS spreads, ASW spreads can also be traded. Although the presence of the CDS indexes such as CDX and iTraxx makes them more accessible to monitor and gauge credit risk and hedge credit portfolios, the ASW spread is a good alternative in evaluating credit risk. As such, in this study, we use ASW spreads in addition to CDS spreads in the empirical analysis.

2. Literature Review

Comovements between asset prices and the dissemination of negative news across the markets expedite the transmission of economic shocks. In this regard, cross-market linkages and trade channels play a vital role in the spillover of returns and volatilities. We have already witnessed the spread of market disruptions and contagious impacts multiple times in the past. We present a literature review for these market developments in recent episodes of financial turbulence: the Asian (1997) and Russian Crises (1998), Global Financial Crisis (2008–2009) and European Debt Crisis (2010–2011), and finally, the COVID-19 pandemic (2020–2021).

2.1. The Asian Crisis of 1997 and Russian Crisis of 1998

Following severe speculative attacks on the Thai baht, the devaluation in its value caused a domino effect in the region and induced one of the most dramatic periods of turbulence in the history of Asian economies. The literature details the causes and channels of spillovers in this period. In one of the early studies, Franklin Allen and Douglas Gale (1999) discussed the possible underlying reasons for the financial contagion of the Asian crisis in 1997 and the Russian crisis in 1998. Similarly, Taimur Baig and Ilan Goldfajn (1999) examined Thailand, Malaysia, Indonesia, Korea, and the Philippines during the period of Asian turbulence in 1997 and documented how exchange rates and the sovereign bond spread increased significantly during the crisis. However, the conclusions regarding stock market contagion are less precise. Using Granger causality and bond spreads of Asian countries, Harald Sander and Stefanie Kleimeier (2003) showed that the regional contagion evolved globally after the 1998 Russian crisis. Philip Arestis et al. (2005) surveyed whether there was a contagious effect during the 1997 Asian crisis from four leading Asian countries toward developed economies. According to the results, there is some evidence that Japan suffered the most as it is the primary fund supplier to the region. By analyzing the dynamic conditional correlations of daily stock returns of nine Asian countries, Thomas C. Chiang et al. (2007) found contagion in two phases in the crisis, in which the first phase is related to the spillover effect, and the second phase includes herd behavior. Using nonlinearity and asymptotic dependency, Juan C. Rodriguez (2007) studied the stock markets of the countries affected by the Asian crisis in 1997 and demonstrated the presence of a dependency structure that varied during the financial turbulence. Huimin Li et al. (2008) examined the impact of sovereign credit ratings on equity returns for five Asian economies from 1990–2013 and found a significant relationship between credit ratings and stock returns, where a change in sovereign credit rating influences other crisis-hit countries. Giancarlo Corsetti et al. (2005) utilized a standard factor model to investigate the contagion effect in financial markets. Results indicate that country-specific shocks in Hong Kong were transmitted to five countries out of a sample of 17.

In the 1990s, different regions also witnessed financial turbulence, such as the ERM crisis in Europe, the Turkish currency crisis of 1994, and the Mexican Tequila Crisis of 1994. While the extent of spillovers was relatively limited in some cases, in others, severe shocks were experienced across the countries and regions. One major crisis was the so-called Tequila Crisis of Mexico. Jose De Gregorio and Rodrigo O. Valdes (2001) analyzed 20 countries that were exposed to the 1982 Mexican debt crisis, the Mexican crisis in 1994, and the Asian crisis in 1997 and showed that some neighborhood effects and trade links escalated this influence. Accordingly, debt composition and exchange rate flexibility are two essential factors limiting the negative influence of contagion. Using a sample of 61 countries, Francesco Caramazza et al. (2000) investigated the impact of external, domestic, and financial deficiency factors along with the financial and trades linkages on financial crises using a panel probit model and tried to uncover factors that had significant roles in emerging economies during the Mexican, Asian and Russian crises in the 1990s.

2.2. Global Financial Crisis of 2008–2009 and European Debt Crisis of 2010–2011

A too-loose monetary policy of the FED (Taylor, 2007), weak financial regulations, subprime lending practices, structured financial instruments, and a steep decline in the value of toxic assets in balance sheets induced a catastrophe in 2008 in U.S. financial markets. However, through the trade channels and financial market linkages, the impact of the crisis was not contained in the U.S. but instead spread across the globe. Manolis N. Syllignakis and Georgios P. Kouretas (2011) examined financial spillovers among the U.S., Germany, Russia, and CEE stock market returns for 1997–2009 through the dynamic conditional correlation model of Robert Engle (2002). Results show high correlations, especially during the GFC in American, German, and CEE markets. Dirk G. Baur (2012) studies financial contagion on a sectoral basis during the GFC. Empirical results from ten sectors in 25 developed and emerging economies showed contagious effects among financial sector stocks with fewer effects in healthcare, telecommunications, and technology. Investigating market comovements during the GFC, Steven B. Kamin and Laurie P. DeMarco (2012) tested whether holding large amounts of U.S. mortgage-backed securities (MBS) and dependency on dollar funding induced a higher degree of financial distress. Results indicate that direct contagious effects from the U.S. to other countries were quite limited. Through a panel regime-switching model, Diptes C. Bhimjee et al. (2016) showed that the global banking performance displayed two clusters before and after the GFC, and both exhibit idiosyncratic regime dynamics. Fabio Caccioli et al. (2014) proposed a network approach for the GFC as the spread of the crisis spiked due to financial links, overlapping portfolios, and leverage. Accordingly, while diversification is beneficial for individual institutions, extreme diversification causes systemic risk and financial contagion amplification. Pami Dua and Divya Tuteja (2016) investigated the contagious effects of the GFC in China, Indonesia, India, Japan, and the U.S. The crisis period was identified through a Markov regime-switching model. The results display high contagious effects and flight to quality across and within asset classes with limited portfolio diversification for this sample of countries. Riadh Aloui et al. (2011) analyzed the cross-market relationship of some emerging countries with the U.S. through Capula functions, which consider fat tails and nonlinear dependency. Results demonstrate time-varying dependency between the U.S. and BRIC countries where linkages are relatively high, especially in commodity markets. Dimitris Kenourgios et al. (2011) studied the transmission of shocks through a multivariate time-varying asymmetric framework for five financial crises. According to the results, BRIC countries are more prone to the propagation of crisis. The authors also found limited success in policy responses to prevent the crisis's spread. Following the financial turmoil and downturn in the U.S. housing market, the crisis severely hit European countries with excessive deficit spending and macroeconomic imbalances. The dramatic slowdown in economic activity induced significant job losses and severe economic contractions. Significant spillovers from the U.S. to European economies and contagion had a crucial role in worsening the problems stemming from sovereign debt. Europe's most troubled economies were severely affected and encountered the greatest economic pain. Nicholas G. Polson and James G. Scott (2011) examined financial contagion by incorporating regional and global market risk factors during the European sovereign debt crisis and documented volatility spillovers between markets. Dimitris Kenourgios and Dimitrios Dimitriou (2014) examined the propagation of the crisis from financial markets to the real economy due to the developments during the GFC. Results show that financial turmoil lowered the potential benefits of portfolio diversification in the U.S. and Europe because of the crisis transmission mechanism. Likewise, Steven Ongena et al. (2015) studied volatility spillovers between the real economy and financial markets during the GFC. Results show that firms with a high dependency on international funds and slower contract enforcement suffered more from externality.

