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The Interaction between Oil Price and Financial Stress: Evidence from the U.S. Data[1]

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ABSTRACT

This study examines linkages between daily oil price dynamics and financial stress. We analyze the dynamic interaction mechanism between daily WTI crude oil prices and financial stress index of the United States developed by Polat (2017) with Structural VAR model in 01/10/1993-11/18/2016 period. The empirical results of the study suggest that there exist a significant relationship between oil price dynamics and financial stress and the relationship is dominated by the short-run.

[1] This study has been produced from Ph. D. Dissertation of Onur POLAT titled "The Impacts of Oil Price Shocks on Financial Stability" published in Hacettepe University Institute of Social Sciences Department of Economics.

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1. Introduction

Energy price shocks can have detrimental effects into economies by different transmission channels due to energy dependency of emerging/developed countries. Along with that; since oil consumption constitutes the largest amount in total energy consumption[3], catastrophic effects oil price shocks may quickly disperse into macro economy or financial system of the countries. 1973 and 1979 oil price shocks set example of these since both emerging and developed countries' economies were adversely affected. For example; 1973 oil price shocks triggered 1973-1975 US stagflation together with the collapse of the Bretton Woods system.

As a consequence, the impacts of oil price shocks on financial or macroeconomic indicators have been investigated by a vast number of studies. Some of them focus on the impacts of oil price shocks on economic activity. For instance; early studies dated to 1970's find evidence of negative impacts of oil on macroeconomy of the United States (Pierce and Enzler, 1974; Rasche and Tatom, 1977). Even though some studies can't determine a significant relationship between oil price shocks and macroeconomic indicators (Hamilton, 1983; Loungani, 1986), another strand of studies find evidences of the effects of oil price shocks on the economy. Among them, i) asymmetric linkages between oil price shocks and macroeconomic indicators (Mork, 1989 ; Mork et al., 1994, Lee et al., 1995), ii) negative effects of oil price shocks on the U.S. macroeconomy (Hamilton, 1986; Ferderer, 1997, Brown and Yucel, 1999), and specifically during recession (Hooker, 1996; Raymond and Rich, 1997) can be mentioned.

Adverse and significant impacts of oil price shocks on economic activity were found in several studies (Lee et al., 2001 (for the U.S.); Papapetrou, 2001 (for Greece); Cuñado and Gracia, 2003 (for 15 European countries); Barsky and Kilian, 2004 (for the U.S.); Guo and Kliesen, 2005 (for the U.S.); Tang et al., 2010 (for China)).

[3] See https://www.bp.com/content/dam/bp/pdf/energy-economics/energy-outlook-2016/bp-energy-outlook-2016.pdf for details.

On the other hand, the relationship between oil price shocks on financial indicators have been examined by the literature. Some quantitative studies analyze the impacts of oil price shocks on stock price returns with application of different econometric methods (GARCH, Granger Causality, Haar A Trous Wavelet, SVAR, VAR) (Jones and Kaul, 1996; Huang et al., 1996, Faff and Brailsford, 1999; Sadorsky, 1999; Ciner, 2001; Hammoudeh and Aleisa, 2005; Park and Ratti, 2008; Apergis and Miller, 2009; Cong et al., 2009; Miller and Ratti, 2009; Arouri and Nguyen, 2010; Filis et al., 2011; Jammazi, 2012; Aloui et al., 2012; Wang et al., 2013; Cuñado and Gracia, 2014; Kang et al., 2015).

In this study, we investigate the impacts of oil price and volatility shocks on high frequency (daily) financial stress index (FSI) of the United States[4] using Structural Vector Autoregressive (SVAR) model[5] in 01/10/1993-11/18/2016 period. We also employ Toda-Yamamoto (1995) test in order to determine mean causality between financial stress and oil price shocks. This study differs from the other related studies since we use proxy for financial stability of the U.S. as high frequency (daily) financial stress index developed by (Polat, 2017) and we investigate the impacts of oil price and volatility shocks on financial stress in high frequency.

This study is structured as follows: Section 1 is the Introduction. Section 2 gives literature review. Section 3 identifies the methodology and gives data. Section 4 gives dynamics of FSI, finds and discusses empirical results and Section 5 concludes the study.

