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“FINANCIAL CRISIS CONTAGION THROUGH ETFs”

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DECLARATION:

I, Alexia P. Thomaidou, certify that the submitted thesis is personal, except where otherwise indicated and acknowledged.

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ABSTRACT

This paper investigates the contagion effects of the Global Financial Crisis (August 2007-March 2009) and the European Sovereign Debt Crisis (November 2009- March 2016) by examining fifteen sectoral ETFs and 5 regional ETFs. A Dynamic Conditional Correlation (DCC) model is used to test the time-varying conditional correlation among a pair of ETFs each time. Evidence show that there is contagion effect for the regional and sectoral ETFs, except the USA regional ETF, during both crisis periods. Moreover, we examine the impact of several control variables, which represent various risks, to the correlation of each pair of ETFs and the results show the influence of the interest rate risk and interbank liquidity risk during the Global Financial Crisis and the European Sovereign Debt Crisis.

KEYWORDS: ETF; contagion; GFC; ESDC, DCC-GARC

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1.INTRODUCTION

The recent financial crisis, both the Global Financial Crisis (GFC) and the European Sovereign Debt Crisis (ESDC) stimulate the appetite of the academic society to study the subject from all angles. One of them is how crisis was transmitted not only among a particular market sector, but also among countries. In the literature, this phenomenon is called "contagion" and there is not a unique and universally accepted definition.

A general definition, which is mostly accepted by economist is set as follows: "*Contagion is the propagation of shocks among markets in excess of the transmission explained by fundamentals*" (Forbes & Rigobon, 2002). According to Forbes & Rigobon (2002), this general definition of contagion raises questions about the meaning of the words "fundamentals" and "in excess", which give the space of the generation of many definitions in the particular phenomenon.

In this paper, we will accept the complexity of the notion and we will adopt the theory by Rigobon, who separates the notion into two categories: pure contagion and shift contagion. The pure contagion is defined as the contagion of shocks which are not transmitted through financial, economic and market fundamentals. The shift contagion is defined as the change in the strength of the propagation of shocks between a crisis period and a normal period (Forbes & Rigobon, 2002; Flavin & Panopoulou, 2010; Pericoli & Sbracia, 2003).

Defining contagion as the excess correlation of economic and financial assets (Bekaert et. al., 2003), contagion is the outcome of optimal portfolio diversification as investors tend to choose assets without being optimal informed about them (Calvo & Mendoza, 2000). Crisis contagion effects might be strength by financial globalization. Baur (2011) found that crisis contagion is a global issue and there is no immunity to shocks even between financial sectors stocks and real economy stocks.

The issue of contagion comes up in the recent literature as a result of the GFC and the ESDC. Many studies examine the contagion effects among different types of assets like; stocks, bonds, commodities, sector stock indices, hedge funds, foreign exchange markets, futures, etc. (Bouaziz et al., 2012; Chiang et al., 2007; Cho & Parhizgari, 2008; Khan & Park, 2009; Dungey et al., 2004; Horen et al., 2006; Tai, 2007; Dungey et al., 2006; Ismailescu & Kazemi, 2008; Tai, 2003; Coudert & Gex, 2008; Jorion & Zhang, 2007; Aloui et. al., 2010, Philippas & Siriopoulos, 2013; Brière et. al., 2012; Ye et. Al., 2012). As far as we know, the only studies which examine the crisis contagion through Exchange Traded Funds (ETFs, hereafter) during the GFC and the ESDC are Itzhan et. al. (2012) who show that actions of arbitrage within ETFs and their underlying asset can stimulate contagion. Broman (2012) shows that one mean of contagion might be the commonality in mispricing due to the systematic risk exposure within the ETF and the underlying asset.

Following several studies (Baur, 2011; Kenourgios & Dimitriou, 2014; Bekaert et al., 2005; Hortal et al., 2010; Phylaktis & Xia, 2009), which separate their data collection and analysis into two ways, aggregate stock indices and sector stock indices, we will adopt the same method as we want to investigate the transmission channels of contagion. Phylaktis & Xia (2009) find that there are sectors which are channels of contagion and others which are not and the last ones can be a useful tool of portfolio diversification during harsh times. Baur (2011) shows even if no country and sector was unspoiled to harsh times and the effectiveness of portfolio diversification was limited, there are some sectors, such as healthcare, telecommunications and technology which were less touched by the shock.

Using daily data on various ETFs from July 31th, 2007 to December 29th, 2017, we estimate a Dynamic Conditional Correlation (DCC) GARCH model introduced by Engle (2002). The particular model is used, as it allows to show the time-varying conditional correlations among ETF's returns during both crisis and after those. Naoui et al. (2010), Hwang et al. (2010) and Bouaziz et al. (2012) examine and appraise the potential existence of contagion between ETFs during GFC, triggered by the U.S. subprime crisis, for a group of developed and emerging countries and deduce the existence of contagion effect among developed and emerging countries, but also across different markets.

This paper aims to investigate the pattern of interdependencies between twenty ETFs and a particular ETF, applying a DCC model to estimate time-varying conditional correlations. Then, using OLS estimation with Newey-West estimated variance-covariance metrics (Newey & West, 1987), we examine if there is contagion effect between the estimated correlations with six control variables across GFC and ESDC.

The purpose of this paper is to shed light of contagion effect through ETFs, investigating how a Global Financial ETF can transmit shocks to sectoral and regional ETFs during the previous crisis and may contribute to the portfolio management and investments in ETFs. Section 2 presents the methodology, section 3 refers the data sample, while section 4 displays the empirical findings.

2.METHODOLOGY

2.1 Benchmark model

A robust empirical analysis of financial contagion requires overcoming a heteroskedasticity problem when measuring correlations and the lack of a dynamic increment in the regressions (Forbes and Rigobon,2002; Pesaran and Pick, 2007). Otherwise, a continued market correlation at high levels is considered to be «no contagion, only interdependence» (Forbes and Rigobon, 2002). To avoid the above restrictions, we utilize the DCC (Engle 2002) derived from the multivariate GARCH model to test for increased co-movement among a portfolio of ETFs in crisis period compared to tranquil period.

The dynamic conditional correlation DCC-GARCH model developed by Engle (2002) investigates the second order moments dynamics of financial time-series and overcomes the heteroskedasticity problem raised by Forbes and Rigobon (2002). The estimation of DCC-GARCH model is composed of two steps: the first step is about the estimation of a univariate GARCH model and the second step estimates the conditional correlations which vary through time.

The DCC-GARCH model is defined as follows;

$$\mathrm{X_t = \mu_t + h_t^{1/2} * \varepsilon_t} \ (1)$$

$$\mathrm{H_t = H_t * R_t * D_t} \ (2)$$

$$\mathrm{R_t = (diag(Q_t))^{-1/2} * Q_t * (diag(Q_t))^{-1/2}} \ (3)$$

$$\mathrm{H_t = diag(\sqrt{h_{ii,t}}} \ (4)$$

where, X_t= (X_1, X_2, ..., X_N) is the vector of the past observations,

H_t are the multivariate conditional variances,

μ_t= (μ_1, $\mu_{2,...,}$ μ_N) is the vector of conditional returns,

ε_t= (ε_1, $\varepsilon_{2,...,}$ ε_N)is the vector of the standardized residuals,

R_t is a N×N symmetric dynamic correlations matrix

D_t is a diagonal matrix of conditional standard deviations for return series, obtained from estimating a univariate GARCH model with $\sqrt{h_{ii,t}}$ on the i^{th} diagonal, i=1, 2,...,N.

The DCC specification is defined as follows;

$$Q_t = (1 - \psi - \zeta) * \bar{Q} + \zeta * Q_{t-1} + c * \delta_{i,t-1} * \delta_{j,t-1} \text{ (5)}$$

$$H_t = H_t^{*-1} * Q_t * H_t^{*-1} \text{ (6)}$$

where,

(Q_t)=$\lfloor q_{ij,t} \rfloor$ is (N×N) time varying covariance matrix of standardized residuals ($\delta_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{i.t}}}$),

$\bar{Q}$ is the unconditional correlations of $\delta_{i,t}$, $\delta_{j,t}$ and ψ and ζ are nonnegative scalar parameters that satisfies $\psi + \zeta‹1. Q_t^* = [q_{ii,t}^*] = \sqrt{q_{ii.t}}$ is a diagonal matrix with the square root of the i^{th} diagonal element of Q_t on its i^{th} diagonal position.

