

Forex and Equity Markets Spillover Effects among USA, Brazil, Italy, Germany and Canada in the Aftermath of the Global Financial Crisis

Konstantinos Tsiaras^{1*} Theodore Simos¹

Abstract

In this paper we investigate the spillover effects of FOREX and equity markets for USA, Brazil, Italy, Germany and Canada on the basis of daily data. We test for contagion co-movements for the period 2010-2018 post global financial crisis, using the trivariate AR-diagonal BEKK model. The estimated dynamic conditional correlations show the strongest contagion effects for the pairs of markets: S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX. For institutions, multinational corporations and active investors, a portfolio consisting of financial assets from the above markets is extremely risky.

Keywords: Financial contagion, Global Economic Crisis, ARdiagonal BEKK model, International equity market, Foreign exchange market

Introduction

The purpose of this paper is to investigate the interdependence of equity and FOREX market returns between USA and four other countries² of G20 namely the Germany, Italy, Brazil and Canada in the aftermath³ of the recent Global Financial Crisis 2007. Based on the conditional second moments of the distribution of equity and FOREX market returns, we quantify the volatility spillover effects

³At first, we applied the trivariate models for the crisis period and the after crisis period. Unfortunately we faced two major problems in the crisis period and we used only the after crisis period: (1) the optimization algorithm failed to converge for the most countries, and (2) we didn't find consistent diagnostic tests for all the countries of G20.



¹University of Ioannina, Ioannina, Greece

^{*}Corresponding author: konstantinos.tsiaras1988@gmail.com

²Initially, we wanted to apply the model for all the countries of G20. However, the optimization algorithm failed to converge for the rest countries of G20 except the under investigation countries.

by using four trivariate BEKK models⁴: (1) S&P500, BOVESPA, BRL/USD, (2) S&P500, FTSEMIB, EUR/USD, (3) S&P500, DAX30, EUR/USD, and (4) S&P500, DAX30, EUR/USD.

The contagion among financial markets is now at the center of financial analysis (Ku & Wang, 2008; Yilmaz, 2010; Jiang & Xing, 2010; Akar, 2011; Sehgal, Ahmad, & Deisting, 2015). The recent global financial crisis (GFC) (2007-2009) has brought significant attention to the financial contagion phenomenon (Billio & Caporin, 2010; Dimitriou & Kenourgios, 2015; Li & Giles, 2015). Initially, the financial crisis was triggered by the subprime mortgage market crisis in the USA 2007 and developed into a full-blown international banking crisis with the collapse of Lehman Brothers 2008, generating financial distress in the global financial markets. The growing globalisation of financial markets played an important role for the increased spread of the crisis. Serious financial crises (Mexican crisis of 1994, Asian financial crisis of 1997, Russian dept crisis of 1998, Brazilian currency crisis of 1999, Greek debt crisis of 2010) forced investors to rekindle their perspective about the way that financial markets operate and interact (Burzala, 2015). Thus, the way that shocks are transmitted from one financial market to another financial market after major crises have been studied by many researchers, i.e. Forbes and Rigobon (2002), Pericoli and Sbracia (2003), among others. Forbes and Rigobon (2002) defined contagion phenomenon as a significant increase in cross-market linkages after a shock. Focusing on the above narrow definition of contagion, we empirically investigate the linkages among major FOREX and equity markets in light of the financial crisis of 2007.

Earlier, the authors have suggested that during a financial crisis, FOREX markets are under significant pressure, resulting to a risk transfer from FOREX markets to equity markets (Corsetti, Pericoli, & Sbracia, 2005). Several researchers note that exchange rates have an impact on daily equity markets (Joseph, 2002; Kim, 2003; Kurihara, 2006). Today, empirical tests of the volatility spillover effects between equity market returns and exchange rate returns



⁴We tried different multivariate models without success. The diagonal BEKK model was the only model that we succeeded to employ by finding consistent diagnostic tests.

have been limited to the use of either simple regression of cointegration methods.

Smith (<u>1992</u>) contacts a regression analysis between stock markets and exchange rate markets for Germany, USA and Japan. He uses quarterly data from 1974 to 1988 obtained from OEDC. He finds that both USA and German stock prices have a significant effect on the German mark - US dollar exchange rate, and that Japanese and USA stock prices affect the Japanese yen - US dollar exchange rate.

Ayayi and Mougoue (<u>1996</u>) examine the sensitivity of stock prices to exchange rate changes. They use daily closing stock market indices and exchange rates for Canada, France, Germany, Italy, Japan, The Netherlands, United Kingdom, and United States sourced from Citibase Data Services and Data Resource International. They examine the period from April 1985 to July 1991. By employing an error correction model, they find that an increase in aggregate domestic stock price has a negative short-run effect on domestic currency value.