2. Literature Review

The financial stress index literature has developed over the last decade. Researchers have constituted low frequency (weekly, monthly, quarterly or annual) or high frequency (daily) financial stress indexes. Among them; low frequency financial stress index studies suggested weekly (Nelson and Perli, 2007; Brave and Butters, 2011; Holló et al., 2012; Cerquera and Murcia, 2015; Kliesen and Smith, 2015), monthly (Balakrishnan et al., 2009; Hakkio and

[4] High frequency (daily) financial stress indexes of the U.S. is developed by Polat (2017) with an application of Composite Indicator of Systemic Stress (CISS) (Holló et al., 2012) and DCC-GARCH (Engle, 2002) methodologies. The methodology and data in developing FSI are given in Appendices A-1, A-2 and A-3.
[5] In line with the study of Chen et al. (2014), SVAR model is estimated by using 30 lags of each variable to determine potential long run impacts of oil price shocks on financial stability.

Keaton, 2009; Morales and Estrada, 2010, Cardarelli et al., 2011; Yiau et al., 2010; Cevik et al., 2013), quarterly (Sinenko et al., 2013; Arzamasov and Penikas, 2014; Eidenberger et al., 2014; Vermeulen et al., 2015) and yearly (Bordo et al., 2001; Hatzius et al., 2010) indexes.

Since the number of FSI studies are limited, most of the studies in this area have examined that the impacts of oil price shocks on financial indicators. Different findings are reported by these studies. Among them; i) non-linear relationship between oil prices and stock price returns (Ciner, 2001; Basher and Sadorsky, 2006; Wang et al., 2013, Wang et al., 2013), ii) asymmetric relationships between oil prices and stock returns (Cong et al., 2009; Aloui et al., 2012) can be counted.

Another strand of studies find evidence of adverse and significant effect of oil price shocks on stocks price returns (Jones and Kaul, 1996; Sadorsky, 1999; Park and Ratti, 2008; Miller and Ratti, 2009, Cuñado and Gracia, 2014; Kang et al., 2015).

Supply/demand side of oil price shocks on stock price returns are also investigated by few studies (Arouri, and Miller, 2009; Cuñado and Gracia, 2014).

Only a few study analyze the impacts of oil price shocks on financial stress indexes (Chen et. al, 2014; Nazlioglu et al., 2015). Chen et al. (2014) investigate the impact of oil price shocks on financial market conditions with an application of SVAR model which consists of an oil supply shock, an aggregate demand shock, an oil-specific demand shock, and a financial shock. They preferred using Kansas City Financial Stress Index (KCFSI) as a proxy for global financial conditions and concluded that a positive financial shock results to a statistically significant decline in oil prices and it has a relatively high explanatory power for oil price fluctuations.

Nazlioglu et al. (2015) examine the mean and volatility spillovers between oil prices and financial stress (Cleveland Financial Stress Index, CFSI) during pre-crises, crises and post-crises periods (2008 as a crisis period). Results of the study can be summarized as follows: i) Oil prices and the financial stress index are dominated by the long-run volatility, ii) there exists a causality from oil prices to financial stress during post-crisis, iii) there exists a causality running from financial stress to oil prices in the crises.

3. Methodology and Data

SVAR model6 is employed to estimate short/long run effects of shocks on financial stress index. Toda and Yamomoto (1995) causality test is implemented in order to determine mean spillover between series. In this section, these methodologies and data are given.

3.1. Structural VAR Model

The structural shocks are defined to capture changes in oil price oil price and financial stress with VAR model. Accordingly, we identify structural oil price shocks (oil price volatility changes) and structural financial shocks. Therefore, the representation of SVAR model is given as follows:

$$B_0 y_t = \beta + \sum_{i=1}^{p} B_i y_{t-i} + \varepsilon_t \qquad (1)$$

where y_t is (3×1) vector that includes financial stress index, daily oil price returns (logarithmic difference of oil prices) and daily oil prices volatility (obtained with $GARCH(1,1)$), B_0 is contemporaneous coefficient matrix, β is vector of constant terms and ε_t represents vector of serially and mutually uncorrelated error terms (structural shocks).

Therefore, structural shocks can be estimated by the following reduced form errors:

$$e_t = B_0^{-1} \varepsilon_t \qquad (2)$$

The reduced-form VAR can be obtained as follows:

$$\begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ b_{21} & 1 & 0 \\ b_{31} & b_{32} & 1 \end{pmatrix} \times \begin{pmatrix} \varepsilon_{financial\ shock} \\ \varepsilon_{oil\ price\ shock} \\ \varepsilon_{oil\ price\ volatility\ shock} \end{pmatrix} \qquad (3)$$

[6] We estimate SVAR model using 30 lags of each variable in order to capture potential long run impacts of shocks on financial stability. Similar to the related literature (Chen et al., 2014; Nazlioglu et al., 2015), the short run impacts are observed within the first 10 days for the most of series and the long run impacts are observed in the rest of the month.