2.3. COVID-19 Pandemic

The COVID-19 pandemic rapidly spread immediately after it emerged in China. In just a few months, it became a worldwide health threat, spreading at an alarming rate. Along with the virus, the financial stress of the markets also spread throughout the system and the swift propagation of shocks exacerbated the economic downturn. The measures taken against the outbreak, such as lockdowns, travel restrictions, and social distancing, induced a severe economic contraction by disrupting the supply chain and labor markets. Today, a broad literature presents evidence regarding the effects of the pandemic on finances and economies in general. In one of the early studies, Dayong Zhang et al. (2020) examined the effect of COVID-19 on ten stock markets focusing on countries with the highest number of confirmed cases. Empirical results showed that the global pandemic significantly increased risks in the global financial market and stock markets in the sample reacted significantly to the COVID-19 outbreak. The global pandemic led to increased volatility and uncertainty in the global financial markets. HaiYue Liu et al. (2020) investigated the short-term effect of the global pandemic on countries affected by COVID-19. The results showed that all stock markets were negatively affected by the global pandemic, where the transmission channel of the global pandemic to stock markets was investor sentiment and fear. Shaen Corbet et al. (2020) discussed the "flight to quality" in financial markets during the pandemic. According to the results, there was an enormous rise in volatility in the relationship between the Chinese stock markets and Bitcoin. Xuan Vinh Vo and Thi Tuan Anh Tran (2020) examined the volatility spillovers from U.S. stock markets to ASEAN economies during the pandemic through EGARCH and ICSS algorithms. The authors report significant volatility spillovers when controlling for volatility breaks. Claudiu T. Albulescu (2020) tests the impact of the official new case and death toll announcements on U.S. financial market volatility. Results show the health crisis induced greater volatility in the S&P 500 index. Similarly, Cosmin-Octavian Cepoi (2020) studied the influence of COVID-19-related news on the equity markets and found that the pandemic caused asymmetric dependencies with outbreak-related news. While the disease originated in China, Samet Gunay and Gokberk Can (2022) showed that the source of financial contagion and spillovers was the U.S. The authors shed light on the fact that the network mechanism of various global shocks that stem from political issues, natural disasters, economic factors, or even outbreaks may take different paths in transmitting risks or returns. The empirical evidence presented by Seungho Baek et al. (2020) is also worth mentioning regarding the variation in receiving and transmitting shocks. Using a Markov Switching AR model, the authors presented evidence of regime shifts in U.S. stock market volatility. Results demonstrated varying systematic risks within the industries examined. Scott R. Baker et al. (2020) examined various outbreaks from a historical perspective, including the Spanish Flu, and found that the U.S. reacted unprecedentedly to the pandemic due to its service-oriented economy. Manel Youssef et al. (2020) studied volatility spillovers between equity markets of the eight countries most exposed to the pandemic through a TVP-VAR model. The results show that European equity markets were net volatility transmitters except for Italy. The authors also state that the pandemic reached its peak in volatility spillovers in the first quarter of 2020. Elie Bouri et al. (2020) explored the return connectedness in different variable pairs through TVP-VAR. While stock and currency indexes were the primary volatility transmitters before COVID-19, the bond index became the transmitter as the pandemic spread. The negative oil price experience of 2020 was also of interest to researchers, as discussed by Shaen Corbet et al. (2020). Other studies also examined spillovers associated with oil and energy markets. For instance, Neluka Devpura and Paresh K. Narayan (2020) showed that oil price volatility rose between 8% and 22% due to pandemic cases and deaths. Ngo Thai Hung (2020) investigated return spillovers among five European crude oil prices and stock markets. Results show the LSE, CAC, and IBEX were net volatility recipients in return transmissions. Kgotso Morema and Lumengo Bonga-Bonga (2020) investigated gold and oil price volatility in the South African stock market, with the results from VAR-

ADCC-GARCH showing severe transmissions in volatility between gold and stock and oil and stock markets. The hedge ratio and effectiveness statistics demonstrate a "gold and stock combination" as the best strategy to hedge equity market risk during the COVID-19 pandemic. Arshian Sharif et al. (2020) explored the nexus between the pandemic, oil price shocks, equity markets, geopolitical risk, and uncertainty in economic policy in the U.S. and found that geopolitical risk soared following the pandemic and was higher than U.S. economic uncertainty.

3. Econometric Framework

We use the volatility spillover analysis developed by Francis Diebold and Kamil Yilmaz (2009) to examine volatility spillovers among the variables. We prefer the volatility spillover analysis in the empirical section because, although the volatility spillover analysis is a multivariate approach in nature, we can study bivariate relationships simultaneously in the system. In this context, Lan Wu et al. (2022) emphasized an important advantage of the spillover analysis in that it allows for examining pairwise relationships. While there are also other methods that examine volatility spillovers in the literature, such as causality-in-variance tests suggested by Yongmiao Hong (2001) and Christian M. Hafner and Helmut Herwartz (2006), they are not multivariate analyses in nature. Furthermore, the volatility spillover analysis also allows us to examine the dynamic relationship in the system.

Volatility spillover analysis is based on the variance decomposition of innovations obtained from a Vector Autoregressive (VAR) model. Hence, the methodology requires the estimation of the following VAR (p) model in the first step:

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

where x_t is a vector of endogenous variables, Φ_i shows the estimated parameters and ε_t is a vector of *i.i.d.* disturbances. While x_t should consist of the level of the variables for mean spillovers, volatility spillover analysis should consist of the volatilities of the variables. The stationarity VAR(p) model can be written in the moving average form as follows:

$$x_t = \sum_{j=0}^{\infty} \Theta_j \varepsilon_{t-j} \tag{2}$$

where Θ_j is the coefficient matrix for moving average parameters and can be obtained by the following recursion: $\Theta_j = \sum_{t=1}^{p} \Theta_{j-t} \Phi_t$, with Θ_0 being a NxN identity matrix, and $\Theta_j = 0$ for $\forall j < 0$. As is typical in the VAR analysis, the moving average representation is used to compute variance decompositions. Calculation of the spillover index relies on variance decompositions that allow estimating the fraction of the H-step-ahead error variance in forecasting xi that is due to shocks to xj $\forall j \neq i$, for each *i*.

The calculation of variance decomposition requires orthogonal innovations since VAR innovations are generally contemporaneously correlated. Identification schemes such as the Cholesky factorization achieve orthogonality, but the variance decompositions critically depend on the ordering of the variables. Diebold and Yilmaz (2012) suggest using the generalized error variance decompositions proposed by Gary Koop et al. (1996) and H. Hashem Pesaran and Yongcheol Shin (1998) that do not depend on the ordering of the variables. In the generalized error variance decompositions, the sum of the contributions to the variance of the forecast error is not necessarily equal to one. Depending on the VAR framework, the H-step-ahead forecast error variance decomposition can be calculated as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{3}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation, and e_i is the selection vector, with one as the ith element and zero otherwise. In order to use the information available in the variance decomposition matrix in the calculation of the spillover index, each entry of the variance decomposition matrix is normalized using the row sum as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{4}$$

Note that by construction, $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. The total spillover index that measures the contribution of spillovers of volatility shocks across variables to the total forecast error variance can be calculated as follows:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{5}$$

The directional volatility spillovers received by market *i* from all other markets *j* is:

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{6}$$

The directional volatility spillovers transmitted by market *i* to all other markets *j* is:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{7}$$

Finally, net volatility spillover can be calculated as follows:

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \tag{8}$$

4. Data and Empirical Results

Turkey and Brazil are two important emerging markets with some similarities and distinctive features. Being open to external shocks often leaves both countries on the edge of financial turbulence and induces instability in applying targeted economic programs. Furthermore, Turkey’s geographical location poses some additional risk factors stemming from the neighborhood. All these facts are essential elements of credit risk since they can affect countries' economic performance and their ability to meet financial obligations. This study attempts to investigate the extent of the connectedness of selected financial variables with the credit risk of these two economies. While credit risk is comprehensively examined through CDS spreads in the literature, we also study ASW spreads in addition to CDS spreads. As discussed in ECB (2009) and Chan-Lau (2006), ASW spreads can approximate CDS spreads if the initial price of the underlying bond equals the face value and the occurrence of defaults are independent of interest rate fluctuations. However, in practice, we see a significant divergence between these two spreads, such as in the case of the 2008 Lehman Brothers failure. Thus, we assume that the modeling structure of these spreads may suggest valuable information in response to market developments. Considering this insight, we compare these two spreads in the aforementioned countries' financial markets through spillover analysis to provide further evidence to credit risk literature. In addition, we present evidence from other perspectives. In addition to domestic variables, we use global economic and financial indicators that also allow us to monitor both markets' integration into international markets. To that end, to account for the spillovers, we utilize two domestic (stock markets and exchange markets) and two global (volatility index and global economic activity proxied by Baltic Dry Index) variables. Finally, by providing evidence from the time-varying domain, we can evaluate results in light of the developments in domestic and global markets, such as economic downturns (European Debt Crisis) and the COVID-19 pandemic.

It is established that global economic activity is an important indicator that affects macroeconomic and financial developments in relatively open economies. Since “global economic activity” cannot be observed directly, many studies focus on measuring global economic activity by a proxy. Following Lutz Kilian (2009), the Baltic Dry Index (BDI) has been widely used as a proxy for global economic activity. A well-documented literature validates a significant relationship between BDI and stock markets (Gurdip Bakshi et al., 2011; Oral Erdogan et al., 2013; Qingsong Ruan et al., 2016). The BDI is a freight index published by the Baltic Exchange in London and represents the prices asked by shipbrokers on cargo (finished products, raw materials, etc.) in global shipping activities. In terms of markets, the BDI index can be used to monitor global economic activity; hence, the index represents dynamics in global trade through commercial activities. Another key global variable closely monitored because it measures uncertainty in global stock markets is the VIX index, which measures the implied volatility of the S&P 500 index options and represents expected stock market volatility over the following month. Therefore, an increase in the VIX indicates that the market uncertainty is expected to increase in the following 30 days, and hence the index is dubbed the "fear index". The effects of the VIX on financial markets have been empirically validated in the literature, where the relationship becomes more significant during periods of financial turmoil (Robert E.