Kanas (2000) investigates the volatility spillovers of stock returns and exchange rate changes within the same economy for the US, the UK, Japan, Germany, France and Canada. He uses daily closing stock prices denominated in local currency for all the equity markets for the period from 1 January, 1986 to 28 February, 1998 (3173 obs.). Additionally, he employs a bivariate EGARCH model. He finds evidence of spillover effects from stock returns to exchange rate changes for five of the six countries except the case of Germany.

Grambovas (2003) uses cointegration methods to quantify the sensitivity of equity prices to exchange rate changes for Greece, Czech Republic and Hungary. He uses weekly data for the time period 1994-2000. The data is obtained from datastream. He finds that there is relationship between Hungarian exchange rates and stock prices, as well in the case of Greece. He concludes that these results illustrate that changes in the stock markets may affect the exchange rates.

Vygodina (2006) investigates the causality relation between USA stock prices and USA dollar exchange rate controlling for the size and international exposure of the sample firms. He uses daily

data for the time period 1987-2005. Additionally, he employs the Granger (1969) causality test. He finds evidence of Granger causality form large-cap stock prices to exchange rate, but no such relation between small-cap stock prices and the exchange rate is observable.

Yau and Nieh (2006) examine the interrelationships among stock prices of Taiwan and Japan and NTD/Yen exchange rate. They use monthly observations for the period 1991-2005. They employ unit root, cointegration and Granger's causality tests. First, they find that the stock prices of Taiwan and Japan impact each other for short durations. Second, they prove that the portfolio approach is supported for the short-term and the traditional approach is more plausible for the long-term in the Taiwanese financial market, whereas the portfolio approach is not suitable for the Japanese stock market. Third, they find no long-term relation between NTD/Yen exchange rate and the stock prices of Taiwan and Japan.

This paper contributes to the literature on equity and FOREX markets volatility modeling in several ways. S&P 500 appears to have the strongest own volatility spillovers, meaning that the equity markets of USA have not been mainly affected by the GFC (2007) in contrast to the rest equity and FOREX markets. Dynamic conditional correlations reveal evidence of contagion for the pairs of markets: S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX. Recapping, these results are of interest to institutions, to multinational corporations, which can use risk management strategies in order to mix equity and FOREX market investments within their portfolios.

The structure of the present paper has the following form: Chapt. 2 presents the methodology, while in Chapt. 3 we discuss the data and the empirical results. The conclusions are stated in Chapt. 4.

2. Econometric Methodology

At first step, we calculate the daily returns (y_t) , using an autoregressive AR(1) process and a constant (μ) in the mean equation as follows:

 $(1 - fL)y_t = \mu + \varepsilon_t, \text{ with } t = 1, \dots, T.$ (1)

AR(1) term captures the speed that market information is reflected in market values. Additionally, |f| < 1 is a parameter, L is



back shift operator and $\varepsilon_t | \Omega_{t-1} \sim N(0, H_t)$, where Ω_{t-1} is the information set at time *t*-1.

Next, we employ the Engle and Kroner $(\underline{1995})^5$ representation of multivariate GARCH model. Specifically, we use the diagonal BEKK (p,q) model, in order to parameterize the multivariate conditional variance H_t as follows:

$$H_t = C'C + \sum_{k=1}^q A_k A'_k \varepsilon_{t-k} \varepsilon'_{t-k} + \sum_{l=1}^p G_l G'_l H_{t-l}$$
(2)

where H_t is multivariate conditional variance matrix of daily returns and positive definite for all t. C is a N x N upper triangular matrix and A_k and are G_l diagonal matrices of dimension N x 1. Coefficients of matrix C state the constant components, coefficients of matrix A_k measure the intensity of spillover effects and coefficients of matrix G_l show the persistence of conditional variance.

We finally estimate the diagonal BEKK (1,1) model, as Bollerslev, Chou, and Kroner $(\underline{1992})$ has mentioned sufficient to estimate the trivariate conditional variance matrix, of the following form:

$$H_{t} = C'C + A_{1}A'_{1}\varepsilon_{t-1}\varepsilon'_{t-1} + G_{1}G'_{1}H_{t-1}$$
(3)

where H_t depends on H_t and ε_t for each market lagged one period. The coefficients of $C(c_{i,j}, \text{with } i, j = 1, ..., N)$, $A_1(a_{i,j}, \text{with } i = j = 1, ..., N)$ and $G_1(g_{i,j}, \text{with } i = j = 1, ..., N)$ matrices are estimated as follows:

$$C = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{12} & c_{22} & 0 \\ c_{13} & c_{23} & c_{33} \end{bmatrix}, A_1 = \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix}, G_1 = \begin{bmatrix} g_{11} & 0 & 0 \\ 0 & g_{22} & 0 \\ 0 & 0 & g_{33} \end{bmatrix}$$

We use the diagonal BEKK (1,1) type model, which is more parsimonious and reduces the number of ARCH and GARCH parameters to [N(N+1)/2](1+p+q) = 18, where N is the number of

⁵BEKK model of Engle and Kroner (<u>1995</u>) is a special case of the VEC model of Bollerslev, Engle and Wooldridge (<u>1988</u>).

markets. The diagonal BEKK model trivially satisfies the equation $G_1=A_1D$, where D is a diagonal matrix.