2.2 Dynamic conditional correlations across the phases of the crises

In this part of the analysis, we create dummy variables which are equal to one for each phase of the three periods and zero otherwise. This procedure would allow testing whether the magnitude of the contagion coefficients changes across the phases of each crises and whether it differs across regions and sectors with different classification. The latter would indicate the existence of capitalization-specific contagion on the regional level and the sectoral level, on a crisis level. Further, we took into our analysis six control variables, by which we will examine if each of them influences the estimated time-varying conditional correlation. To avoid endogeneity problems, we use lags to the control variables. In this set up, we investigate the dynamic patterns of correlation changes across the different phases of the two crises by estimating regressions for ETFs of the form:

$$\hat{\rho}_t = \sum_{d=1}^{3} \beta_{0,d} * D_{t,d} + \sum_{j=1}^{6} \sum_{d=1}^{3} \beta_{j,d} * D_{t,d} * X_{t,d}(-1) \text{ (7)}$$

where,

d counts the three different periods; j counts the six control variables; t counts the dates of our sample

$\beta_{0,d}$ refers to the change in the degree of correlation in the different crisis periods defined by the dummy $D_{t,d}$, which is equal to one if *t* is referring in a crisis period or zero otherwise.

D_1 refers to the GFC (1st August 2007- 31th March 2009), D_2 refers to the ESDC (5th November 2009-31th March 2016), D_3 refers to the stable period (1st April 2016- 29th December 2017),

$\beta_{j,d}$ refers to the change in the degree of correlation in the different crisis periods defined by the dummy $D_{t,d}$, which is equal to one if t is referring in a crisis period or zero otherwise and the $X_{t,d}$ refers to the control variables, which are VIX, DJIA, EU interest rate term spread, US interest rate term spread, the change in the TED spread and the change in the European counterpart of the TED spread.

2.3 Testing hypothesis

Estimating the DCC-GARCH model and the conditional variance equation (7), we will test if there is contagion between the two pairs of ETFs[1] and the six different control variables. To conclude if such an event occurs, we will apply several different tests, regarding the three dummies and the control variables.

In general, under the null hypothesis, the coefficients level of the variables of equation 7 is zero or/and negative across turmoil and stable periods, indicating the absence of contagion effects. Alternatively, a statistical significant coefficients level bigger than zero across the three periods implies the spread of the crisis from a global financial ETF to the examined ETF. Specifically, the null hypothesis (H_0) is tested against the one-sided alternative (H_1) that the turmoil conditional correlations are greater at the 10%, 5% and 1% significance levels.

The **first test** refers to the examination of the existence of contagion effect during the three periods. $H_0: \beta_{0,d} \leq 0$ (no contagion) $H_1: \beta_{0,d} > 0$ (contagion)

The **second test** refers to the examination of the potential influence of the control variables to the estimated time-varying conditional correlations.

$H_0: \beta_{j,d} = 0$ (no influenced) $H_1: \beta_{j,d} \neq 0$ (influenced)

[1] Each pair of ETF's is consisted by the Global Financial ETF which is the same for all of our analysis and the other one is different every time.

3.DATA

3.1 Data set

The data comprises daily closing prices of fifteen sectoral ETFs, which are from global and US regions, five regional ETFs[2] and a global financial ETF, which is considered as source of contagion taking into account that the crises started from the financial sector. The sectors are the following: Basic Materials, Financial, Real Estate, Mortgages, US Banks, Financial Services, Broker Deals & Services Exchange, Consumer Cyclical, Industrials, Utilities, Private Equity, Energy, Technology and Gold Miners. The asset class[3] is equity ETFs and they are following a benchmark index which is different in each case. The control variables are the following; VIX, DJIA, EU interest rate term spread, US interest rate term spread, the change in the TED spread and the change in the European counterpart of the TED spread. The data collected from Bloomberg and Yahoo. Finance covering the period of 08/01/2007 until 12/29/2017, leading to a sample size of 2624 observation. For each ETF and control variable, the return is estimated as $r_{t=\frac{(p_t - p_{t-1})}{p_{t-1}}}$, where p_t is the price on day t. Table 1 shows the ticker name of each ETF and the name we give for the purpose of our empirical analysis [r_i with i = (1,2,…,20)].

As regards, the control variable, first differences of the returns are taken. To investigate if there are other variables, which influence the correlation of the pair of ETFs, we take into account four risks; volatility risk (VIX), interest rate risk (USIR, EUIR), interbank liquidity risk (TED, EUTED) and market risk (DJIA). The interest rate term spread, otherwise known as the change in the yield slope, is used as a prognosticator of real economic activity. It is computed as the difference between 10-year government bond yield and 3-month bond yield of the respective government bond. The change in the TED spread counts the funding liquidity (Brunnermeir, 2009; Pelizzon et. al., 2016). It is computed as the difference between the three-month EURIBOR (Euro Interbank Offered Rate),[4] (in the case of the European counterpart of TED spread) or the LIBOR (London Interbank Offered Rate) expressed in US dollars and the 3-month respective government bond rate[5]. VIX is a volatility index created by the Chicago Board options Exchange (CBOE), which represents the expected level of fear by investors. VIX collects all of the closet at-the-money call and put S&P500 index option premium prices to obtain the weighted average of the implied volatility series (Chang et.

[2] Europe (Total Market), USA (Total Market), Latin America (Large Cap), Asia-Pacific (Large Cap), Global (Large Cap)
[3] There are six different asset classifications: Alternatives, Asset Allocation, Commodities, Currencies, Equity, Fixed-Income, according to ETF.com
[4] EURIBOR is transformed to US dollars
[5] In our analysis, the government bond, which we use are the German Government Bund (expressed to US dollars) and the Treasury Bill.

a., 2017). DJIA (Dow Jones Industrial Average) is an indices, giving a price-weighted average of 30 significant stocks traded on the New York Stock Exchange (NYSE) and the NASDAQ.

Descriptive statistics for each ETF and the six control variables are presenting in the tables 2,3,4. Table 2 refers to sectoral ETFs and shows high value of kurtosis and in some cases negative and positive skewness. Standard Deviation implies the risk an investor has. In our set of date, we observe that approximately the standard deviation is the same, indicating the same risk. Table 3 presents the descriptive statistics for the regional ETFs across the period of our analysis and Table 4 presents the descriptive statistics of the first differences of the six control variables. Among the six control variables, VIX has the highest standard deviation, which is logical as VIX measures the volatility in the market. Variables expressed in € are denominated in USD.

3.2 Identification of the periods

The identification of the turmoil period and the stable period is determined by three different approaches according to the existing contagion literature. The first approach is introduced by Forbes and Rigobon (2002) and bases on major economic and financial events, the second is a statistical approach of endogenously identification of turmoil periods (Boyer et. al., 2006; Rodriquez, 2007) and the third approach is about a combination of the first two approaches (Baur, 2012; Dimitriou et. Al., 2013).

For the purpose of this study, we will use the first method, introduced by Forbes and Rigobon (2002). Regarding the GFC, the Bank of International Settlements (BIS,2009) and the FED (Federal Reserve Board of St. Louis) (2009) provides a timeline, separating the GFC into four phases[6]. So, the GFC starts 1st August 2007 and overs the 31st March 2009. Based on the provided timeline by the European Commission[7], the ESDC started on the 5th November 2009 and stopped with the exit of Cyprus from the economic adjustment program on the 31th March 2016. After those periods, we assume that there is stabilization.