Whaley, 2000; Turhan Korkmaz and Emrah İ. Çevik, 2009; Ghulam Sarwar, 2012 and Massaporn Cheuathonghua et al., 2019).

The statistical analysis is carried out using Diebold and Yılmaz's (2012) volatility spillover method. In the empirical analysis, we include the natural log difference of the following variables: economic activity index, credit default swap spreads (CDS), asset swap spreads (ASW), Stock Market Index (Istanbul Stock Exchange 100 Index and Brazil Sao Paulo Stock Exchange Index), and the foreign exchange rate vis-a-vis the U.S. dollar. The daily data run from January 1, 2010 to May 28, 2020, and are taken from the Thomson Reuters Eikon database.

The descriptive statistics in Table 1 show that the daily mean return of all variables is positive except for the economic activity index. Standard deviation statistics indicate that although ASW and CDS exhibit higher levels of volatility than other variables in both Turkey and Brazil, exchange rates have the least volatility. As shown by skewness and kurtosis values, all variables display departures from normality as the gaussian distribution has skewness and kurtosis statistics of zero and three, respectively. When the skewness statistic equals zero, the distribution depicts symmetry. Results show that all variables are positively skewed, except for the Turkish stock market, meaning these return series have a long right tail in their probability distributions. In other words, the frequency of the negative returns is higher than positive returns in these variables. However, all financial variables have negative skewness in Brazil except for ASW. The presence of higher kurtosis statistics than the reference values for normal distribution shows that all series are leptokurtic. Finally, based on skewness and kurtosis, Jarque-Bera test statistics are rejected for all variables indicating non-normality in the return series. ADF and P.P. unit root test results in Table 1 show that all variables are stationary at the 1% significance level.

Table 1 Descriptive Statistics

Turkey	**EA**	**VIX**	**CDS**	**ASW**	**STOCK**	**EXCH**
n	2713	2713	2713	2713	2713	2713
Mean	-0.009	17.481	0.041	0.041	0.025	0.056
Std. Dev.	0.383	2.865	3.018	3.829	1.409	0.884
Skew.	0.096	0.430	0.585	0.196	-0.611	1.806
Kurtosis	5.854	9.787	9.890	8.347	7.255	37.890
JB Stat.	952.8	5290.2	5520.6	3249.5	2215.0	139084.7
ADF	-14.786***	-5.149***	-14.654***	-20.782***	-25.702***	-12.440***
PP	-21.784***	-5.996***	-46.342***	-58.256***	-52.708***	-48.320***
Brazil	**EA**	**VIX**	**CDS**	**ASW**	**STOCK**	**EXCH**
Mean	-0.009	17.481	0.044	0.043	0.011	0.056
Std. Dev.	0.383	2.865	7.500	6.620	1.691	1.079
Skew.	0.096	0.430	-0.157	0.103	-0.357	-0.289

Kurtosis	5.854	9.787	51.321	39.745	9.523	9.625
JB Stat.	952.8	5290.2	197214.7	114038.4	3636.9	3735.3
ADF	-14.786*	-5.149*	-8.532*	-8.433*	-8.709*	-31.743*
PP	-21.784*	-5.996*	-66.339*	-60.155*	-42.522*	-49.797*

Note: * indicates the stationarity at the 1% significance level.

Diebold and Yilmaz's (2012) volatility spillover analysis enables us to measure total and directional volatility spillovers by decomposing the forecast-error variance in a generalized vector autoregressive model where variance decompositions are independent of variable ordering. To ascertain volatility spillover effects, we take the absolute values of the log differences of the variables to measure volatility, except for the VIX, which is a measure of volatility and hence taken as is. In estimating the VAR model, the optimum lag length is set according to the Akaike information criterion (AIC), which suggests five lags. To set the time-varying spillover index, we consider 200 days as a rolling sample size, as in Diebold and Yilmaz (2012). Also, generalized variance decompositions are used to estimate the 10-day volatility forecast error. The results are presented in Table 2.

The upper and lower panels of Table 2 show the volatility spillover analysis results from two alternative models in which CDS and ASW spreads are utilized in proxying credit risk for Turkey. The table shows that some results are somewhat sensitive to the proxy used for credit risk. For example, the upper panel in Table 2 indicates that the greatest contribution to other variable volatility comes from CDS among the variables. On the other hand, the lower panel results of Table 2 highlight the foreign exchange rate as a volatility contributor to the rest of the variables. Using ASW spread as a credit risk indicator instead of CDS spreads; we find its contribution to volatility is limited. According to static connectedness measures, the CDS spread seems to be a more aggressive volatility transmitter than ASW spread as a credit risk indicator. Interestingly, the contributions of global indicators to the volatility of other variables seem to be very limited and similar for each model. Specifically, the volatility contribution of global economic activity to the other variables is minimal and is estimated at 0.5% in both models. On the other hand, the contribution of the VIX is higher than economic activity. As such, the VIX has greater effects on the volatility of financial variables than the global economic activity in Turkey.

The last column indicates the gross directional volatility spillovers received from other variables. According to the results in the upper panel of Table 2, the volatility transmitted from other variables to CDS is the highest. The foreign exchange rate and the stock market index provide the greatest contribution to the volatility of CDS in Turkey, which is consistent with the results of Chang Liu et al. (2020). Moreover, the extent of the transmitted shocks received by the stock market in Turkey is relatively sizable. Of these shocks, the greatest contribution comes from CDS at 10.9 percent, the foreign exchange rate contributes 4.8 percent, and the VIX contributes 4.7 percent. As the contribution of CDS is twice the contribution of the foreign exchange rate, we can state that the volatility of the Turkish Stock Market Index incorporates default risk considerations more than the influence of exchange rate risk. The results in the lower panel of Table 2 indicate that, unlike the first model, the stock market receives the highest gross directional volatility spillovers (14%). It should be noted that the impact of ASW on the stock market is minimal compared to CDS. The stock market, as a recipient, is followed by ASW. The spillovers from others explain 12.22% of the forecast error variance of ASW.

Table 2 Volatility Spillover Analysis for Turkey

Model I: CDS is Default Risk Indicator						
	EA	VIX	CDS	STOCK	EXCH	From
EA	99.30	0.30	0.20	0.20	0.10	0.70
VIX	0.10	96.20	0.90	2.40	0.30	3.80
CDS	0.20	4.40	73.60	10.00	11.90	26.40
STOCK	0.20	4.70	10.90	79.40	4.80	20.60
EXCH	0.10	0.80	7.90	2.70	88.50	11.50
To	0.50	10.20	19.80	15.30	17.10	63.00
Net	-0.2	6.4	-6.6	-5.3	5.6	
Total Spillover Index						12.6%

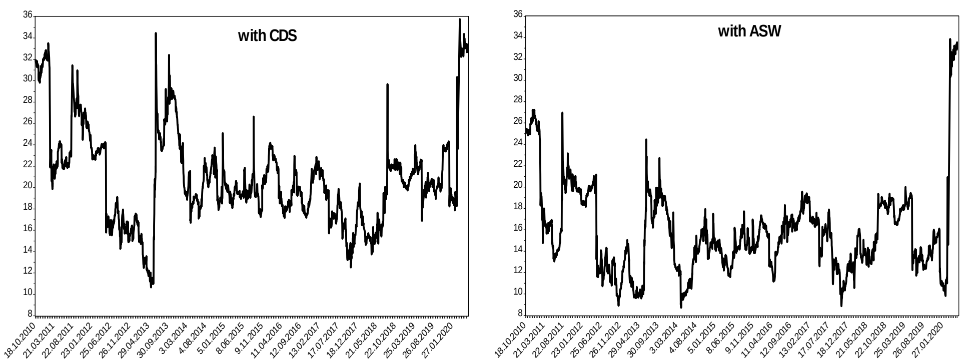
Model II: ASW is Default Risk Indicator						
	EA	VIX	ASW	STOCK	EXCH	From
EA	99.10	0.20	0.40	0.20	0.00	0.90
VIX	0.10	95.70	1.70	2.20	0.30	4.30
ASW	0.20	3.30	87.80	3.40	5.30	12.20
STOCK	0.10	5.20	3.40	86.00	5.30	14.00
EXCH	0.00	0.90	2.50	3.00	93.60	6.40
To	0.50	9.60	8.00	8.70	10.90	37.70
Net	-0.4	5.3	-4.2	-5.3	4.5	
Total Spillover Index						7.50%

Note: To, From, and Net indicate Directional to Others, Directional from Others and Net Directional Volatility Spillovers respectively.