3.2. Data

We use daily FSI of the U.S. developed by (Polat, 2017) as a proxy of financial conditions for the U.S. and West Texas Intermediate (WTI) spot crude oil prices. FSI is developed by 12 financial market indicators from banking sector, bond market, equity market, money market and foreign exchange market of the US. The detailed information regarding to FSI is given in Appendices A-1, A-2 and A-3. WTI spot crude oil prices have been downloaded from (FRED, 2017) database from 01/10/1993 through 11/18/2016.

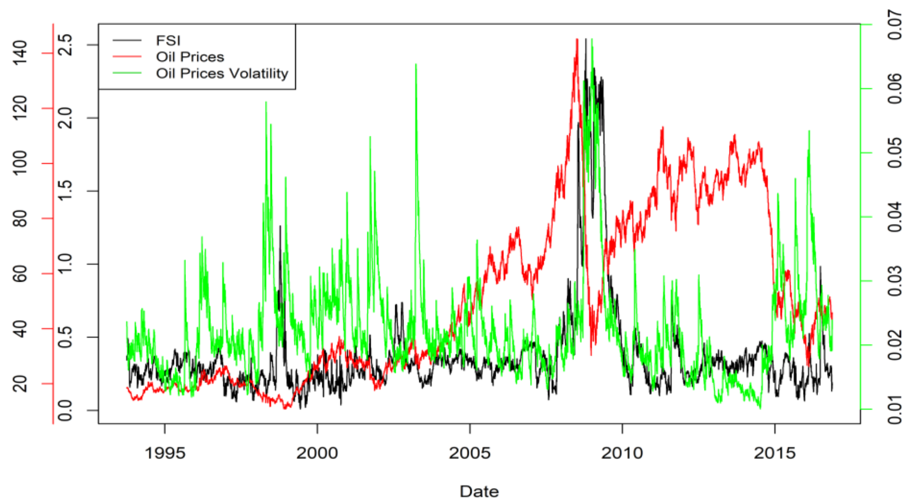
4. Dynamics and Empirical Results

In this section; dynamics of FSI, oil price, oil price volatility and empirical results are given.

4.1. Dynamics of FSI, Oil Price and Oil Price Volatility

Figure 1 illustrates dynamics of FSI, oil price and oil price volatility in 01/10/1993-11/18/2016.

Figure 1. Dynamics of Financial Stress Indexes in 01/10/1993- 11/18/2016



It appears from Figure 1 that; during 2008 financial crisis, there exist upward trends in financial stress index and oil prices volatility, meanwhile oil prices plumps. Besides, comovements and correlations between series strengthen during 2008 financial crisis. Oil price volatility tends to increase in the recent period. Correlation structure of the series are given in Figure 2:

Figure 2. Correlation Structure of FSI, Oil Prices and Oil Prices Volatility

Figure 2 shows that financial stress index and oil prices are positively and weakly correlated. Besides, financial stress index and oil prices volatility are positively and moderately correlated. Therefore; we estimate SVAR in order to capture linkages between FSI and oil price dynamics.

4.2. Empirical Results

Before SVAR analysis, ADF, PP, DF-GLS unit root tests are employed to financial stress index of the U.S., oil prices and oil prices volatility. The results of unit root tests are given in Table 1.

Table 1. Unit Root Test Results for FSI, Oil Prices (log) and Oil Prices Volatility

Unit Root Test	Financial Stress Index	Oil Prices	Oil Prices Volatility
ADF	-3.8921 **	-1.7867	-5.7832 ***
DF-GLS	-4.2485 ***	-2.0797 ***	-7.0452 ***
PP	-4.342 ***	-1.8062	-6.854 ***

Notes: *, ** and *** show significance level at 10, 5 and 1 percent.

ADF, DF-GLS and PP unit root tests confirm that, daily financial stress index for the U.S. and oil prices are stationary, while oil prices has a unit root. Therefore, we estimate SVAR that contains FSI of the U.S., oil prices returns[7] and oil prices volatility.

Toda-Yamamoto approach is employed in the next step to determine mean spillovers between the series[8]. The results of Toda-Yamamoto causality analysis is given in Table 2.