[6] The methodology of the identification has been followed by Kenourgios (2014)
[7] http://europa.eu/rapid/press-release_IP-17-2401_en.htm

MXI	iShares Global Materials ETF
RXI	iShares Global Consumer Discretionary ETF
EXI	iShares Global Industrials ETF
JXI	iShares Global Utilities ETF
IXC	iShares Global Energy ETF
IXN	iShares Global Tech ETF
GDX	VanEck Vectors Gold Miners ETF
PSP	PowerShares Global Listed Private Equity Portfolio ETF
IAI	iShares U.S. Broker-Dealers & Securities Exchanges ETF
IYG	iShares US Financial Services ETF
IYF	iShares U.S. Financials ETF
IYR	iShares U.S. Real Estate ETF
REM	iShares Mortgage Real Estate Capped ETF
KBE	SPDR S&P Bank ETF
VAW	Vanguard Materials ETF
EZU	iShares MSCI Eurozone ETF
ADRA	BLDRS Asia 50 ADR ETF
ITOT	iShares Core S&P Total U.S. Stock Market ETF
ILF	iShares Latin America 40 ETF
IOO	iShares Global 100 ETF
IXG	iShares Global Financials ETF

Table 1: ETF's name and its ticker

	EUROPE	ASIA-PASIFIC	USA	LATIN AMERICA	GLOBAL
	EZU	ADRA	ITOT	ILF	IOO
MEAN	0.000186	0.000236	4.25E-05	0.000259	0.000267
MEDIAN	0.000737	0	0.000731	0.000817	0.000626
MAX.	0.146064	0.179105	0.107828	0.262458	0.120479
MIN.	-0.11512	-0.115929	-1,000,000	-0.194667	-0.103536
Std. Dev.	0.018126	0.016421	0.023287	0.022314	0.01335
Skewness	0.049098	0.301179	-3,020,854	0.339878	-0.014503
Kurtosis	10.815400	13.640570	1,298.179000	17.391300	13.714470
J-B test	6679.179	12418.570	1.84E+08	22694.51	12551.54
Prob.	0.000000	0.000000	0.000000	0.000000	0.000000
Obs.	2624	2624	2624	2624	2624

Table 2: Descriptive statistics for the regional ETFs from 8/1/2007 until 12/29/2017

	GLOBAL								USA						
	MXI	RXI	EXI	JXI	IXC	IXN	GDX	PSP	IAI	IYG	IYF	IYR	REM	KBE	VAW
MEAN	0.00024	0.000392	0.000318	0.000159	0.000192	0.000471	0.000214	0.000199	0.000351	0.000344	0.000316	0.000444	0.001334	0.000346	0.000416
MEDIAN	0.000487	0.000786	0.000824	0.000664	0.000648	0.000924	-0.000277	0.000949	0.000823	0.000246	0.000498	0.000793	0.0008	0.000381	0.000906
MAX.	0.163693	0.112909	0.107132	0.157058	0.154173	0.112311	0.265384	0.18383	0.151288	0.171007	0.156634	0.163253	3,028,763	0.202143	0.108868
MIN.	-0.130898	-0.108517	-0.091795	-0.090061	-0.131509	-0.08445	-0.155322	-0.131973	-0.155959	-0.172414	-0.156959	-0.206112	-0.16103	-0.196304	-0.123041
Std. Dev.	0.018332	0.013668	0.014365	0.012646	0.017582	0.013412	0.02808	0.019595	0.020598	0.022425	0.019923	0.021178	0.061534	0.02456	0.016512
Skewness	-0.0729	-0.31885	-0.223286	0.314117	-0.017914	-0.146267	0.367974	-0.033895	0.159003	0.413123	0.256296	0.052565	4,540,249	0.466197	-0.427161
Kurtosis	11.842710	10.769690	9.814838	21.495150	12.782410	9.275454	8.645362	14.811500	12.296820	14.938550	14.802670	17.136140	2,234.662000	15.510420	9.548755
J-B test	8,551.477	6,644.707	5,099.465	37,442.880	10,462.850	4,315.048	3,543.683	15,253.760	9,460.835	15,657.800	15,259.190	21,849.340	5.45E+08	17206.880	4768.689
Prob.	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Obs.	2624	2624	2624	2624	2624	2624	2624	2624	2624	2624	2624	2624	2624	2624	2624

Table 3: Descriptive statistics for the sectoral ETFs from 8/1/2007 until 12/29/2017

	D(VIX)	D(DJIA)	D(EUIR)	D(EUTED)	D(TED)	D(USIR)
MEAN	2.98E-05	-5.68E-06	0.000413	0.000416	-3.05E-05	0.000387
MEDIAN	0.004184	-0.000292	-0.001918	0.001	0	-0.0009
MAX.	0.678501	0.127585	0.638967	0.7989	0.99	0.628
MIN.	-0.769583	-0.115294	-0.602155	-0.6726	-0.8	-0.5461
Std. Dev.	0.112221	0.017826	0.085312	0.054437	0.060349	0.073679
Skewness	-0.353901	0.417223	0.16621	-1.05142	0.773742	0.243309
Kurtosis	7.311616	11.5187	12.01181	65.18757	72.64302	13.04916
J-B test	2086.489	8007.203	8887.954	423146.3	530342.7	11062.76
Prob.	0	0	0	0	0	0
Obs.	2624	2624	2624	2624	2624	2624

Table 4: Descriptive statistics for the control variables from 8/1/2007 until 12/29/2017

4. EMPIRICAL ANALYSIS

Using the framework described in the previous section, we will present the results as clearly as possible can be. It is proper to see again the parameters, we use; first, we separate the period from 08/01/2007 to 29/12/2017 into three parts: the GFC from 08/01/2007 until 03/31/2009, the ESDC from 11/05/2009 until 03/31/2016 and a stable period from 04/01/2017 until 12/29/2017. Second, we estimate the DCC-GARCH model to derive the time-varying conditional correlations among a particular ETF (IXG) and each ETF, respectively. Extracting the results, as a third stage we estimate an OLS regression using the three different periods, six control variables and the results from the DCC-GARCH model.

The diagrammatical depiction of the DCC results are shown in the Figure 4. We can observe from the graphs that as regard the sectoral ETFs that there is a potential contagion effect across the three periods as the correlation is up to zero. The regional ETFs graphs depict that all of them, except the US region ETF (ITOT), are influenced by the Global Financial ETF, which is a sign of contagion.

Table 5: Estimation results about the first test across the GFC, ESDC and stable periods

Sectoral ETFs

Global Region

	Basic Materials		Consumer Cyclicals		Industrials		Utilities		Energy		Technology		Gold Miners		Private Equity	
GFC	0.684	C***	0.775	C***	0.843	C***	0.701	C***	0.608	C***	0.809	C***	0.192	C***	0.847	C***
ESDC	0.832	C***	0.865	C***	0.894	C***	0.756	C***	0.791	C***	0.814	C***	0.252	C***	0.876	C***
STABLE	0.701	↓***	0.749	↓***	0.803	↓***	0.265	↓***	0.555	↓***	0.676	↓***	-0.034	-	0.754	↓***

U.S. Region

	Broker Deals & Services Exchanges		Financial Services		Financials		Real Estate		Mortgages		U.S. Banks		Basic Materials	
GFC	0.882	C***	0.903	C***	0.917	C***	0.785	C***	0.655	C***	0.852	C***	0.750	C***
ESDC	0.838	C***	0.894	C***	0.914	C***	0.658	C***	0.328	C***	0.814	C***	0.814	C***
STABLE	0.835	↓***	0.896	↓***	0.906	↓***	0.306	↓***	0.237	↓***	0.828	↓***	0.724	↓***

Regional ETFs

	Europe		Asia-Pacific		USA		Latin America		Global	
GFC	0.854	C***	0.813	C***	-0.018***	-	0.729	C***	0.907	C***
ESDC	0.891	C***	0.690	C***	-0.018***	-	0.741	C***	0.934	C***
STABLE	0.75	↓***	0.507	↓***	-0.018***	-	0.547	↓***	0.821	↓***

Notes: This table presents the results from the eq.7 during the GFC (August 2007–March 2009), the ESDC (November 2009-March 2016) and stable (April 2016–December 2017) periods. The rejection of the null hypothesis against the one-sided alternative that the correlation is greater than zero, at the 10%, 5%, and 1% significance levels, is denoted by *, **, and ***, respectively. A positive and statistical significant coefficient during the crisis period provides evidence on contagion (C). In the stable period, we use the symbol (↓), as we want to depict a positive and statistical significant coefficient and the symbol (-) if there is rejection of the alternative hypothesis or no statistical significant results.