Finally, we present the total volatility spillover index in the lower right-hand corner of the table. This value is estimated at 12.6% for the first model (where CDS is considered the country's default risk indicator). The implication is that, on average, 12.6% of the volatility forecast error variance in all variables is induced by the spillovers in other variables. On the other hand, the total volatility spillover index is 7.5% for the second model (where ASW is considered the country's default risk indicator). On average, this ratio can be interpreted as the extent of exposure of these variables in terms of vulnerability to the risks carried by other variables. Regarding the impact of volatility spillovers, the net directional volatility spillovers also convey important information where it is calculated as the difference between directional spillover to others and directional spillover from others. Positive results demonstrate that the gross volatility transmitted is greater than that received from other variables. The highest value for net directional volatility spillovers is obtained from the VIX and the foreign exchange rate. As such, the VIX and foreign exchange rates are net transmitters of shocks to others. On the other hand, default risk indicators (CDS and ASW) and the stock market index provide the least net directional volatility spillovers. Furthermore, default risk indicators, the stock market, and the global economic activity index are net receivers of volatility from other variables in Turkey.

In Figure 1, we present the historical behavior of total volatility spillovers for five asset classes. As seen, the COVID-19 outbreak period brings about the highest peak since 2010 in volatility spillovers in Turkey. The lowest total volatility spillover is observed during the first half of 2013. The total volatility spillover started to increase at the beginning of 2020 and reached its highest value in March 2020. The second peak in the total volatility spillovers index was at the end of 2013, which corresponds to the *Gezi Park* protests in Turkey and the announcement of a reduction in asset purchases by the FED.

Figure 1 Total Volatility Spillover for Turkey



We also report time-varying directional, net, and pairwise volatility spillover results in Appendix A1, which clearly show that the magnitude of the volatility spillover effects varies over time. The directional volatility spillovers from five asset classes show that the gross volatility spillovers from global economic activity, VIX, and the stock market, to others, significantly increased during the COVID-19 outbreak. These are consistent with empirical results that are documented by Erdogan et al. (2013) and Ruan et al. (2016). They showed that the spillover effect of global economic activity measured by the BDI on exchange rates and stock markets is more significant during financial turmoil episodes. Also, Ghulam Sarwar and Walayet Khan (2017) found that the VIX has a greater impact on emerging stock markets during a financial crisis than in other periods. On the other hand, the gross volatility spillovers from default risk indicators to others increased in the middle of 2018 due to speculative attacks on the Turkish lira. Similarly, the directional volatility spillovers to five asset classes results indicate that directional volatility spillovers to default risk indicators and the stock market had a relatively higher increase during the COVID-19 pandemic than in tranquil times. Although net volatility spillovers from the stock market and the VIX were positive during the COVID-19 outbreak, net volatility spillovers from global economic activity and foreign exchange rates were negative. More interestingly, while CDS seems to be a net volatility receiver during COVID-19, ASW seems to be a net volatility transmitter. This behavior of ASW spread can be interpreted as the sensitivity of the instrument to market developments. This result is consistent with Samet Gunay's (2019) findings, in which the performance of CDS and ASW spreads are compared as early risk indicators.

To study volatility spillovers in Brazil, we estimate a VAR model with three lags. As in Turkey, the rolling window size is set to 200 days to estimate the time-varying volatility spillover index, and generalized variance decompositions are used to obtain a 10-day volatility forecast error. Table 3 shows that the results are not very different when we use CDS or ASW as a proxy for credit risk. For example, the results in Table 3 indicate that the greatest contribution to other variables' volatility comes from the stock market in both models, followed by the foreign exchange rate. The default risk indicators come third in terms of contributing to the volatility of other variables. The effect of ASW on volatility spillovers is higher than the impact of CDS in Brazil (5.12 percent vs. 3.87 percent, respectively). We find that the global variable contribution to Brazil's financial variables' volatility is limited in both models. For example, the volatility contribution of global economic activity to the other variables is estimated at 0.4 percent in both models. On the other hand, although the VIX provides relatively more contribution to volatility than global economic activity, its influence is also minimal compared to country-based variables.

These results can be explained in terms of the limited integration of emerging countries with global markets. Increasing market integration yields converging mean returns and risk levels. However, departures induce divergence in these parameters. Therefore, the integration of Turkish and Brazilian financial markets with advanced economies may affect the degree of the volatilities transmitted. For example, Omar M. Al Nasser and M. Hajilee (2016) reported a limited long-term integration between emerging and developed stock markets. Accordingly, this integration can be validated for emerging markets and Germany in the long term. Geert Bekaert et al. (2009) also reported the absence of an upward trend in the comovements of stock market correlations. Likewise, Andrew K. Rose and Charles Engel (2000) could not find a significantly high risk-sharing even among members of a monetary union. Regarding the relatively limited impact of the VIX, one can surmise that our results may be related to the nature of the variable. For example, although the global fear index, the VIX, successfully measures and reflects the tension in global markets, its construction is computed based on S&P 500 index options. Therefore, the behavior of the VIX is dominated mainly by U.S. market dynamics. Hence, in any given country, trade openness and financial market integration will affect the economic vulnerability of the VIX. Comparing Brazil and Turkey, the relatively higher net directional volatility of the VIX in Turkey may reflect these factors. Second, the weak spillover impact from global economic activity to financial markets in Turkey and Brazil may be linked to lags within which global economic activity may affect financial markets. Although the global economic activity index successfully captures the tendencies in economic developments, as Philip Arestis et al. (2001) asserted, the linkage between economic activity and stock markets is weaker than the relationship between economic activity and bank-based financial intermediation. Likewise, Ake Boubakari and Dehuan Jin (2010) reported that the relationship between stock market developments and economic growth is significant only for countries that have highly active and liquid markets. In another study, Roger D. Huang et al. (1996) used oil futures as an economic activity indicator and examined their relationship with stock market indexes. As in our results, the authors could not validate a significant effect of oil futures on stock markets.

Table 3 Volatility Spillover Analysis for Brazil

Model I: CDS is Default Risk Indicator						
	EA	VIX	CDS	STOCK	EXCH	From
EA	99.44	0.23	0.02	0.15	0.16	0.60
VIX	0.09	95.09	0.84	3.61	0.37	4.90
CDS	0.05	0.87	88.80	5.84	4.44	11.2
STOCK	0.09	3.64	3.87	78.07	14.33	21.9
EXCH	0.15	0.53	3.02	12.91	83.38	16.6
To	0.40	5.3	7.70	22.50	19.30	55.2
Net	-0.2	0.4	-3.5	0.6	2.7	
Total Spillover Index						11.0%

Model II: ASW is Default Risk Indicator						
	EA	VIX	ASW	STOCK	EXCH	From
EA	99.4	0.23	0.01	0.16	0.16	0.6
VIX	0.09	94.93	1.01	3.60	0.37	5.1
ASW	0.07	1.50	85.89	7.28	5.56	14.4
STOCK	0.09	3.61	5.12	77.02	14.16	23.0
EXCH	0.15	0.53	3.82	12.80	82.71	17.3
To	0.40	5.9	10.0	23.8	20.2	60.3
Net	-0.2	0.8	-4.4	0.8	2.9	

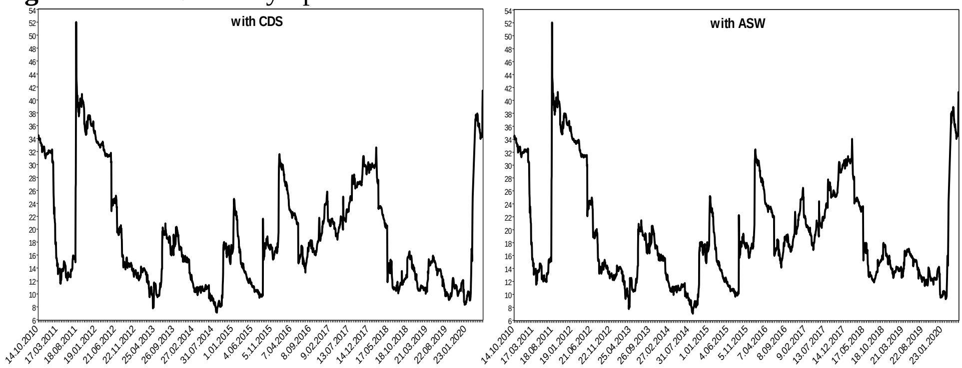
Total Spillover Index	11.1%

Note: To, From, and Net indicate Directional to Others, Directional from Others and Net Directional Volatility Spillovers respectively.