We estimate the model using Full Information Maximum Likelihood (FIML) methods with student's t-distributed errors. The estimates of FIML are generated by maximizing the log-likelihood $\sum_{t=1}^{T} l_t$, where

$$l_{t} = \log \frac{\Gamma(\frac{\nu+r}{2})}{[\nu\pi]^{\frac{r}{2}}\Gamma(\frac{\nu}{2})\nu - 2^{\frac{r}{2}}} - \frac{1}{2}\log(|H_{t}|) - \left(\frac{r+\nu}{2}\right)\log\left[1 + \frac{\varepsilon_{t}'H_{t}^{-1}\varepsilon_{t}}{\nu-2}\right]$$
(4)

v is the degrees of freedom, $\Gamma(.)$ is the Gamma function and r the number of equations.

3. Data, Results and Economic Analysis of Dccs

This section is divided into three subsections. In sub-sect. 3.1., we present the data and descriptive statistics. In sub-sect. 3.2, we present the results from the AR(1)-diagonal BEKK(1,1) model and the diagnostic tests. In sub-sect. 3.3, we provide an economic analysis of dynamic conditional correlations (DCCs).

3.1. Data and Descriptive Statistics

Our sample construction begins with daily values for S&P500 (USA), BOVESPA (Brazil), S&PTSX (Canada), FTSEMIB (Italy), DAX30 (Germany), USD, CAD, BRL and EUR from 13th April 2010 until 18th April 2018. The data were sourced from Datastream® Database. Local currencies are denominated in USD, logarithmic whilst returns are generated by $r_t =$ $log(p_t) - log(p_{t-1})$ for $t = 1, 2, \dots, 2091$, where p_t is the price of the market at the end of the day t and p_{t-1} is the price of the market at the end of the day t - 1. While daily data can reveal disruptions lasting for only a day, the use of that data may entail noisy problems. Additionally, we set the beginning of our research one month before the creation of European Financial Stability Facility (EFSF) April 2010 due to the ongoing European Sovereign Debt Crisis (ESDC).

Table 1 provides the summary statistics for equity and FOREX markets returns. In general, we observe positive sample mean for all variables of interest. The Jarque-Bera (JB), kurtosis (>3) and skewness (negative) statistics imply that the returns are not distributed normally, indicating the appropriate use of student-t distribution for the empirical analysis (Massacci, 2014).



Surprisingly, FTSEMIB exhibits the highest standard deviation, the highest maximum and the lowest minimum return prices, suggesting that FTSEMIB experience larger fluctuations compared to the of the rest markets. Additionally, the findings of Augmented Dickey and Fuller (1979) and SCHMIDT-PHILLIPS with the Z(tau) and Z(rho) statistics tests suggest the rejection of unit root at 90%.

In Appendix A we present graphs of the actual series and their respective logarithmic returns for S&P500 (Graph A), S&PTSX (Graph B), DAX30 (Graph C), FTSEMIB (Graph D), BOVESPA (Graph E), BRL/USD (Graph F), CAD/USD (Graph G), EUR/USD (Graph H). We observe time varying levels of fluctuations. Specifically, results reveal time periods of relative calm, whilst there are time periods of positive and negative outliers. Based on the above graphs, clearly there are evidence of volatility clustering effect and heteroskedasticity⁶.

3.2. Estimates of Mean and Variance Equations and Diagnostic Tests

Tables 2 and 3 report the estimated coefficients of $C(c_{i,j}, \text{ with } i, j = 1, ..., N)$, $A_1(a_{i,j}, \text{ with } i = j = 1, ..., N)$ and $G_1(g_{i,j}, \text{ with } i = j = 1, ..., N)$ matrices, parameter H_t (Equation 3). We extract some important drawbacks. According to the estimates, we note some statistically insignificant coefficients for the constant C matrix. The matrices governing the own volatility and the intensity of spillovers $(A_1 \text{ and } G_1)$ exhibit statistically significant coefficients $(a_{i,i}, g_{i,i})$ for all triplets of markets. Interestingly, the diagonal elements of matrix A_1 of own volatility suggest that the S&P500 exhibits the strongest own spillover effects. This implies that the S&P500⁷ presents the strongest one way causal relationship between past volatility shocks and current volatility, showing that the effects of the shock take longer time to dissipate and indicating that the equity market of USA has not been affected extensively as a result of the recent Global Financial Crisis 2007.

⁷S&P500 is one of the most widely quoted USA index, representing the largest publicly traded corporations in the USA and leading the global equity market.



⁶A time series is defined as heteroscedastic if its variance changes over time, otherwise it is called homoscedastic.