The Table 5 shows the extracted results from the first part of equation 7, indicating the correlation among the Global Financial ETF and each ETF across the three periods. The results show that the financial sector can influence every sector and region in stable and turmoil periods. As regard the sectoral ETFs, only the Gold Miners ETF is not influenced during the stable period and under the first test, and regarding the regional ETFs, there is no evidence of contagion between the Global Financial ETF and the American ETF during both crisis.

The results extracted by the table 5 also show similarities between ETFs and the Global Financial ETF. There is a significant decrease of the coefficients level between the GFC and the stable period and between the ESDC with the stable period. About the global sectoral ETFs, a positive and significant coefficient implies contagion for each of the two crisis periods. The results show that all the global sectoral ETFs are affected during the GFC and the ESDC. From the eight global ETFs, the seven are affected during the crisis periods, indicating contagion effect as the coefficient level is decreased in the stable period. The gold miners' ETF is not affected during the stable period and also the correlation with the global financial ETF is weak during the crisis periods, indicating independency from the financial sector.

The USA sectoral ETFs are affected all the seven of them across all the crisis periods. The results show a significant decrease of the coefficients from the GFC period to the stable period and from the ESDC to the stable period. The most affected during the GFC is the Financial Services ETF, Financials ETF, U.S Banks ETF and Broker Deals & Services Exchanges ETF with coefficient approximately equals to 0.89. During the ESDC, the most affected ETFs are Financials ETF and Financial Services ETF. The stable period, the ETFs which the coefficient of them are significant reduced are the Real Estate ETF and the Mortgages ETF.

Regarding the regional ETFs, the results show that a positive and significant correlation suggesting a contagion effect. Among the five regional ETFs, only the USA ETF is not affected by the Global Financial ETF showing no contagion, as the null hypothesis from the test 1 is not rejected. During GFC, the coefficient of the global region ETF is the largest among the other three and the least affected is the Latin America ETF. During the ESDC, the most affected is the Global ETF and the least affected is the Asia- Pacific with coefficient equals to 0.0690. Regarding the stable period, the results show a decrease in the coefficient level from the crisis period, with the most affective- even declined- to be the Global ETF.

Moving forward, there are evidence indicating that all sectors and regions have been influenced differently during the two crisis periods by the different control variables. Table 6 and 7 displays the estimation results from the second part of the equation 7 testing the potential influence of the control variables to the estimated time-varying conditional correlation (test 2). The linkages between the estimated correlations and the control variables are different in each case, indicating that if an investor wants to include an ETF in her portfolio, she has to take into account different factors to achieve a diversified portfolio, such as the region, sector, the exposure of the ETF in interest rate risk, the volatility and the composition of the ETF.

Table 6 shows that during the GFC, the control variable VIX affects only the Mortgages ETF's correlation with the Global Financial ETF and no other ETF is affected by the volatility risk. TED affects the correlation with the Global Financial ETF with the following

ETFs each time: Technology ETF, Financial Services ETF, Financials ETF and U.S. Banks ETF. EUTED affects the correlation with the Global Financial ETF with the following ETFs each time: Utilities ETF, Broker Deals & Services Exchanges ETF and Mortgages ETF. USIR affects only the Broker Deals & Services Exchanges ETF. The EUIR affects the correlation with the Global Financial ETF with the following ETFs each time: Private Equity ETF, Financial Services ETF, Financials ETF, Mortgages ETF and U.S. Banks ETF. The linkages between the control variables and the correlation between the Global Financial ETF and each ETF in every case does not exist for the 40% of the sectoral ETFs during the GFC period.

During the ESDC, the only control variable which is positive and statistical significant is the EUTED. The least affects the Industrials ETF's correlation with the Global Financial ETF and the Basic Materials ETF's correlation with the Global Financial ETF. Regarding the stable period, the results show that only USIR control variable positively affects the correlation of the Global Financial ETF with the Mortgages ETF., meaning the connection of the composition of the particular ETF with the US interest rates. Across all the periods, the control variable DJIA do not affect any correlation of the Global Financial ETF with each ETF every time.

Table 7 presents the estimations results for regional ETF, extracted from the second part of equation 7 and tests if the control variables affect the estimated correlation from the DCC model. The control variables VIX and DJIA do not affect any pair of ETF's correlation, indicating the volatility risk and the market risk do not influence the particular ETF's correlation and so there is no evidence of dependency. During the GFC, the correlation of Global ETF with the Global Financial ETF is affected by the TED and the EUIR and during ESDC Latin America ETF is affected by the EUTED. It is notable that even if the USA ETF has no sign of contagion, the control variable EUIR affects it during both crisis periods. We cannot say the reason for this event, as the composition of an ETF is a very complex and other variables has to be taken under consideration to answer such questions.

The overall pattern of contagion based on the tables 6 and 7 depicts that the most affected sectors from the control variables are: Broker Deals & Services Exchanges, Financial Services, Financials, Mortgages and U.S. Banks. The least affected are Industrials, Utilities, Technology, Private Equity and Basic Materials. Across every period, the only unaffected sectors are Basic Materials, Consumer Cyclicals, Energy, Gold Miners and Real Estate.

Table 6: Estimation results based on conditional correlations across the GFC, ESDC and stable periods

Sectoral ETFs

GLOBAL REGION

	VIX			TED			DJIA			EUTED			USIR			EUIR		
	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE
Basic Materials														↓**				
Consumer Cyclicals										↓**			↓**					
Industrials											↑*							
Utilities										↑**	↓*							
Energy																		
Technology				↑**										↓**				
Gold Miners					↓***													
Private Equity										↓*			↓*			↑***		

U.S. Region

	VIX GFC	VIX ESDC	VIX STABLE	TED GFC	TED ESDC	TED STABLE	DJIA GFC	DJIA ESDC	DJIA STABLE	EUTED GFC	EUTED ESDC	EUTED STABLE	USIR GFC	USIR ESDC	USIR STABLE	EUIR GFC	EUIR ESDC	EUIR STABLE
Broker Deals & Services Exchanges										↑**			↑***					
Financial Services				↑**										↓**		↑**		
Financials				↑**										↓**		↑**		
Real Estate												↓**						
Mortgages	↑*									↑***				↓*	↑**	↑***		
U.S. Banks				↑**										↓*		↑**		
Basic Materials											↑***							

Notes: This table presents the results from the second part of eq.7 during the GFC (August 2007–March 2009), the ESDC (November 2009-March 2016) and stable (April 2016–December 2017) periods. For the test 2, the rejection of the null hypothesis against the two-sided alternative that the coefficient is different than zero, at the 10%, 5%, and 1% significance levels, is denoted by *, **, and ***, respectively. A positive and statistical significant coefficient shows positive influence (↑). A negative and statistical significant coefficient shows negative influence (↓). The (-) symbol presents the no rejection of the null hypothesis of test 2 or no statistical significant results. Volatility risk (VIX), interest rate risk (USIR, EUIR), interbank liquidity risk (TED, EUTED) and market risk (DJIA)

Table 7: Estimation results based on conditional correlations across the GFC, ESDC and stable periods

Regional ETFs																		
	VIX			TED			DJIA			EUTED			USIR			EUIR		
	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE	GFC	ESDC	STABLE
Europe														↓**				
Asia-Pacific																		
USA																↓*	↑**	
Latin America											↑**							
Global				↑**												↑**		

Notes: This table presents the results from the second part of eq.7 during the GFC (August 2007–March 2009), the ESDC (November 2009-March 2016) and stable (April 2016–December 2017) periods. For the test 2, the rejection of the null hypothesis against the two-sided alternative that the coefficient is different than zero, at the 10%, 5%, and 1% significance levels, is denoted by *, **, and ***, respectively. A positive and statistical significant coefficient shows positive influence (↑). A negative and statistical significant coefficient shows negative influence (↓). The (-) symbol presents the no rejection of the null hypothesis of test 2 or no statistical significant results. Volatility risk (VIX), interest rate risk (USIR, EUIR), interbank liquidity risk (TED, EUTED) and market risk (DJIA)

5. CONCLUSIONS

This paper investigates the financial crisis contagion across a sample of ETFs and a set of control variables, which indicate each of them a specific risk, on regional and sectoral level, using daily returns from August 2007 to December 2017. The dynamic conditional correlation (DCC) analysis across GDC, ESDC and a stable period indicates that the Global Financial ETF (which is considered as source of contagion taking into account that the crises started from the financial sector) affects all the sectoral and regional ETFs, only the regional USA ETF is unaffected during all periods but is vulnerable to the European interest rate risk during ESDC period.