The last column in Table 3 shows the gross directional volatility spillovers received from other variables. According to the results, the volatility transmitted from other variables to the stock market is high compared to other variables. We find the foreign exchange rate in both models provides the greatest contribution to Brazil's stock market volatility. This interaction is slightly different in Turkey's case, where the highest transmission to the stock market comes from the CDS spreads in the first model and the foreign exchange rate and the VIX in the second model. The difference in the results in the two countries can be attributed to Turkey's relatively high credit risk and the influence of credit risk on financial variables. Similarly, when we compare the volatility spillovers to foreign exchange rates in the first model (CDS model) of both countries, we see a relatively influential role for CDS in Turkey, while the stock market is the primary volatility provider to the exchange rate in Brazil. Finally, we present the total volatility spillover index value in the lower right corner of the table. This is estimated to be 11% for both models in Brazil. This ratio can be interpreted as the extent of exposure of these variables, on average, against the risks carried by other variables.

The time-varying total volatility spillovers index for Brazil is presented in Figure 2. Note that the time path of both models is very similar. The index reached its highest value in 2011 due to the European Debt Crisis. During this period, the stock market declined and the VIX increased significantly. Then, the total volatility spillover index started to decrease and the lowest total volatility spillover was observed at the end of 2014. A peak was observed in the total volatility spillovers index in 2015 due to a sharp increase in the default risk indicators (CDS and ASW) and the index remained at a high level between 2015 and 2017. The total volatility spillover again started to increase at the beginning of 2020 when it reached its second-highest value in March 2020 due to the COVID-19 outbreak. Results indicate that while the total volatility index displayed its record high in Turkey during the COVID-19 pandemic, the worst value was not observed in Brazil after the COVID-19 pandemic. However, when we compare the latest values, which correspond to the impact of the pandemic, we see that the extent of market stress is significantly greater in Brazil than in Turkey during the outbreak. While the index value is 34% in Turkey, it hits 42% in Brazil. Directional spillovers also confirm the greater impact of the pandemic on Brazil, as we discussed below.

Figure 2 Total Volatility Spillover for Brazil



The time-varying directional, net and pairwise volatility spillover results are given in Appendix A2. The results in Appendix A2 indicate that the magnitude of the volatility spillover effect varies over time. The directional volatility spillovers from five asset class results show that the gross volatility spillovers from all variables significantly increased during the COVID-19 outbreak. However, the directional volatility spillovers from five asset class results indicate that directional volatility spillovers to default risk indicators and the stock market increased relatively more during the COVID-19 outbreak. Although net volatility spillovers from the stock market and default risk indicators were positive during the COVID-19 outbreak, net volatility spillovers from global economic activity, the VIX, and foreign exchange rates were negative. The impact of the pandemic appears to be higher in the credit risk of Brazil than in Turkey. CDS spreads of the country turned into net volatility transmitters during the pandemic, unlike the case of Turkey.

The results of this study provide important contributions to the literature in several ways. It appears that the current literature mainly uses CDS spreads to examine credit risk without distinguishing the period before or after the pandemic. For example, Hasan et al. (2023) explored the effect of the pandemic on the credit risk of selected companies across the globe. Authors report that firms possessing higher leverage and worse governance are exposed to elevated credit risk. Likewise, Pan et al. (2021) used only CDS spreads in proxying credit risk and investigated the relationship between the pandemic and sovereign credit risk of selected countries. According to their results, the pandemic's negative effect has become more extensive in developed countries with worse healthcare systems. Another recent study that examines the nexus between the global pandemic and corporate credit risk was carried out by Apergis et al. (2021). As in previous studies, the authors used CDS spreads in measuring credit risk and reported heterogeneous impacts across the sectors. The greatest effects are observed in the banking, transportation, restaurant and travel & leisure sectors. This preference, using CDS spreads as a proxy for credit risk, is also seen in several other studies. For example, Ito (2022) reported that the United States, United Kingdom, Germany and Japan illustrated a varying extent of credit risk before and after the pandemic due to differences in taking actions during the pandemic. The author used CDS spread to measure credit risk following the practice in the literature. Unlike these studies, in this paper, we also present evidence from another credit risk indicator, ASW spreads. According to our results, the ASW spread in Turkey became the net transmitter of spillovers, while CDS spreads were the net receiver of spillovers during the pandemic. This result highlights the importance of selected credit risk indicators in empirical analysis. Moreover, unlike the studies cited above, by working with a longer sample, we attempted to present evidence from other episodes, such as the European Debt Crisis of 2010-2011. Our study reveals that this crisis was as impactful as the COVID-19 pandemic for both countries, but particularly for Turkey due to its trade linkages and its proximity to Europe. Indeed, this is confirmed by Sensoy et al. (2014), who argue that the Turkish economy is not immune to global shocks and possesses greater sensitivity to the economic developments in Europe due to market integration that increased with the Global Financial Crisis. Kosaroglu et al. (2017) attribute this result to the export potential of Turkey to European countries and, thus, reduced demand during the sovereign debt crisis. As in the 2010–2011 period, we also observed increasing spillovers received or transmitted by the Turkish CDS spread in 2018–2019. Akcay and Güngen (2019) attribute this to a deterioration in economic indicators due to global developments. According to the authors, the turmoil was attributable to a local currency crisis as well as a liquidity crunch in global markets. Indeed, this observation aligns with our results as we also observed the same spillover patterns in Brazil. It should be noted that in both countries, the sources of risks were associated with foreign exchange market developments with an earlier deterioration in Brazil. Thus, we conclude that these vulnerabilities in currency markets necessitate urgent and effective reforms in both economies.

5. Robustness Check

For a robustness check, as in He et al. (2020) and Wu et al. (2022), we used different forecast horizons in variance error decompositions. The results in Table 4 and Table 5 show the spillover analysis results for a 20-day forecast horizon. The results in Table 4 and Table 5 are very similar to the results in Table 2 and Table 3, which suggest the spillover analysis results are consistent over the different forecast horizons.

Table 4 Volatility Spillover Analysis for Turkey (forecast horizon: 20 days)

Model I: CDS is Default Risk Indicator						
	EA	VIX	CDS	STOCK	EXCH	From
EA	99.19	0.39	0.16	0.21	0.06	0.81
VIX	0.06	96.46	0.81	2.45	0.22	3.54
CDS	0.17	5.4	72.6	9.97	11.87	27.4
STOCK	0.16	5	10.9	79.1	4.84	20.9
EXCH	0.09	0.85	7.88	2.66	88.52	11.48
To	0.48	11.64	19.75	15.29	16.98	64.14

Net	-0.33	8.1	-7.66	-5.6	5.5	
Total Spillover Index						12.83%

Model II: ASW is Default Risk Indicator

	EA	VIX	ASW	STOCK	EXCH	From
EA	98.96	0.36	0.39	0.24	0.05	1.04
VIX	0.05	94.86	2.63	2.23	0.23	5.14
ASW	0.25	3.43	87.54	3.46	5.32	12.46
STOCK	0.17	5.28	3.37	85.78	5.4	14.22
EXCH	0.09	0.9	2.53	2.98	93.5	6.5
To	0.57	9.98	8.92	8.9	11	39.37
Net	-0.47	4.84	-3.55	-5.32	4.5	
Total Spillover Index						7.87%

Note: To, From, and Net indicate Directional to Others, Directional from Others, and Net Directional Volatility Spillovers, respectively.

Table 5 Volatility Spillover Analysis for Brazil (forecast horizon: 20 days)

Model I: CDS is Default Risk Indicator

	EA	VIX	CDS	STOCK	EXCH	From
EA	99.34	0.31	0.02	0.16	0.17	0.66
VIX	0.11	94.46	1.14	3.96	0.32	5.54
CDS	0.05	1.34	88.13	6.01	4.48	11.87
STOCK	0.09	4.64	3.94	77.04	14.3	22.96
EXCH	0.16	0.84	3.06	13.1	82.84	17.16
To	0.4	7.14	8.16	23.23	19.27	58.19
Net	-0.26	1.6	-3.72	0.27	2.1	
Total Spillover Index						11.64%

Model II: ASW is Default Risk Indicator

	EA	VIX	ASW	STOCK	EXCH	From
EA	99.35	0.31	0.01	0.16	0.17	0.65
VIX	0.1	94.4	1.24	3.94	0.32	5.6
ASW	0.07	2.17	84.69	7.49	5.59	15.31
STOCK	0.09	4.61	5.19	75.99	14.12	24.01
EXCH	0.15	0.84	3.88	12.99	82.15	17.85
To	0.42	7.93	10.31	24.58	20.19	63.42

Net	-0.24	2.33	-5	0.57	2.33	
Total Spillover Index						12.68%

Note: To, From, and Net indicate Directional to Others, Directional from Others, and Net Directional Volatility Spillovers, respectively.