Table 1	
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Vo		Summary S	tatistics of l	Market Retui	rns					
lume 2	Depart		EUR/USD	CAD/USD	BRL/USD	DAX30	FTSEMIB	BOVESPA	S&PTSX	S&P500
Issu	ment	Panel A: Bas	sic statistics							
e 1 , Febri	of Finan	Mean	5,1117e- 005	7,1609e- 005	0,00025579	0,00039038	1,9795e- 005	0,00010736	0,0001548	0,00045181
uary	Ce	Minimum	-0,029954	-0,021192	-0,059464	-0,070673	-0,13331	-0,09211	-0,041227	-0,068958
2020		Maximum	0,026528	0,025549	0,071608	0,052104	0,10684	0,063874	0,03941	0,046317
		Std. deviation	0,005865	0,0052088	0,0095988	0,012221	0,015983	0,014022	0,0077482	0,0090938
		Panel B: Not	rmality Test							
		Skewness	0,029443	0,14277**	0,22159***	-0,28160***	·-0,35104***	·-0,15874**	-0,35425***	-0,47591***
		t-Statistic	0,55005	2,6672	4,1397	5,2607	6,5579	2,9656	6,6179	8,8908
		p-Value	0,58229	0,0076475	3,4773e- 005	1,4348e- 007	5,4559e- 011	0,0030213	3,6431e- 011	6,0658e- 019
D YT/J	14 a.	Excess Kyrtosis	1,6097***	1,4379***	3,8934***	2,7823***	4,4818***	2,3173***	2,6357***	5,2019***
Ĩ	CEME	t-Statistic	15,043	13,437	36,384	26,002	41,884	21,656	24,632	48,613
- CONNOT	Old a	p-Value	3,8388e- 051	3,6652e- 041	0,00000	4,7432e- 149	0,00000	5,3552e- 104	5,8045e- 134	0,00000

-75

	EUR/USD	CAD/USD	BRL/USD	DAX30	FTSEMIB	BOVESPA	S&PTSX	S&P500
Jarque-Bera	226,05***	187,23***	1337,8***	702,11***	1793***	476,64***	649***	2436,5***
p-Value	8,1846e- 050	2,2062e- 041	3,1837e- 291	3,4565e- 153	0,00000	3,1553e- 104	1,1784e- 141	0,00000
Panel C: Un	it Root tests	5						
ADF	-27,5757	-26,4972	-27,8283	-26,7387	-27,4469	-26,8204	-27,4178	-28,031
Critical value: 1%	-2,56572	-2,56572	-2,56572	-2,56572	-2,56572	-2,56572	-2,56572	-2,56572
Critical value: 5%	-1,94093	-1,94093	-1,94093	-1,94093	-1,94093	-1,94093	-1,94093	-1,94093
Critical value: 10%	-1,61663	-1,61663	-1,61663	-1,61663	-1,61663	-1,61663	-1,61663	-1,61663
SCHMIDT- PHILLIPS Test Z(tau)	-44,807	-42,5879	-42,3001	-39,2284	-41,4633	-26,9359	-17,1964	-42,1005
Critical value: 1%	-3,56	-3,56	-3,56	-3,56	-3,56	-3,56	-3,56	-3,56
Critical value: 5%	-3,02	-3,02	-3,02	-3,02	-3,02	-3,02	-3,02	-3,02
Critical value: 10%	-2,75	-2,75	-2,75	-2,75	-2,75	-2,75	-2,75	-2,75

		EUR/USD	CAD/USD	BRL/USD	DAX30	FTSEMIB	BOVESPA	S&PTSX	S&P500
Denartment	SCHMIDT- PHILLIPS Test Z(rho)	-2086,87	-2001,12	-1975,2	-1786,73	-1924,41	-1056,99	-497,156	-1993,84
of Finan	Critical value: 1%	-25,2	-25,2	-25,2	-25,2	-25,2	-25,2	-25,2	-25,2
CP.	Critical value: 5%	-18,1	-18,1	-18,1	-18,1	-18,1	-18,1	-18,1	-18,1
	Critical value: 10%	-15	-15	-15	-15	-15	-15	-15	-15

Notes. We used intercept and a time trend to generate ADF statistic with 2 lags. Additionally, we calculated SCHMIDT-PHILLIPS Z(tau) and Z((rho) statistics with the bandwidth parameter equal to zero. ** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table 2

Estimates of µ and AR(1), degrees of freedom and log-likelihood, for S&P500-BOVESPA-BRL/USD and S&P500-FTSEMIB-EUR/USD

a suba		S&P500	BOVESPA	BRL/USD	S&P500	FTSEMIB	EUR/USD
a Entrange	Panel A: estimates	s of µ					
	S&P500	0,000754**	**		0,000825**	*	
	t-Statistic	6,052			7,113		