The examination of the existence of contagion effect during the three periods is presented in the Table 5. The results show that all sectors are affected during the GFC and ESDC but during the stable period the Gold Miners ETF does not affected by the Global Financial ETF. Gold Miners ETF is the only sector which has the lowest correlation with the Global Financial ETF, indicating the independency from the Financial Sector during all periods. It is noticeable that the correlation between the Global Financial ETF with any ETF is declined from the GFC period to the stable period and the same is occurring between the ESDC period and the stable period, as well. This implies that the previous crises do not affect any more the sectoral ETFs and indeed there was contagion in the ETF market. About the regional ETFs, only the US region ETF is not affected by the Global Financial ETF and the least affected is during the GFC is the Latin America ETF, while during the ESDC the least affected is the Asia-Pacific ETF. As ETF is a very complex product with the composition of them to be very multidimensionally, we can not identify the reasons for these occasions. This can be happened in a further research.

Regressing the estimated correlations with the 3 dummies and the control variables, to examine potential influence of the control variables to the estimated time-varying conditional correlation, we conclude that the volatility risk (expressed by VIX) and the market risk (expressed by DJIA) do not affect any of the regional and sectoral ETFs, except Mortgages ETF which is influenced by the volatility in the market. This implies that the volatility and the tense in the market do not enhance the contagion effect among ETFs. The interest rate risk and the interbank liquidity risk do affect every sectoral ETF, showing the existence of a shift contagion, during the GFC and ESDC. There is no evidence of influence in the sectoral ETFs during the stable period, except from U.S. Energy ETF, which is affected by the European interest rate risk, indicating the dependence of this particular ETF with the European interest rates.

Regarding the regional ETFs, the correlation of Europe ETF and Asia-Pacific ETF with the Global Financial ETF is not affected by any control variable, depicting the immunity in any risk. The significant result is that, even if there is no contagion effect from the Global Financial ETF to the USA ETF, there is effectiveness of the European interest rate risk and implying the potential channel of creating shocks to the particular ETF in period which has similarities with those happened during the ESDC. Concluding, it is highly important for an investor, who wants to include ETFs to her portfolio, to take into account all the risks, classify them of what kind of risks wants to exposure and search the composition of the ETF, the benchmark index and the invested sectors.

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APPENDIX

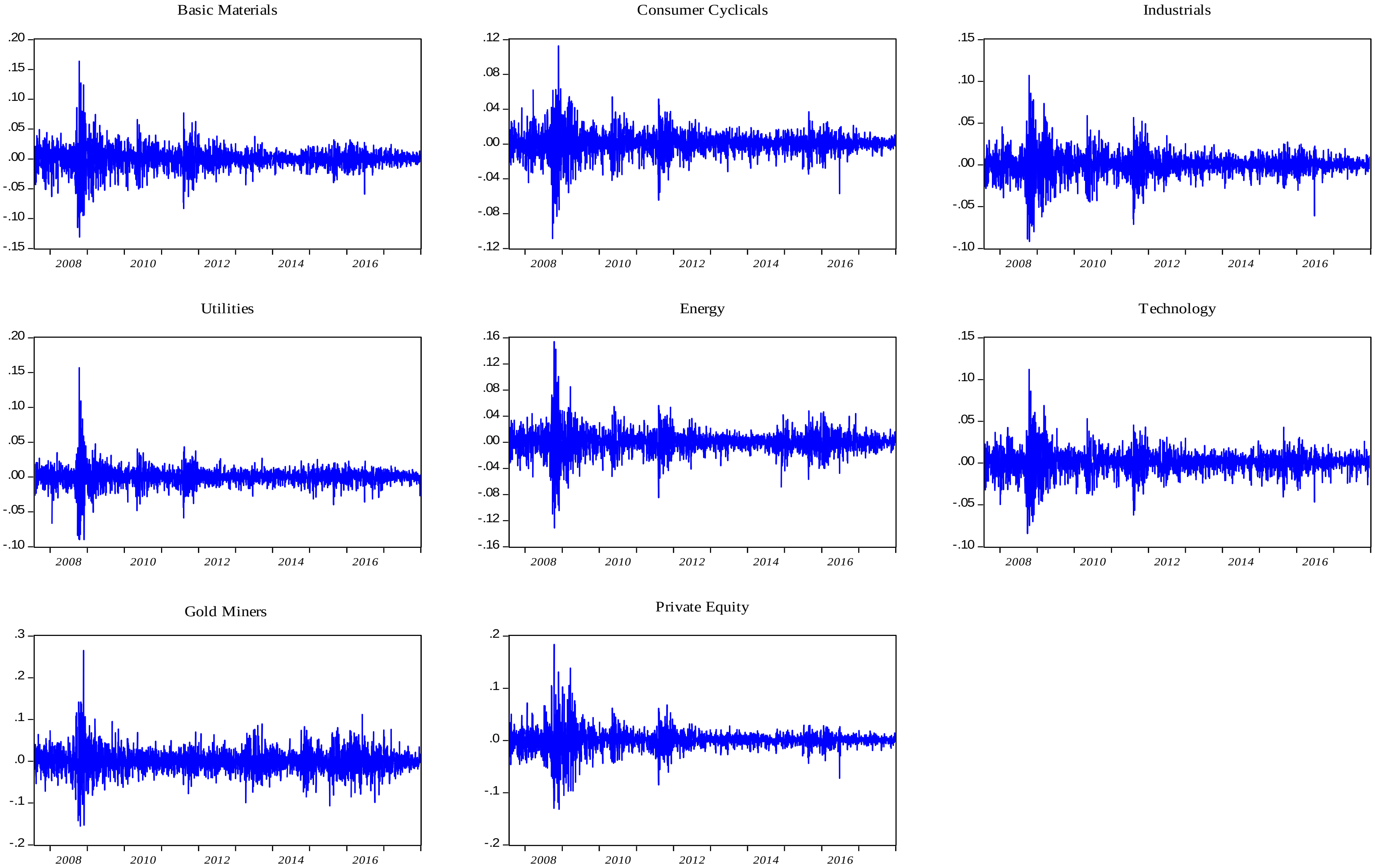

Figure 1: Global Sectoral ETFs. Notes: The Fig. 1 shows the evolution of the global sectoral ETFs returns during the August 2007- December 2017