Table 2. Toda-Yamamoto Test Results

Equation		Excluded	chi2	df Prob chi2
Oil Prices	Oil Prices Volatility	8.3553	2	0.015
Oil Prices	FSI	1.4093	2	0.494
Oil Prices	ALL	9.7393	4	0.045
Oil Prices Volatility	Oil Prices	56.903	2	0.000
Oil Prices Volatility	FSI	11.81	2	0.003
Oil Prices Volatility	ALL	69.077	4	0.000
FSI	Oil Prices	.11654	2	0.943
FSI	Oil Prices Volatility	9.1656	2	0.010
FSI	ALL	9.2666	4	0.055

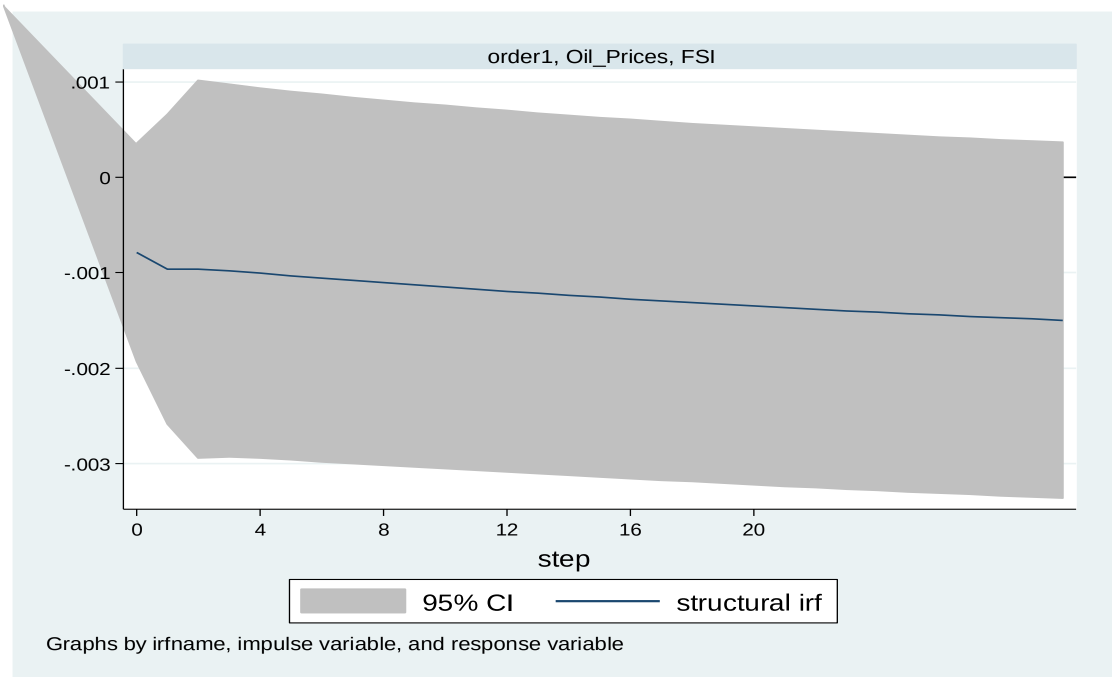
By the results of Toda-Yamamoto causality tests, the null hypothesis "oil prices does not Granger cause financial stress" could not be rejected, while the null hypothesis "oil prices volatility does not Granger cause financial stress" could be rejected at 1%, 5% and 10%

[7] Unit root tests are repeated for oil prices returns. ADF, DF-GLS and PP unit root tests confirm stationarity of the first difference of oil prices returns.
[8] In the Toda-Yamamoto approach, the lag is selected as 10 by AIC (Akaike Information Criteria) in the *VAR* model.

significance levels. On the other hand, the null hypothesis "financial stress does not Granger cause oil prices" could not be rejected while the null hypothesis "financial stress does not Granger cause oil prices volatility" could be rejected at 1%, 5% and 10% significance levels.