6. Conclusions

The recent COVID-19 pandemic has severely impacted both Brazil and Turkey. However, it was not the only hazard these two countries encountered in the last decade. Structural problems such as current account deficits and fiscal imbalances, and openness to speculative currency attacks often caused financial turbulence in these economies.

In this study, we examine the volatility spillovers between global variables and domestic financial markets in these two emerging markets. Using two measures of credit risk indicators (CDS and ASW spreads) to gauge the tension in credit risk, we examine variables that receive and transmit the volatilities, such as the stock market and the exchange rate as country-based variables, and the Baltic Dry Index (BDI) and the VIX as global variables.

Results of the static and dynamic analysis indicate that Turkey and Brazil display different characteristics in terms of the variables that play a significant role in the network of spillovers. In the case of Brazil, we end up with a consistent and solid pattern across the analysis, while we observe varying results for Turkey under different methods. For example, according to the static connectedness analysis results, the spillovers received and transmitted are mainly driven by Brazil's stock and exchange markets. However, unlike Brazil, credit risk is a leading factor in Turkey's financial markets. As such, the country's CDS index is the primary element in transmitting and receiving spillovers from other variables. Stock and exchange markets follow the CDS spreads in spillovers received and transmitted, respectively. The second model, which utilizes the ASW spread as a credit risk indicator, shows that stock and exchange markets are significant variables in transmitting and receiving spillovers. ASW, on the other hand, is ranked second after the stock market in exposing spillovers from other variables. The results of static connectedness analysis reveal that Turkey is subject to a substantially higher level of credit risk than Brazil.

To further examine the interactions of variables regarding spillovers received and transmitted, we also implement a time-varying connectedness analysis that allows us to ascertain the periods where spillovers emerged or faded out. The pattern obtained for Turkey becomes considerably apparent in the time-varying analysis. It appears that the most intense spillovers received by the CDS index from other variables occurred during the 2010–2011 European Debt Crisis and the 2018–2019 currency crisis in Turkey.

The spillovers during the pandemic do not exceed those levels. In terms of the spillovers transmitted by CDS to other variables, all of these events (including the 2010–2011 European Debt Crisis, the 2018–2019 currency crisis in Turkey, and the

COVID-19 pandemic) test historical highs. Unlike previous episodes, the spillovers transmitted from CDS to other variables become considerably higher even during the COVID-19 pandemic. Pairwise connectedness analysis reveals that the primary source of the spillovers received by the CDS spreads in Turkey is the U.S. dollar/Turkish lira exchange rate. The Turkish economy appears to be highly sensitive to exchange market developments even after long attempts at stabilizing the economy. This sensitivity becomes even more evident in periods other than the COVID-19 pandemic and its consequences. Economic policies should consider the fragility of exchange markets and prioritize foreign exchange stability. Unlike Turkey, time-varying analysis for Brazil shows that CDS and ASW display spikes and record highs during the pandemic in receiving and transmitting spillovers. This result might be attributed to the slowdown in global economic activity during the pandemic, resulting in declining fortunes for Brazil in oil exports and tourism. When we focus on the drivers of spillovers toward CDS and ASW, foreign exchange markets played a significant role during 2017–2018 in Brazil, whereas they figured prominently in 2018–2019 in Turkey.

To conclude, credit risk plays a significantly greater role in the financial markets in Turkey than in Brazil. However, exchange rates come to the fore as an essential element associated with both countries' credit risk, especially during the European Debt Crisis and approximately in 2017–2019 in both countries. Thus, we suggest economic reforms in Brazil and Turkey to stabilize exchange markets.

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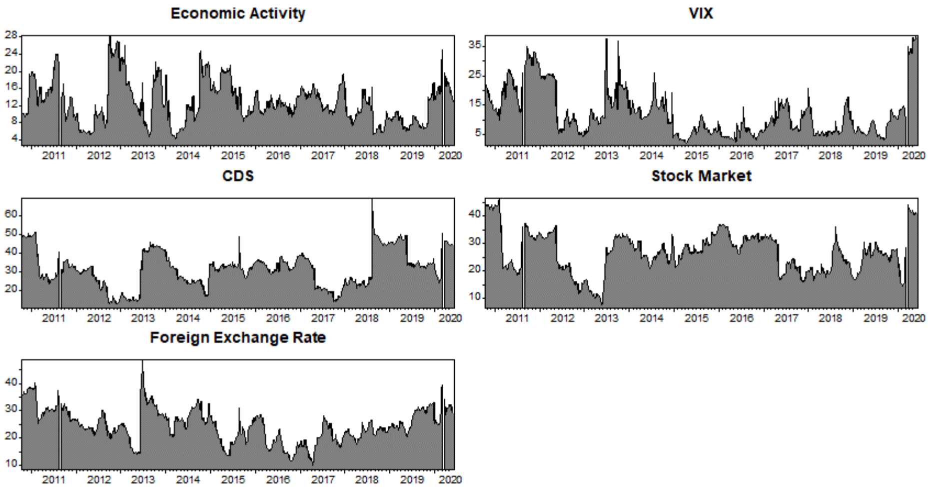
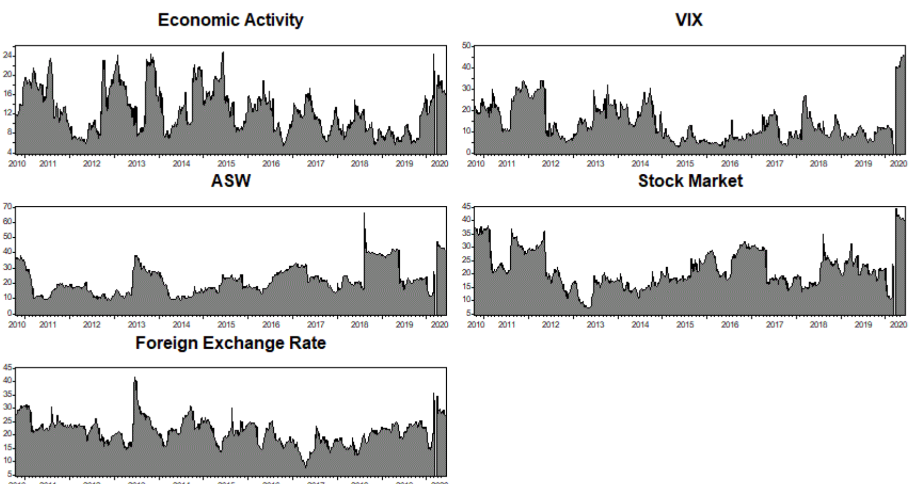
Appendix

A1. Time-varying Volatility Spillover Analysis Results for Turkey Directional Gross Volatility Spillovers from Five Assets Class