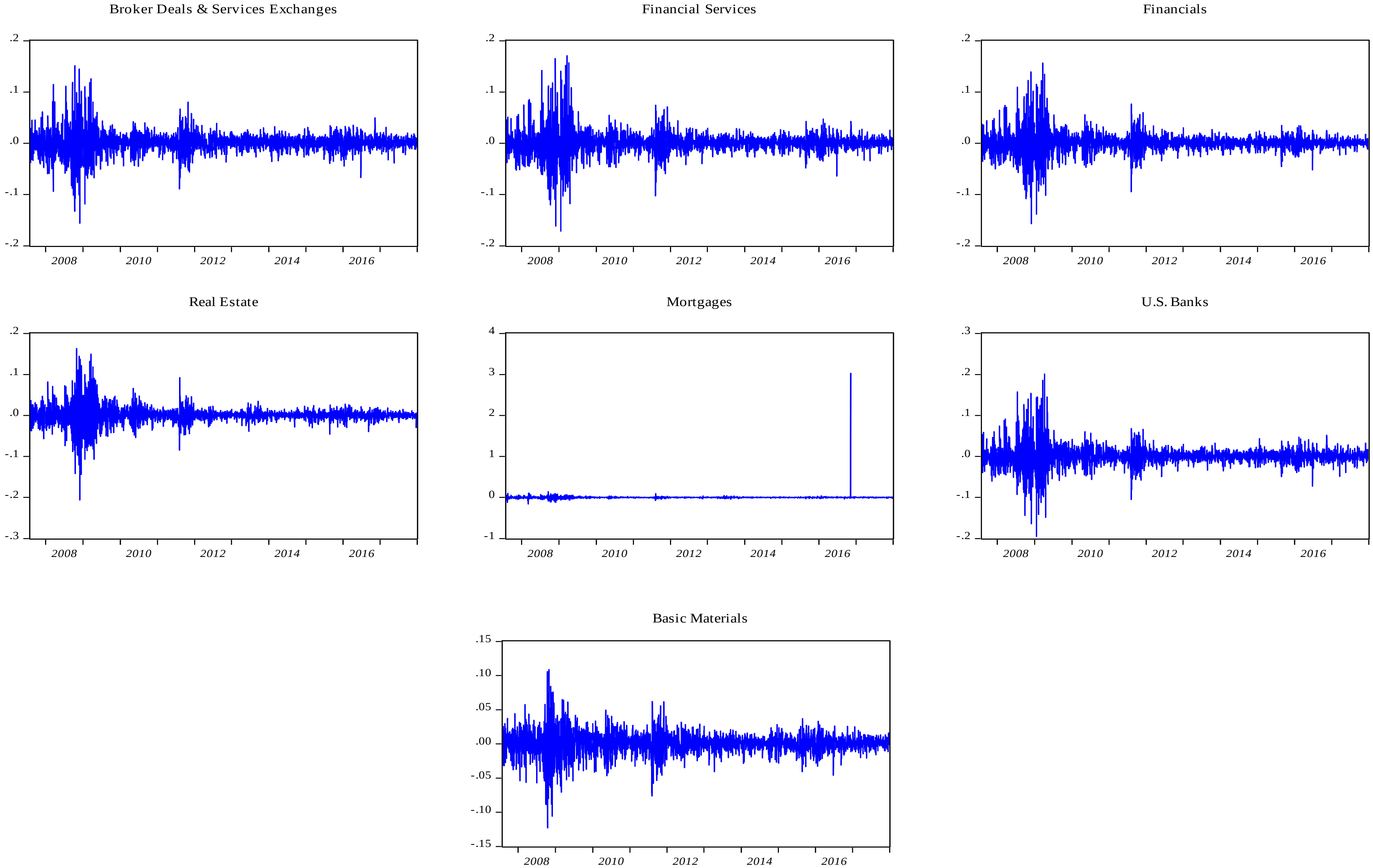

Figure 2: U.S. Sectoral ETFs. Notes: The Fig. 2 shows the evolution of the U.S. sectoral ETFs returns during the August 2007- December 2017

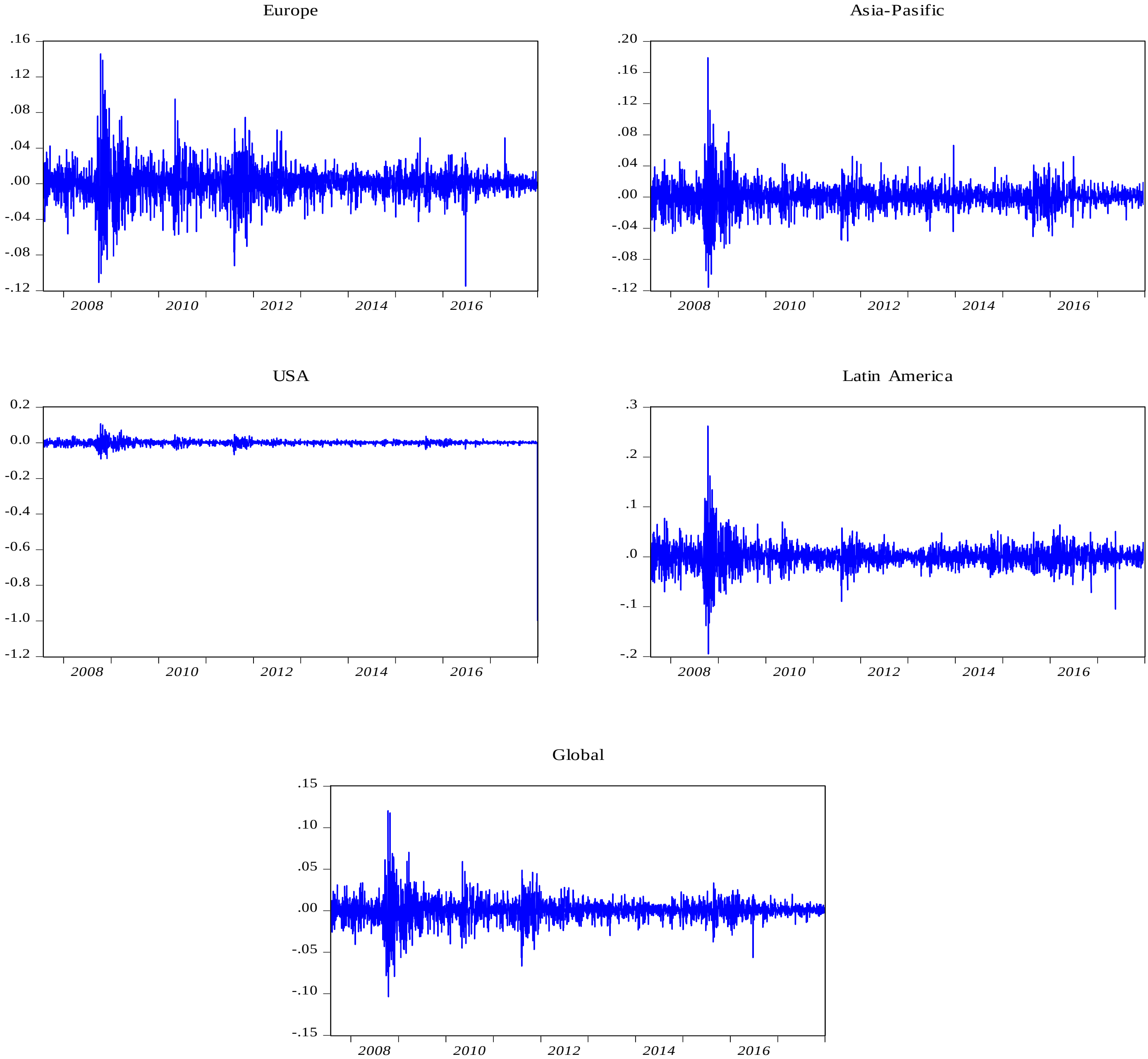

Figure 3: Regional ETFs. Notes: The Fig. 3 shows the evolution of the regional ETFs returns during the August 2007-December 2017

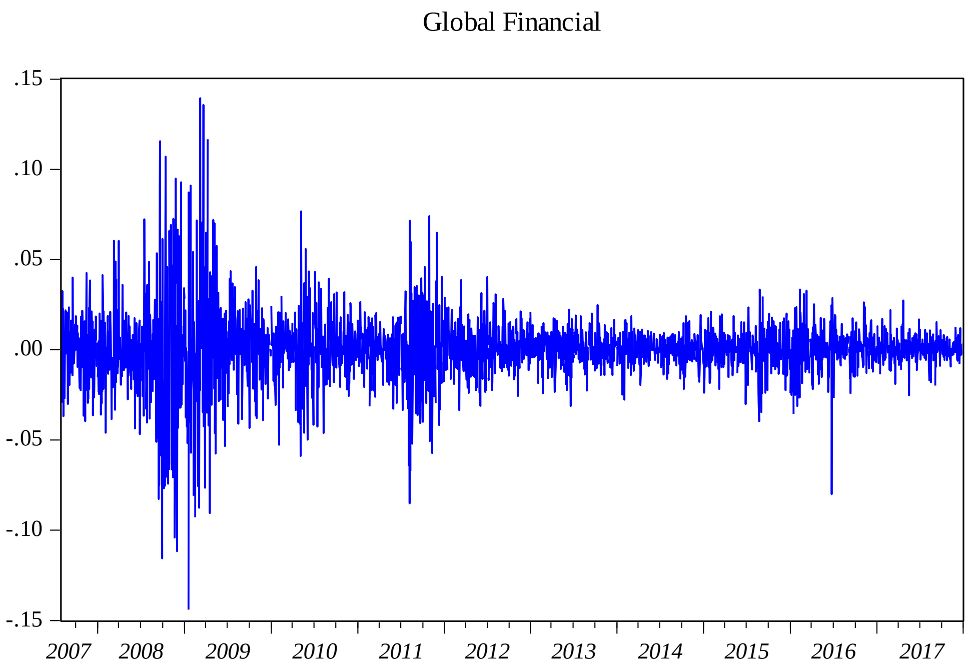

Figure 4: Global Financial ETF. Notes: The Fig.4 shows the evolution of the Global Financial ETF during the August 2007- December 2017