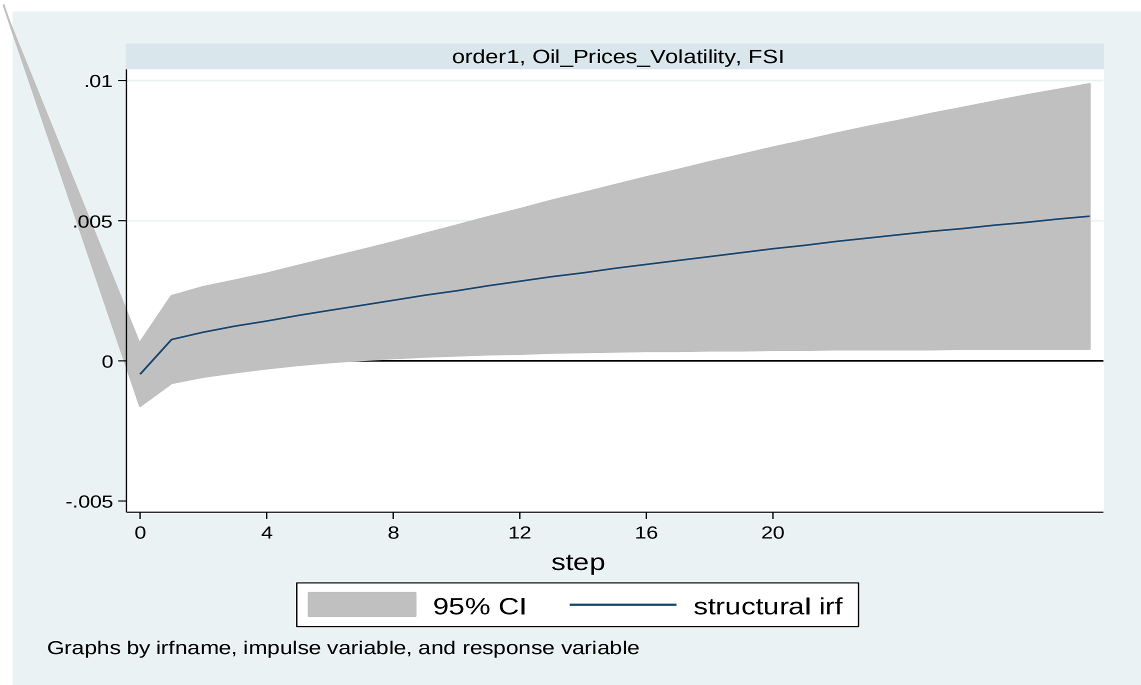
In the next step, SVAR is implemented in order to determine short/long run relationships between series. The impulse responses of financial stress index to 1 standard deviation shock (oil price and volatility shock) are illustrated in the Figure 3 and Figure 4 respectively:

Figure 3. Response of the US's FSI to Oil Prices Shock



The response of FSI to positive oil prices shock is illustrated in Figure 3. It is clear from figure that the response of FSI to positive oil price shock is dominated by short-run and negative.

Figure 4. Response of the US's FSI to Oil Prices Volatility Shock



It appears from Figure 4 that the response of FSI to positive oil prices volatility shock is initially positive and tend to be positive in the long run.

5. Conclusion

Hazardous effects of energy price shocks can quickly dispersed into economies thanks to the energy dependency of both emerging and developed countries. Along with that; since oil consumption constitute the greatest amount in energy usage, the research area that focuses on the impacts of oil price shocks on financial or macroeconomic indicators has developed since 1970s.

In this study; we investigate the impacts of oil prices and oil prices volatility shocks on financial condition of the United States. We identify SVAR model that includes oil price returns, oil price volatility and high frequency (daily) financial stress index of the U.S. that has been developed by Polat (2017).

The results of this study can be summarized as follows: i) The interaction mechanism between financial stress and oil prices are significant and dominated by the short run. ii) Financial conditions initially and slightly improve as a result of positive oil price shock. iii)

Financial conditions worsen in the face of positive oil price volatility shock in the short and in the long run.

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A. Appendix

In this section, the methodology of developing financial stress index, selection of indicators and data in FSI are given.

A.1. Methodology

The methodology of developing financial stress index is based on the two-steps portfolio aggregation method which is called as $CISS$ (Holló et al., 2012). They define $CISS$ in sub open interval $[0,1)$ as below:

$$CISS_t = (w^\circ s_t)C_t(w^\circ s_t)' \quad \text{(A1)}$$

Where, $w = (w_1, w_2, w_3, w_4, w_5)$ is sub index weight vector, $s_t = (s_1, s_2, s_3, s_4, s_5)$ is sub-markets index vector, $w^\circ s_t$ is Hadamart product, C_t is the estimated correlation coefficients matrix $(\rho_{ij,t})$ across sub-market indexes i $(i = 1,2,3,4,5)$ and j $(j = 1,2,3,4,5)$ given as follows:

$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{14,t} & \rho_{24,t} & \rho_{34,t} & 1 & \rho_{45,t} \\ \rho_{15,t} & \rho_{25,t} & \rho_{35,t} & \rho_{45,t} & 1 \end{pmatrix} \quad \text{(A2)}$$

In their original methodology, the cross correlations $(\rho_{ij,t})$ that have $\sigma_{ij,t}$ covariance and $\sigma_{i,t}^2$ variances that are estimated by Exponentially-Weighted Moving Average (EWMA) method given as below:

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\tilde{s}_{i,t}\tilde{s}_{j,t} \quad \text{(A3.a)}$$

$$\sigma_{i,t}^2 = \lambda\sigma_{i,t-1}^2 + (1-\lambda)\tilde{s}_{i,t}^2 \quad \text{(A3.b)}$$

$$\rho_{ij,t} = \sigma_{ij,t}/\sigma_{i,t}\sigma_{j,t} \quad \text{(A3.c)}$$

$i = 1, \dots, 5$, $j = 1, \dots, 5$, $t = 1, \dots, T$ and $\tilde{s}_{i,t} = (s_{i,t} - 0.5)$.

Holló et al. (2012) used transformed indicators based on cumulative distribution function (CDF) and Exponentially Weighted Moving Average (EWMA) methodology in order to obtain the financial stress index. However, we use standardized indicators and DCC-GARCH methodology (Engle, 2002) to develop financial stress indexes.

Engle (2002) proposed a new class of multivariate GARCH estimators that can be viewed as a generalization of constant correlation estimators that are developed by Bollerslev (1990). In this model, multivariate series r_t can be given as follows:

$$r_t|\varphi_{t-1} \sim N(0, H_t) \text{ where } H_t = D_t R_t D_t,\ D_t = diag(\sqrt{\mu_{i,t}}) \quad \text{(A4.a)}$$

$$\mu_{i,t} = \omega_i + \sum_{k=1}^{K_i} \tau_{ik} r_{it-k}^2 + \sum_{j=1}^{J_i} \rho_{ij} \mu_{it-j} \quad \text{(A4.b)}$$

where R_t represents the time varying correlation matrix that contains the conditional correlations and it is defined with a positive matrix Q_t as follows:

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2} \quad \text{(A5)}$$

Engle showed that the parameters of the model can be maximized by the following log likelihood function:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + 2log|D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \varepsilon_t'\varepsilon_t + log|R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t) \quad \text{(A6)}$$

where $\varepsilon_t \sim N(O, R_t)$.

Once the conditional correlations are estimated for each pair of sub-market indexes, the dynamic correlation coefficient matrix, C_t is constructed.

Finally, daily financial stress index (CISS) is obtained by the following equation:

$$CISS_t = \sqrt{(w^\circ s_t) C_t (w^\circ s_t)'} \quad \text{(A7)}$$

We compute CISS as volatility-equivalent terms which was suggested by Holló et al. (2012) by square root of equation A1.

A.2. Selection of Indicators in Financial Stress Index

We use banking sector, bond, equity, money and foreign exchange markets indicators to construct financial stress indexes. Time periods of the financial stress indexes vary due to availability of country specific financial market indicators. The data has been downloaded from three sources: Bloomberg, Quandl, FRED databases. In addition to some common indicators and methodologies, country specific indicators are used in the FSIs.

A.2.1. Banking Sector

Realized volatility of return of DJUSBK: Realized volatility of the Bank Sector Index is obtained by $GARCH$ (1,1).

CMAX for DJUSBK: Following Hollo et al. (2012), we use daily bank index with 2 years window to determined large losses in financial system with an application of CMAX (the maximum cumulated loss over a specific time frame). Patel and Sarkar (1998) proposes CMAX and it measures maximum cumulated loss over a specific time span (T) for stock market index (x) as follows:

$$CMAX_t = \frac{x_t}{max\left\{x \in \{x_{t-i} | i = 0, 1, \dots, T\}\right\}} \qquad \text{(A8)}$$

Dynamic betas of the banking sector: We use time varying betas of the banking sector. Time varying betas of the banking sector is calculated by employing the DCC-GARCH methodology of Engle (2002) within the scope of the Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM). They are evaluated as follows:

$$\beta_t = \frac{cov(r_t, m_t)}{var(m_t)} \qquad \text{(A9)}$$

where, β_t represents time varying beta, r_t correspond to bank index returns and m_t represents stock market returns.