1

7							
8 		S&P500	BOVESPA	BRL/USD	S&P500	FTSEMIB	EUR/USD
	p-Value	0,0000			0,0000		
	BOVESPA		0,000481*			0,000562**	
	t-Statistic		1,963			2,364	
	p-Value		0,0498			0,0182	
	BRL/USD			-0,000013			0,0000359
	t-Statistic			-0,09497			0,3703
	p-Value			0,9243			0,7112
	Panel B: estimate	s of AR(1)					
	S&P500	-0,055905**	:		-0,099369***	<	
Jou	t-Statistic	-2,934			-5,261		
urnal	p-Value	0,0034			0,0000		
of I	BOVESPA		-0,037509**			-0,070821***	
Finai me 2	t-Statistic		-2,037			-3,746	
nce a	p-Value		0,0418			0,0002	
and . ue 1	BRL/USD			-0,089926***			-0,050431**
Acco	t-Statistic			-4,304			-2,452
ounti	p-Value			0,0000			0,0143
ng Re y 2020	Panel C: degrees	of freedom and	log-likelihood	Į.			
search	degrees of freedor (v)	ⁿ 6,801400***	*		6,292460***		

	S&P500	BOVESPA	BRL/USD	S&P500	FTSEMIB	EUR/USD
t-Statistic p-Value	11,06 0,0000			12,98 0,0000		
log-likelihood	(l_t) 20995,06	4		21702,008		
Notes. We used	l Full Informatic	n Maximum Lik	celihood methoc	ls to produce th	e maximum lik	elihood parameter.
*, ** and *** c	lenote statistical	significance at t	he 10%, 5% and	11% levels, res	pectively.	
Table 3						
Estimates of μ . S&PTSX-CAD,	and AR(1), degr /USD	ees of freedom ai	nd log-likelihoo	d, for S&P500-	DAX30-EUR/U	SD and S&P500-
	S&P500	DAX30	EUR/USD	S&P500	S&PTSX	CAD/USD
Panel A: estin	iates of μ					
S&P500	$0,000800^{***}$			0,000733***		
t-Statistic	7,290			5,826		
p-Value	0,0000			0,0000		
DAX30		0,000795***			0,000453***	
t-Statistic		4,471			3,647	
p-Value		0,0000			0,0003	
EUR/USD			0,0000749			-0,0000528
t-Statistic			0,7830			-0,6234
p-Value			0,4337			0,5331



	S&P500	DAX30	EUR/USD	S&P500	S&PTSX	CAD/USD
Panel B: estir	nates of AR(1)					
S&P500 t-Statistic p-Value DAX30 t-Statistic p-Value EUR/USD t-Statistic p-Value	-0,143867*** -7,634 0,0000	-0,035510* -0,1981 0,0477	-0,048676** -2,367 0,0180	-0,052292*** -3,165 0,0016	0,037753** 2,084 0,0373	-0,060243*** -3,167 0,0016
Panel C: deg	rees of freedom a	and log-likeliho	od			
degrees of freedom (v)	5,768043***			7,053835***		
t-Statistic -Value	13,66 0,0000			12,13 0,0000		
log- likelihood (<i>l</i> _t)	22424,786			24051,712		

Notes. We used Full Information Maximum Likelihood methods to produce the maximum likelihood parameter. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4

Estimated coefficients of conditional variance (H_t), for S&P500-BOVESPA-BRL/USD and for S&P500-FTSEMIB-EUR/USD

Market i	S&P500 (i=1)	BOVESPA (i=2)	BRL/USD (i=3)	S&P500 (i=1)	FTSEMIB (i=2)	EUR/USD (i=3)
Panel A: c	oefficients c _{i,j} of (C matrix				
$c_{i,1}$ t-Statistic p-Value $c_{i,2}$ t-Statistic p-Value $c_{i,3}$ t-Statistic p-Value	0,001228*** 5,463 0,0000 0,001062*** 5,654 0,0000 -0,0003589*** -3,593 0,0003	0,001764*** 7,422 0,0000 -0,000218** -2,112 0,0348	0,001015*** 5,149 0,0000	0,001292*** 6,574 0,0000 0,000922*** 4,843 0,0000 -0,0000434 -0,9869 0,3238	0,001570*** 6,113 0,0000 0,0000384 0,9098 0,3630	0,000383** 2,793 0,0053
Panel B: c	oefficients a _{i,j} of .	A ₁ matrix				
a _{i,1} t-Statistic p-Value	0,280096*** 10,35 0,0000			0,285548*** 10,51 0,0000		
$a_{i,2}$ t-Statistic		0,196338*** 12.18			0,221053*** 12.54	

BRL/USD (i=3)	S&P500 (i=1)	FTSEMIB (i=2)
0,246544*** 8,929 0,0000		0,0000
	0,944325*** 85,91 0,0000	0 968154***
		202,4 0.0000
0,962461*** 116,7 0,0000		-,

Notes. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

EUR/USD

0,179050***

0,982227***

263,8

0,0000

(i=3)

11,21

0,0000

Market

p-Value

p-Value

 $g_{i.1}$ t-Statistic

p-Value

p-Value

p-Value

 $g_{i,3}$ t-Statistic

 $g_{i,2}$ t-Statistic

 $a_{i,3}$ t-Statistic

1

S&P500

Panel C: coefficients $g_{i,i}$ of G_1 matrix 0,949038***

(i=1)