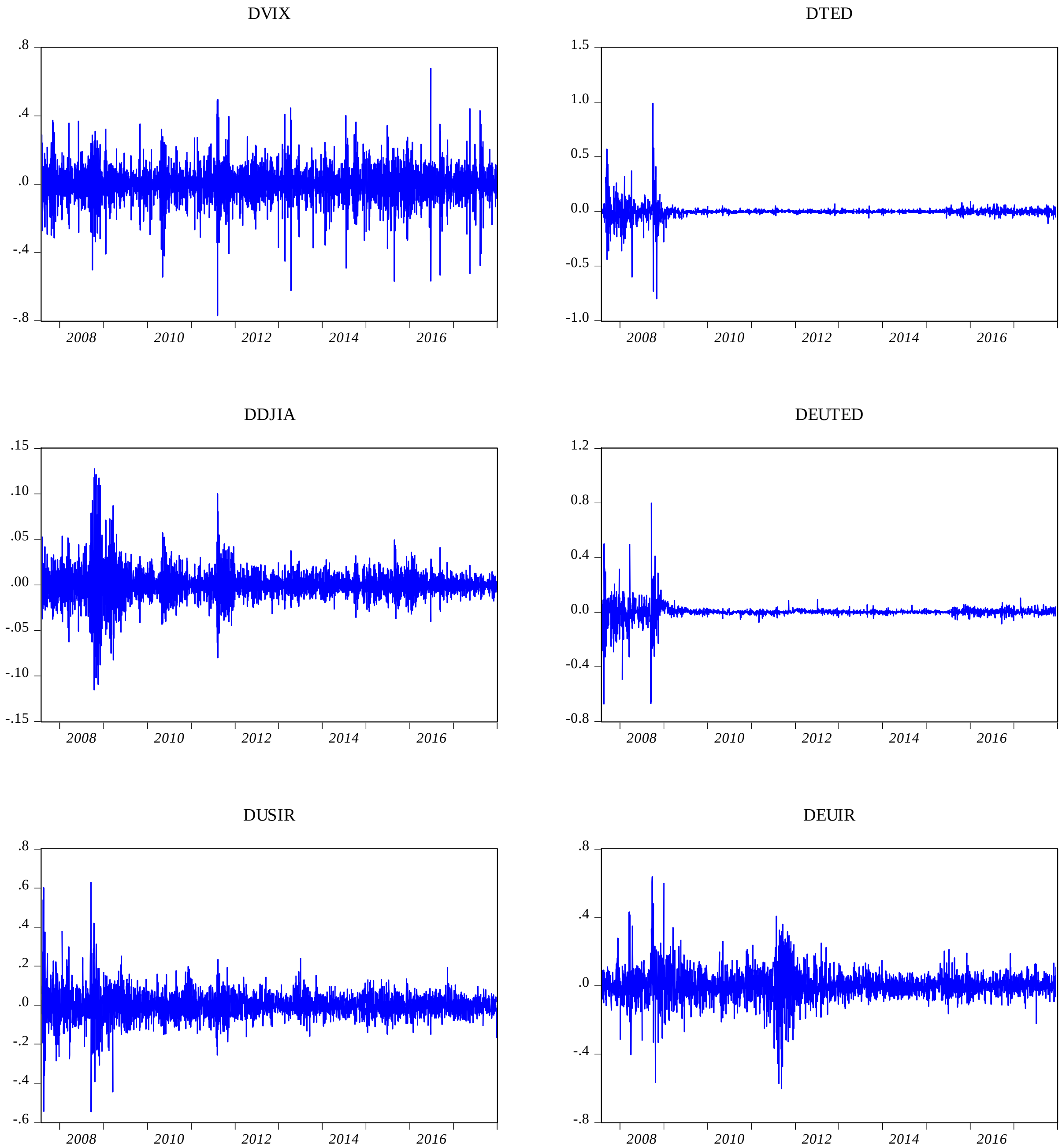

Figure 5: Selected control variables on closing level and first order level differences. Notes: Volatility risk (VIX), interest rate risk (USIR, EUIR), interbank liquidity risk (TED, EUTED) and market risk (DJIA)

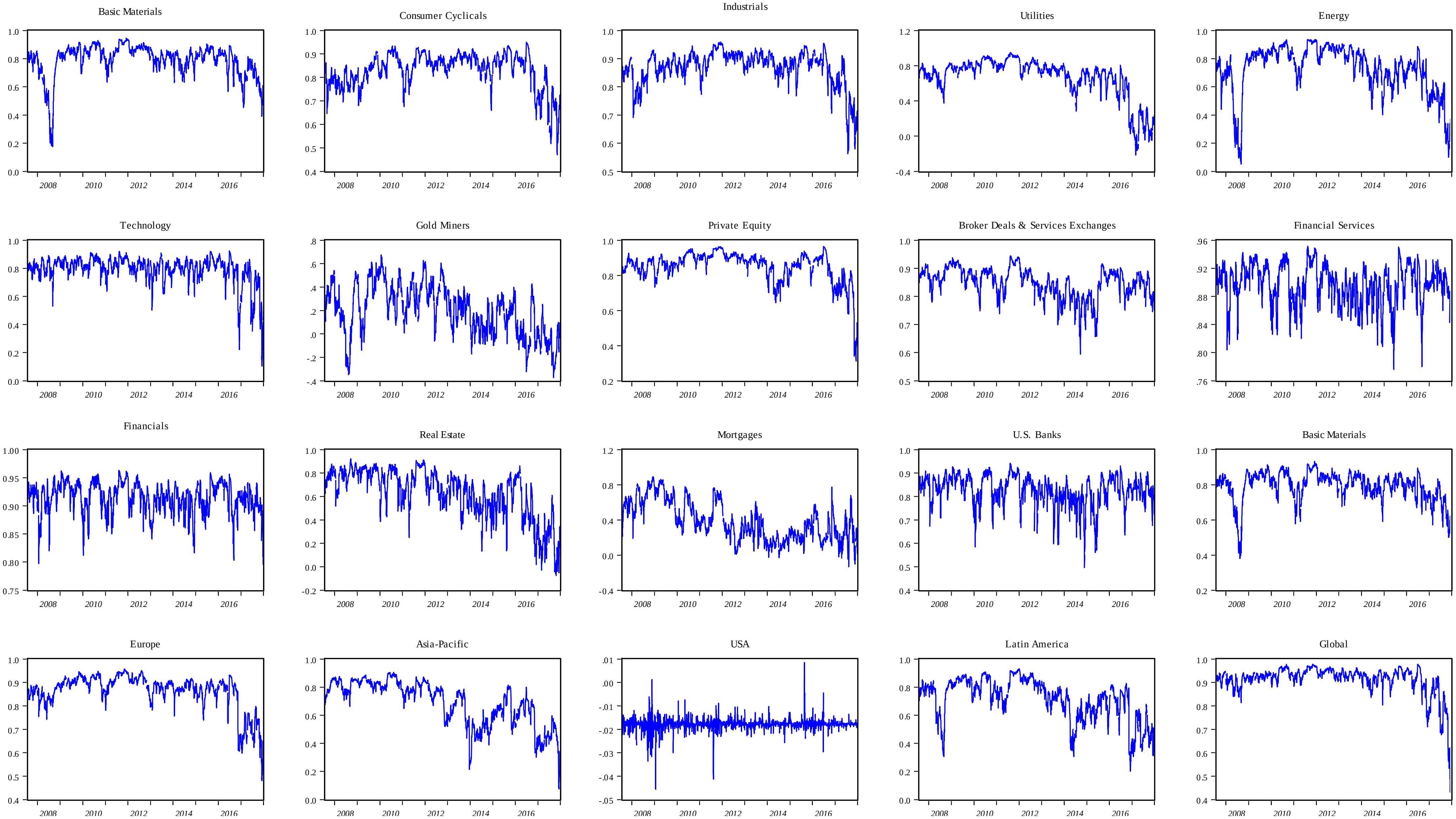

Figure 6: Dynamic conditional correlation. Notes: Fig. 6 shows the DCC for each ETF pair during August 2007- December 2017