A.2.2. Bond Market

The realized volatility of the slope of the yield curve: Cross section of yields at any time, t is modeled by Nelson and Siegel (1987) as follows:

$$y(\tau) = \beta_1 + \beta_2 \left(\frac{1-e^{\mu\tau}}{\mu\tau}\right) + \beta_3 \left(\frac{1-e^{\mu\tau}}{\mu\tau} - e^{\mu\tau}\right) \quad \text{(A10)}$$

where β_1, β_2 and β_3 represent *level*, *slope* and *curvature* respectively and τ denotes maturity. The realized volatility of the slope of the yield curve with $GARCH$ (1,1) is used to determine stress level in the bond market.

The realized volatility of the U.S. 10 year Government generic bid yield: The realized volatility of 10 year Government bond yield with $GARCH$ (1,1) is used as another risk component in the bond market.

The realized volatility of the US 10 Year Corporate Bond Spread: The realized volatility of the corporate bond spread is used to measure bond market risk. It is defined as follows:

$$Corporate\ Bond\ Spread_t = CB_t - TB_t \quad \text{(A11)}$$

where CB is the 10-yr. Moody's Aaa rated corp. bond yields and TB is the 10 year treasury yield. The measure is evaluated with $GARCH$ (1,1).

A.2.3. Equity Market

The realized volatility of S&P 500: We use the realized volatility of stock market index with $GARCH$ (1,1) in order to gauge stress level in equity market.

***CMAX for S&P 500*:** The cumulative maximum loss is calculated for the stock market index to determine risk in equity market. This measure is evaluated same as methodology given for the bank market.

A.2.4. Money Market

The realized volatility of the 3 month USD Libor: 3 month interbank rate is related to the interest rate of short term unsecured interbank lending. High volatility of this measure reflects flight to quality and flight to liquidity as a result of rise in uncertainty in interbank market. The realized volatility of the 3 month USD Libor is obtained with $GARCH$ (1,1).

The realized volatility of TED spread: The spread between 3 month interbank rate and three month Government bond yield is used to measure liquidity and counterparty risk in the interbank loan market. We use the realized volatility of TED spread with $GARCH$ (1,1) in order to capture another risk component in money market.

A.2.5. Foreign Exchange Market

The realized volatility of GBP/USD and JPY/USD: A great amount of stress level in the financial system is originated through currency markets. Therefore, we use the realized volatility of exchange rates with $GARCH$ (1,1) to measure risk level in foreign exchange market.

Table A.1. Financial Market Indicators Used in FSIs

Financial Market	Indicator	Impact of Indicator into Financial Stress	Available Date
Banking sector	Realized volatility of return of DJUSBK	Uncertainty about fundamentals, flight to quality, flight to liquidity	1989/09/11 - 2016/11/29
Banking sector	CMAX for DJUSBK	Flight to quality, flight to liquidity	1989/09/11 - 2016/11/29
Banking sector	Dynamic beta of the banking sector	Uncertainty about fundamentals, flight to quality, flight to liquidity	1989/09/11 - 2016/11/29
Bond market	Realized volatility of slope of the yield curve	Flight to quality, flight to liquidity	1993/10/01 - 2016/11/29
Bond market	Realized volatility of the US 10 year government bond yield	Flight to quality, flight to liquidity	1980/01/02 - 2016/11/29
Bond market	Realized volatility of the US 10 year corporate bond spread	Flight to quality, flight to liquidity	1980/01/02 - 2016/11/29
Equity market	CMAX for stock market index for US	Flight to quality, flight to liquidity	1980/01/02 - 2016/11/29
Equity market	Realized volatility of S&P 500	Flight to quality, flight to liquidity	1980/01/02 - 2016/11/29
Money market	Realized volatility of 3 month USD LIBOR	Uncertainty about fundamentals, flight to quality, flight to liquidity	1984/12/06 - 2016/11/29
Money market	Realized volatility of TED spread	Uncertainty about fundamentals, flight to quality, flight to liquidity	1993/10/01 - 2016/11/29
FX market	Realized volatility of GBP/USD	Flight to quality, flight to liquidity	1980/01/02 - 2016/11/29
FX market	Realized volatility of JPY/USD	Uncertainty about fundamentals, flight to quality, flight to liquidity	1980/01/02 - 2016/11/29