85,87

0,0000

BOVESPA

0,969544***

195,4

0,0000

(i=2)

0.0000

Table 5

Estimated coefficients of conditional variance (H_t), for S&P500-DAX30-EUR/USD and S&P500-S&PTSX-CAD/USD

Market	S&P500	DAX30	EUR/USD	S&P500	S&PTSX	CAD/USD
i	(i=1)	(i=2)	(i=3)	(i=1)	(i=2)	(i=3)
Panel A: co	efficients c _{i,j} of C	matrix				
<i>C</i> _{<i>i</i>,1}	0,001255***			0,001014***		
t-Statistic	6,126			3,663		
p-Value	0,0000			0,0003		
<i>C</i> _{<i>i</i>,2}	0,000780***	0,001016***		0,000478***	0,000615***	
t-Statistic	4,881	6,016		4,136	6,008	
p-Value	0,0000	0,0000		0,0000	0,0000	
<i>C</i> _{<i>i</i>,3}	-0,0000284	0,0000874	0,000385**	-0,0001717**	0,0000805	0,000390**
t-Statistic	-0,6671	1,867	2,418	-2,446	1,531	2,668
p-Value	0,5048	0,0157	0,0157	0,0145	0,1259	0,0077
Panel B: co	efficients a _{i,j} of A	1 ₁ matrix				
$a_{i,1}$	0,283861***			0,232658***		
t-Statistic	10,54			6,548		
p-Value	0,0000			0,0000		
a _{i.2}		0,221872***			0,224026***	
t-Statistic		13,37			13,78	

- 83

Market	S&P500	DAX30	EUR/USD	S&P500	S&PTSX	CAD/USD
i	(i=1)	(i=2)	(i=3)	(i=1)	(i=2)	(i=3)
p-Value	· · · ·	0,0000			0,0000	
$a_{i,3}$			0,176711***			0,198611***
t-Statistic			9,890			9,360
p-Value			0,0000			0,0000
$g_{i,1}$	0,946426***			0,963201***		
$g_{i,1}$ t Statistic	0,946426*** 87.60			0,963201*** 74 84		
<i>g</i> _{i,1} t-Statistic p-Value	0,946426*** 87,60 0.0000			0,963201*** 74,84 0,0000		
$g_{i,1}$ t-Statistic p-Value $g_{i,2}$	0,946426*** 87,60 0,0000	0.969181***		0,963201*** 74,84 0,0000	0 968704***	
$g_{i,1}$ t-Statistic p-Value $g_{i,2}$ t-Statistic	0,946426*** 87,60 0,0000	0,969181*** 218.1		0,963201*** 74,84 0,0000	0,968704*** 191.8	
$g_{i,1}$ t-Statistic p-Value $g_{i,2}$ t-Statistic p-Value	0,946426*** 87,60 0,0000	0,969181*** 218,1 0,0000		0,963201*** 74,84 0,0000	0,968704*** 191,8 0,0000	
$g_{i,1}$ t-Statistic p-Value $g_{i,2}$ t-Statistic p-Value $g_{i,3}$	0,946426*** 87,60 0,0000	0,969181*** 218,1 0,0000	0,982827***	0,963201*** 74,84 0,0000	0,968704*** 191,8 0,0000	0,977131***
$g_{i,1}$ t-Statistic p-Value $g_{i,2}$ t-Statistic p-Value $g_{i,3}$ t-Statistic	0,946426*** 87,60 0,0000	0,969181*** 218,1 0,0000	0,982827*** 233,3	0,963201*** 74,84 0,0000	0,968704*** 191,8 0,0000	0,977131*** 153,3

Notes.*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6

Diagnostic tests and information criteria of AR(1)-diagonal-BEKK(1,1) model for S&P500-BOVESPA-BRL/USD, S&P500-FTSEMIB-EUR/USD, S&P500-S&PTSX-CAD/USD and S&P500-DAX30-EUR/USD

	S&P500-	S&P500-	S&P500-	S&P500-
	BOVESPA-	FTSEMIB-	S&PTSX-	DAX30-
	BRL/USD	EUR/USD	CAD/USD	EUR/USD
Panel A: diagnostic tests				
$x^{2}(6)$	748,63**	451,06**	277,04**	360,65**
p-Value	0,0000	0,0000	0,0000	0,0000
Hosking (50)	470,965	490,887	210,130	554,021**
p-Value	0,2285799	0,0840035	0,0555485	0,0005093
Hosking ² (50)	464,454	459,849	329,114**	497,055
p-Value	0,2859338	0,3391994	0,0000000	0,0542896
Li-				
McLeod	470,540	491,150	210,161	553,972**
(50)				
p-Value	0,2327593	0,0827379	0,553808	0,0005119
Li-				
McLeod ²	465,080	460,731	328,994**	497,867
(50)				
p-Value	0,2790323	0,3286732	0,0000000	0,0515587
Panel B: Information Criteria				

Akaike -20,072788 -20,749290 -22,997811 -21,440944Schwarz -20,021471 -20,697973 -22,946493 -21,389626*Notes.* In Panel B we see the information criteria of AR(1)-diagonal-BEKK(1,1) model, using 1 lag. P-values have been corrected by 2 degrees of freedom for Hosking² (50) and Li-McLeod² (50) statistics and by 1 degree of freedom for Hosking (50) and Li-McLeod (50) statistical.