DCC-GARCH MODEL

```
'change path to program path
%path=@runpath
cd %path

'set sample range
sample s1 2/08/2007 29/12/2017 'drop the first observation in this sample s1

'set number of etf and number of dummies
!netf=20
!nd=3
!nx=6

'for storing results
matrix(2*!netf,2) results_thetas12
group results_rho

'loop over etf
for !j=1 to !netf

'defining the return series in terms of y1 and y2
series y1=r{!j}
series y2=rg
''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''

'fitting univariate GARCH(1,1) models to each of the two returns series
equation eq_y1.arch(1,1,m=1000,h) y1 c
equation eq_y2.arch(1,1,m=1000,h) y2 c

'extract the standardized residual series from the GARCH fit
eq_y1.makeresids(s) z1
eq_y2.makeresids(s) z2

'extract garch series from univariate fit
eq_y1.makegarch() garch1
eq_y2.makegarch() garch2

'Caculate sample variance of series z1, z2 and covariance of z1and z2 and correlation between z1 and z2
scalar var_z1=@var(z1)
scalar var_z2=@var(z2)
scalar cov_z1z2=@cov(z1,z2)
scalar corr12=@cor(z1,z2)

'defining the starting values for the var(z1) var(z2) and covariance (z1,z2)
series var_z1t=var_z1
series var_z2t=var_z2
series cov_z1tz2t=cov_z1z2

'declare the coefficient starting values
coef(2) T
T(1)=0.2
T(2)=0.7

' .............................................................
' LOG LIKELIHOOD for correlation part
' set up the likelihood
' 1) open a new blank likelihood object and name it 'dcc'
' 2) specify the log likelihood model by append
' .............................................................

logl dcc
dcc.append @logl logl

'specify var_z1t, var_z2t, cov_z1tz2t
dcc.append var_z1t=@nan(1-T(1)-T(2)+T(1)*(z1(-1)^2)+T(2)*var_z1t(-1),1)
dcc.append var_z2t=@nan(1-T(1)-T(2)+T(1)*(z2(-1)^2)+T(2)*var_z2t(-1),1)
dcc.append cov_z1tz2t=@nan((1-T(1)-T(2))*corr12+T(1)*z1(-1)*z2(-1)+T(2)*cov_z1tz2t(-1),1)

dcc.append pen=(var_z1t<0)+(var_z2t<0)
```

```
'specify rho12
dcc.append rho12=cov_z1tz2t/@sqrt(@abs(var_z1t*var_z2t))

'defining the determinant of correlation matrix and determinant of Dt
dcc.append detrRt=(1-(rho12^2))
dcc.append detrDt=@sqrt(garch1*garch2)
dcc.append pen=pen+(detrRt<0)
dcc.append detrRt=@abs(detrRt)

'define the log likelihood function
scalar pi=3.14159
dcc.append logl=(-1/2)*(2*log(2*pi)+log(detrRt)+(z1^2+z2^2-2*rho12*z1*z2)/detrRt)-10*pen

'estimate the model
smpl s1
dcc.ml(showopts, m=500, c=1e-5)

''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
'store results

vector thetas12=dcc.@coefs
vector stat_thetas12=dcc.@tstats

results_thetas12(2*!j-1,1)=thetas12(1)
results_thetas12(2*!j-1,2)=thetas12(2)

results_thetas12(2*!j,1)=stat_thetas12(1)
results_thetas12(2*!j,2)=stat_thetas12(2)

rename rho12 rho_{!j}

smpl @all

delete corr12 cov_z1tz2t cov_z1z2 dcc detrdt detrrt eq_y1 eq_y2 garch1 garch2 logl pen t var_z1 var_z1t var_z2 var_z2t y1 y2 z1 z2 thetas12
stat_thetas12

next

'loop over etf
for !j=1 to !netf

series x1=dvix(-1)
series x2=dted(-1)
series x3=ddjia(-1)
series x4=deuted(-1)
series x5=dusir(-1)
series x6=deuir(-1)

'run regression with dummies
equation eq_corr
eq_corr.ls(n) rho_{!j} d1 d2 d3 x1*d1 x1*d2 x1*d3 x2*d1 x2*d2 x2*d3 x3*d1 x3*d2 x3*d3  x4*d1 x4*d2 x4*d3 x5*d1 x5*d2 x5*d3 x6*d1 x6*d2
x6*d3

'store results
vector b=eq_corr.@coefs
vector tstat_b=eq_corr.@tstats
vector pv_tstat_b=eq_corr.@pvals

for !k=0 to !nx

!k1=!k*!nd+1
!k2=!k*!nd+2
!k3=!k*!nd+3

freeze(tab) eq_corr.wald c(!k1)=c(!k2)=c(!k3)
!fstat_b123_{!k}=@val(tab(6,2))
!pv_fstat_b123_{!k}=@val(tab(6,4))
delete tab

freeze(tab) eq_corr.wald c(!k1)=c(!k2)
!tstat_b12_{!k}=@val(tab(6,2))
!pv_tstat_b12_{!k}=@val(tab(6,4))
delete tab

freeze(tab) eq_corr.wald c(!k1)=c(!k3)
```

```
!tstat_b13_{!k}=@val(tab(6,2))
!pv_tstat_b13_{!k}=@val(tab(6,4))
delete tab

freeze(tab) eq_corr.wald c(!k2)=c(!k3)
!tstat_b23_{!k}=@val(tab(6,2))
!pv_tstat_b23_{!k}=@val(tab(6,4))
delete tab

next

delete x1 x2 x3 x4 x5 x6

'store results
matrix(7,!nd*(!nx+1)) results_dum_{!j}=na

for !k=0 to !nx
for !d=1 to !nd

results_dum_{!j}(1,!d+!k*!nd)=b(!d+!k*!nd)

results_dum_{!j}(2,!d+!k*!nd)=tstat_b(!d+!k*!nd)
results_dum_{!j}(3,!d+!k*!nd)=pv_tstat_b(!d+!k*!nd)

results_dum_{!j}(4,2+!k*!nd)=!fstat_b123_{!k}
results_dum_{!j}(5,2+!k*!nd)=!pv_fstat_b123_{!k}

results_dum_{!j}(6,1+!k*!nd)=!tstat_b12_{!k}
results_dum_{!j}(7,1+!k*!nd)=!pv_tstat_b12_{!k}

results_dum_{!j}(6,2+!k*!nd)=!tstat_b13_{!k}
results_dum_{!j}(7,2+!k*!nd)=!pv_tstat_b13_{!k}

results_dum_{!j}(6,3+!k*!nd)=!tstat_b23_{!k}
results_dum_{!j}(7,3+!k*!nd)=!pv_tstat_b23_{!k}

next
next

next

'loop over etf
for !j=1 to !netf

results_rho.add rho_{!j}

next

matrix results_dum=results_dum_1
matrix results_dum_sum=results_dum_1

for !j=2 to !netf

results_dum=@vcat(results_dum, results_dum_{!j})

matrix results_dum_sum=results_dum_sum+ results_dum_{!j}

next

matrix results_dum_aver=results_dum_sum/!netf

for !j=1 to !netf

delete results_dum_{!j}

next

delete pi s1

delete eq_corr b tstat_b pv_tstat_b results_dum_sum
```

Note: The DCC-GARCH program was used as an add-in program founded by the e-views services.