(a) CDS

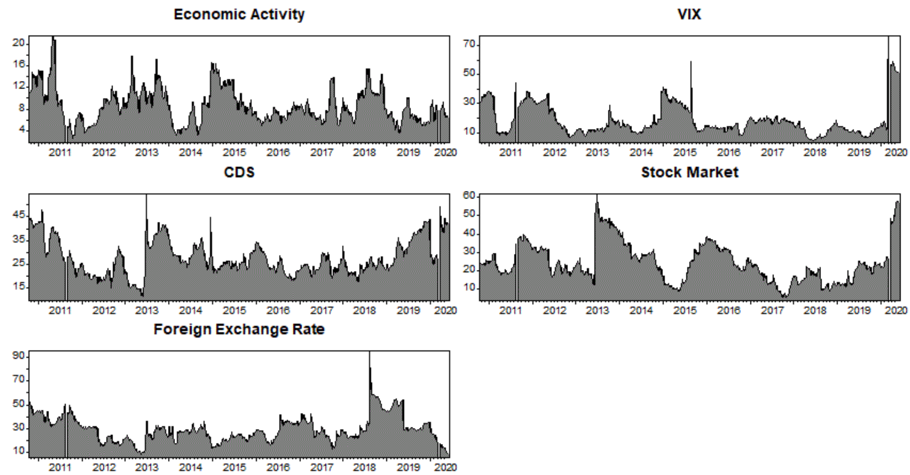


(b) ASW

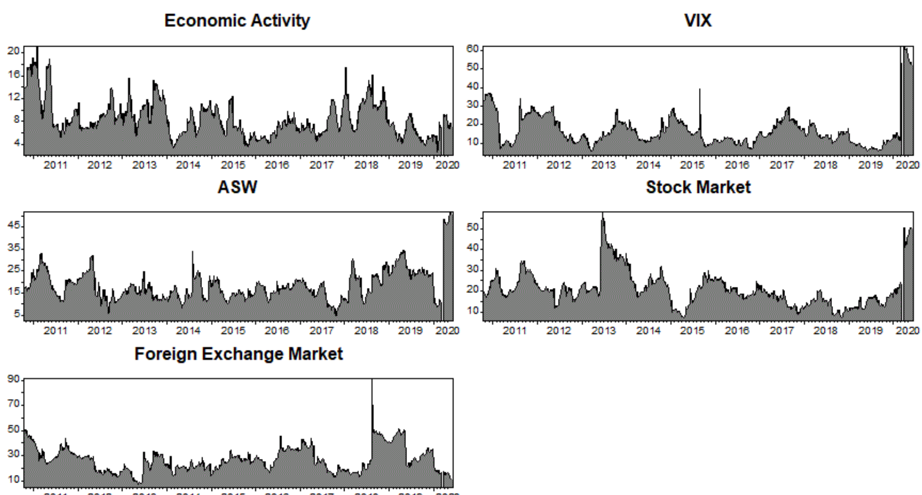


Directional Gross Volatility Spillovers to Five Assets Class

(a) CDS

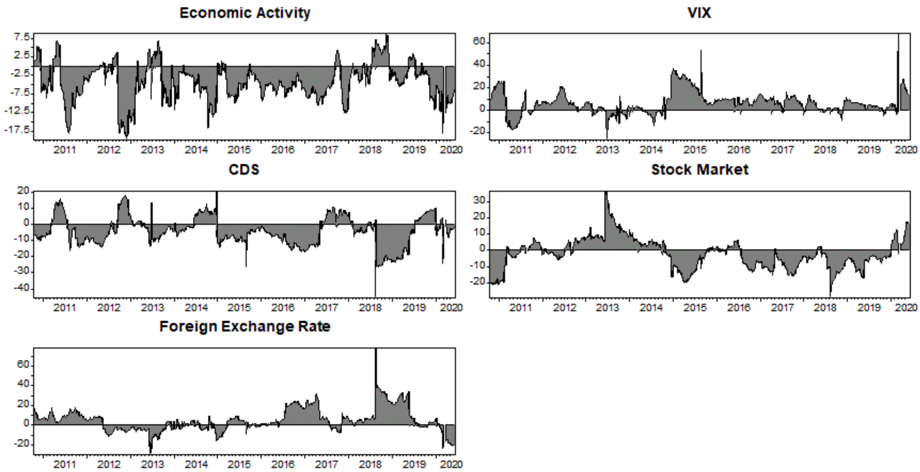


(b) ASW

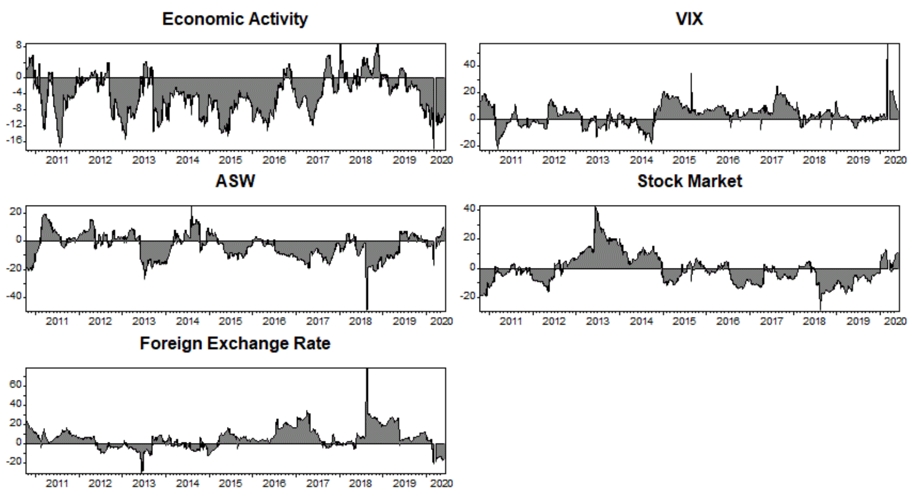


Net Volatility Spillovers

(a) CDS

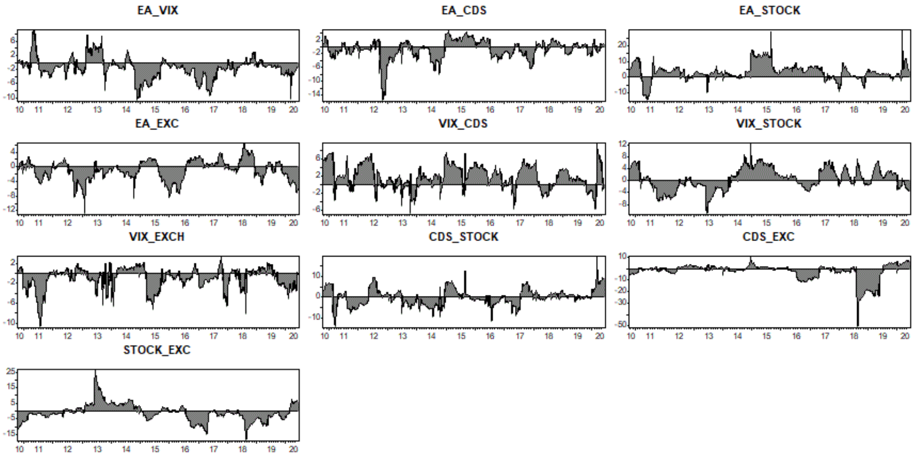


(b) ASW

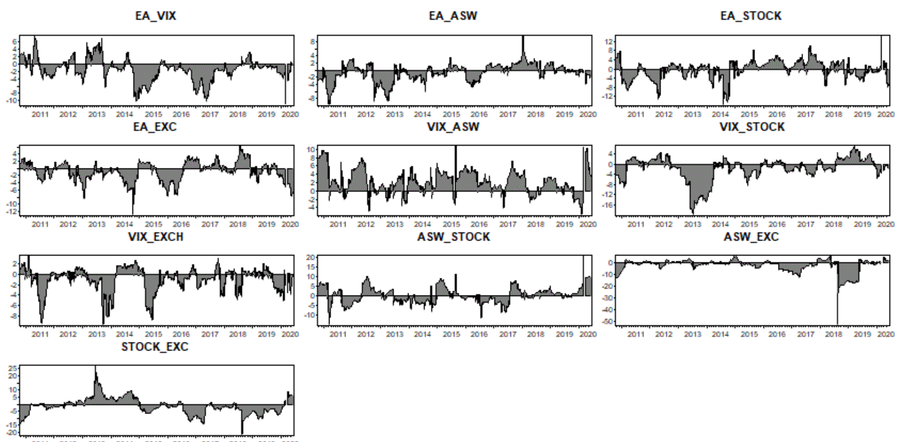


Net Pairwise Volatility Spillovers

(a) CDS

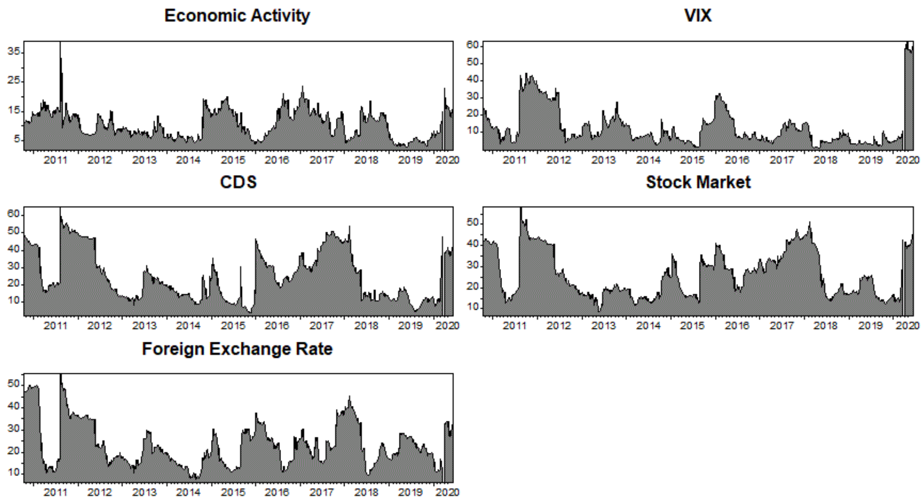


(b) ASW

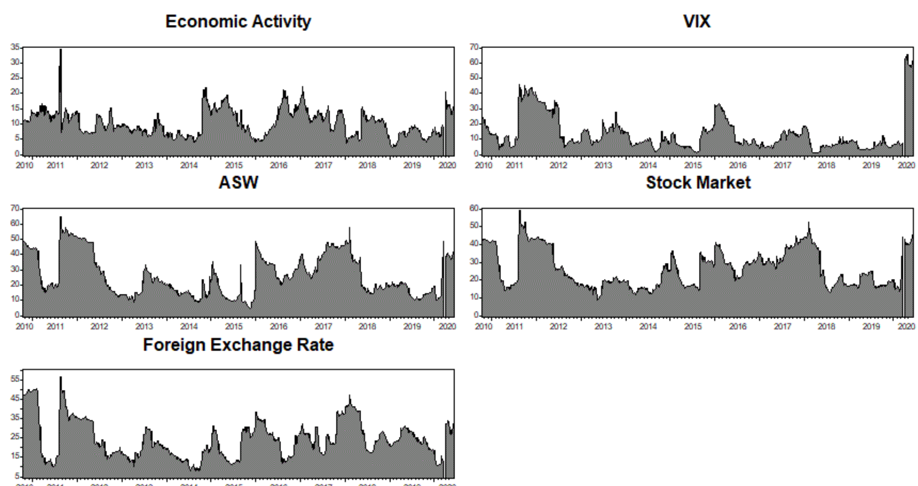


A2. Time-varying Volatility Spillover Analysis Results for Brazil
Directional Gross Volatility Spillovers from Five Assets Class