Tables 4 and 5 report the estimated values for mean equation (Equation 1). While the constant term in the mean equation (μ) is significant for equity markets, FOREX markets demonstrate an insignificant constant term (μ). The negative AR(1) term for



S&P500, DAX30, FTSEMIB, BOVESPA, BRL/USD, CAD/USD and EUR/USD imply evidence of positive feedback, while the positive AR(1) term for S&PTSX suggests partial adjustment and that relevant market information is rapidly reflected in S&PTSX values. Furthermore, we report the estimates of log-likelihood parameter (l_t) (Equation 4). Estimates of degrees of freedom (v) are all around 7, indicating fat tails and the student-t distribution (v > 4) as the most appropriate distribution for the empirical analysis.

Table 6 provides the estimated diagnostic tests and information criteria. Hosking (1980), McLeod and Li (1983) autocorrelation test results provide evidence of no autocorrelation and therefore no evidence of statistical misspecification. x^2 (6) statistic results suggest the rejection of the null hypothesis of no spillover effects at 1% significance level. In addition, we state the AIC and SIC information criteria for the selected model.

Figure 1 below plots the conditional variances. Results reveal a common pattern of movement for conditional variances for all markets triplets. Interestingly, we clearly recognize large ups and downs, revealing extreme volatility levels.



Figure 1. Conditional variances of the AR(1)-Diagonal-BEKK(1,1) model. Notes: Data from Datastream. The red lines represent the conditional variances of the trivariate conditional variance matrix (\mathbf{H}_t) for all markets.

Figure 2 below plots the conditional covariances. All the pair-wise conditional covariances are highly volatile with some jumps over time. This observation is in line with the stochastic properties of the multivariate AR-diagonal BEKK model reported in tables 1 to 6.

Interestingly, we notice that the pair-wise conditional covariances for the pairs of markets S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX have extreme volatility and positive values. The above observation means that investors should be cautious when it comes to investing into two or more of the above equity markets.



Figure 2. Conditional covariances of the AR(1)-Diagonal-BEKK(1,1) model.

Notes: Data from Datastream. The red lines represent the conditional covariances of the trivariate conditional variance matrix (H_t) for all the pairs of markets, generated by Equation 3.



Figure 3. Dynamic conditional correlations (DCCs) of the AR(1)-Diagonal-BEKK(1,1) model. Notes: Data from Datastream. The red lines illustrate the pairwise DCCs for all the triplets of markets, generated by the Oxmetrics.



3.3. Economic Analysis of Dynamic Conditional Correlations (DCCs)

Figure 3 above presents the evolution of dynamic conditional correlations (DCCs) for the triplets of markets: (a) S&P500, BOVESPA, BRL/USD, (b) S&P500, FTSEMIB, EUR/USD, (c) S&P500, DAX30, EUR/USD, and (d) S&P500, DAX30, EUR/USD. Estimates of DCCs indicate the contagion effects between the markets. Contagion means that the financial market participants transmit the risk of economic events to the other markets. The main findings for the pairwise DCCs for all the triplets of markets are as follows.

First, figure 3 provides the estimated DCCs for the pairs of markets S&P500-BOVESPA, S&P500-BRL/USD and BOVESPA-BRL/USD. The estimated DCC between S&P500 and BOVESPA has mostly positive values and is extremely volatile over time, indicating contagion effects and implying a less reliable stability of the correlation for any investor. Moreover, the estimated DCCs for the pairs of markets S&P500-BRL/USD and BOVESPA-BRL/USD have mostly negative values and are extremely volatile. This is not strong enough to support evidence of contagion. Interestingly, the estimated DCCs exhibit some common extreme jumps over time, some of which (27/10/2011, 28/06/2013 and 27/07/2017) are generated by the following economic facts: (a) the Eurozone debt crisis deal⁸ (27/10/2011), (b) Gold fell below \$1200 per ounce for the first time since 2010⁹ (28/06/2013), and (c) President-elect Jair Bolsonaro's announcement of moving Brazil's embassy from Tel Aviv to Jerusalem (27/07/2017).

Next, figure 3 illustrates the estimated DCCs for the pairs of markets S&P500-FTSEMIB, S&P500-EUR/USD and FTSEMIB-EUR/USD. The estimated DCC between S&P500 and FTSEMIB has positive values and is persistently volatile, suggesting contagion

⁸European Union leaders announced an agreement on debt crisis measures, including a hard-fought deal with private sector investors to take a 50% loss on Greek bonds.