(a) CDS

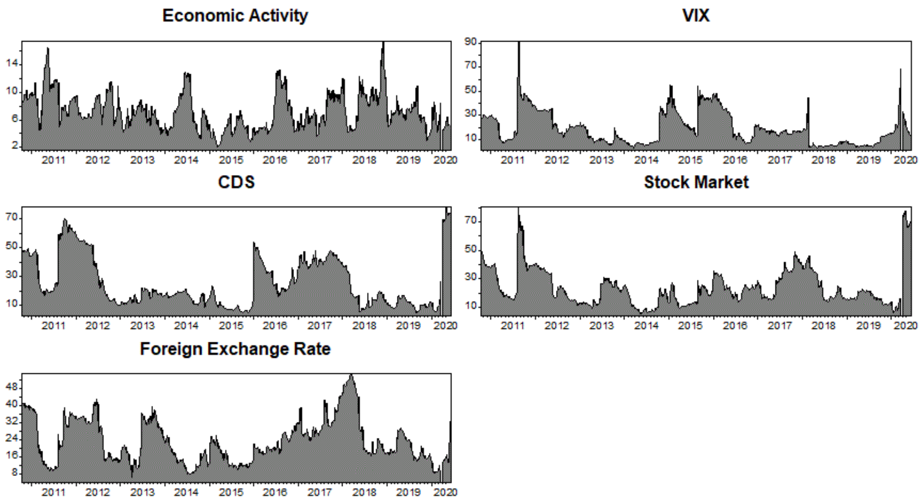


(b) ASW



Directional Gross Volatility Spillovers to Five Assets Class

(a) CDS



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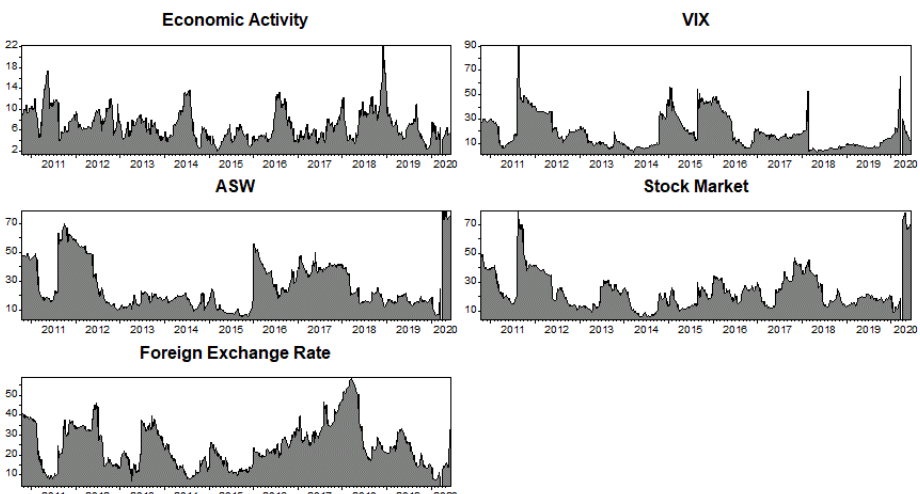
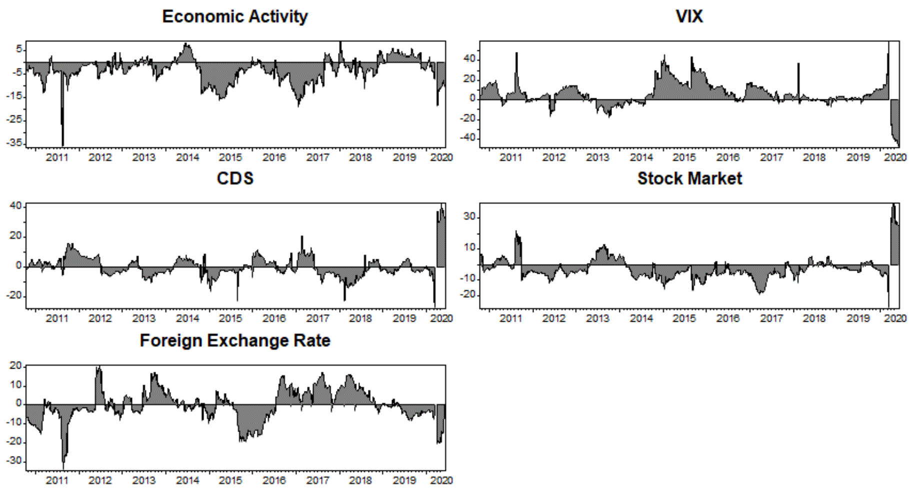
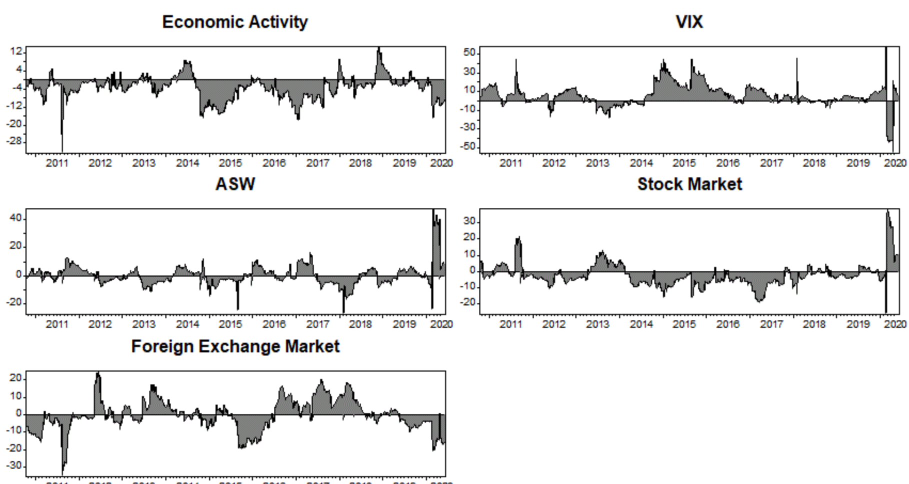


Net Volatility Spillovers

(a) CDS

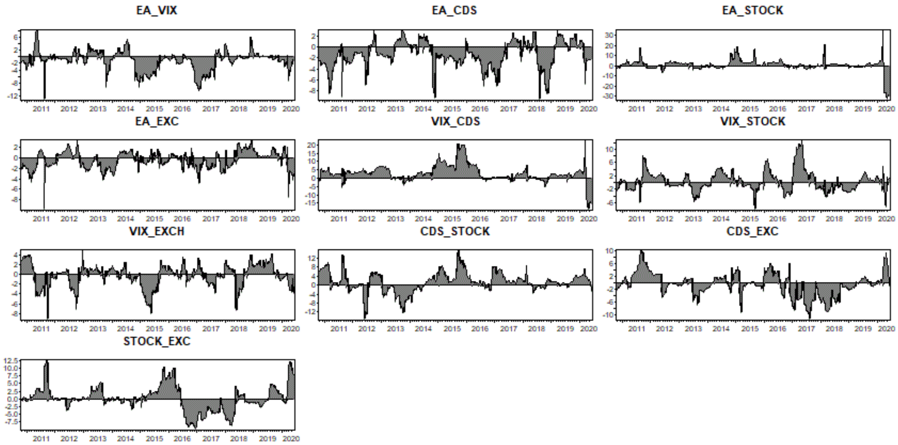


(b) ASW



Net Pairwise Volatility Spillovers

(a) CDS



(b) ASW