⁹Gold fell below \$1,200 an ounce for the first time in almost two years Thursday as traders anticipated an eventual end to the Federal Reserve's economic stimulus program.

and implying that the correlation is risky from an investor's perspective. Additionally, the estimated DCCs for the pairs of S&P500-EUR/USD and FTSEMIB-EUR/USD markets are extremely volatile and have a trending behavior (upward) (from October 2012 until the end of the period) and mostly positive values, providing evidence of contagion effects and suggesting that correlations are risky from an investor's point of view. Furthermore, the estimated DCCs demonstrate two common extreme jumps (03/11/2015 and 12/09/2016) due to the following reasons: (a) the European migrant crisis and the announcement of Angela Merkel's plan¹⁰ to register and distribute the incoming refugees throughout the European Union (03/11/2015), and (b) Federal Reserve set the benchmark interest rate lower than expected (12/09/2016).

Figure 4 plots the estimated DCCs for the pairs of markets S&P500-DAX30, S&P500-EUR/USD and DAX30-EUR/USD. We observe that the estimated DCC between S&P500 and DAX30 is erratic and has positive values, indicating contagion and a risky correlation for any investor. Thus, the estimated DCC between S&P500 and EUR/USD presents high volatility levels, while it has a trending behavior (upward) (from January 2012 until the end of the period) and mostly negative values, providing evidence of contagion effects and indicating for an investor a less reliable stability of the correlation. Moreover, the estimated DCC between DAX30 and EUR/USD is highly volatile, while it has a trending behavior (upward) (from January 2012 until the end of the period) and mostly positive values, suggesting evidence of contagion effects and implying that investors should be cautious about the reliability of the correlation. Additionally, the estimated DCCs show two common extreme jumps (03/11/2015 and 12/09/2016) generated by the following reasons: (a) Angela Merkel announced a new European migrant crisis plan (03/11/2015), and (b) Federal Reserve set the benchmark interest rate lower against all expectations (12/09/2016).

Last, figure 3 graphs the estimated DCCs for the pairs of markets S&P500-S&PTSX, S&P500-CAD/USD and S&PTSX-CAD/USD.



¹⁰Refugees would be stopped at EU borders, have their application processed, and then, if accepted, sent to one of the Union's 28 member states.

The estimated DCC between S&P500 and S&PTSX show extreme volatility levels and has positive values, implying contagion and defining correlation risky for any investor. Moreover, the estimated DCC between S&P500 and CAD/USD has two different trending behaviors: (1) an upward trend from January 2012 until March 2014 and from September 2016 until the end of the period, and (2) a downward trend from March 2014 until September 2016. Additionally, it fluctuates violently and has mostly negative values. The above drawbacks are not robust enough to support evidence of contagion. Furthermore, the estimated DCC between S&PTSX and CAD/USD present two different trending behaviors as follows: (1) an upward trend from January 2012 until March 2014 and from September 2016 until the end of the period, and (2) a downward trend from March 2014 until September 2016. In addition, it demonstrates some extreme fluctuations, while it has mostly negative values, suggesting contagion effects and a risky correlation for investors. Additionally, estimated DCCs show two common extreme jumps (02/11/2015 and 12/09/2016) due to the following economic events: (a) Territorial disputes in the South China Sea between China and USA (02/11/2015), and (b) Federal Reserve set the benchmark interest rate lower than expected (12/09/2016).

4. Conclusions

In this paper, we study the spillover dynamics among returns of equity and FOREX markets for USA, Germany, Italy, Brazil and Canada between 2010 and 2018. We employ the Engle and Kroner (1995) AR(1)-diagonal BEKK(1,1) model. We utilize four trivariate models, each using S&P500, equity markets with the respective FOREX markets. We believe this work to be the first of its kind that empirically investigates interdependence between equity and FOREX markets, by using our trivariate models and by taking into consideration the conditional second moments of the distribution (volatility spillovers).

Our main findings can be summarized as follows: (a) Using the diagonal BEKK modeling structure, first we measure own volatility spillovers. The main empirical results show that S&P500 exhibits the highest own volatility spillover effects, indicating that the USA's equity market has been affected to a smaller extend from the GFC

of 2007. (b) Then, we take into consideration the DCCs. The analysis of DCCs confirms mounting evidence of the strongest contagion for the pairs of markets: S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX. (c) These results are of interest to institutions, to multinational corporations and to investors. Institutions can diversify their portfolios by taking into consideration the international equity market. Multinational corporations can manage their FOREX market exposures effectively. Investors can build a profitable portfolio through equity and FOREX market investments.

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APPENDIX: A

Actual series and logarithmic returns of the markets

Graph A. S&P500



Graph B. S&PTSX



Graph C. DAX30



94 — **J-** AR

Graph D. FTSEMIB



Graph E. BOVESPA



Graph F. BRL/USD



Graph G. CAD/USD



Graph H. EUR/USD



Notes. Data from Datastream. Logarithmic returns are generated by using the following equation: $r_t = log(p_t) - log(p_{t-1})$

