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Measuring Financial Systemic Stress for Turkey: A Search for the Best Composite Indicator

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Measuring financial systemic stress for Turkey: A search for the best composite indicator *

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Abstract

In this study, we aim to construct a single financial stress indicator (FSI) for Turkey adopting weekly data between April 2005 and December 2016. To do so, we compose 15 different FSIs using 14 variables that will represent five different markets, i.e. money market, bond market, foreign exchange market, equity market and banking sector. We aggregate these five different markets using variety of techniques, including principal component analysis (PCA), basic portfolio theory, variance equal weights and Bayesian dynamic factor model. We compare 15 different FSIs on the basis of their relation to and forecasting power of different variables such as the growth rate of industrial production, OECD business condition index and OECD composite leading indicator for Turkey. Our results suggest that there does not exist a simple best indicator for Turkey that will measure the financial systemic stress. Some indicators offer a good forecasting power for economic growth while others have a stronger correlation with the systemic risk. Therefore, we offer a final FSI for Turkey conducting a model averaging method via a rolling-correlation based weighting scheme to benefit from the information content of all the FSIs and observe that the final FSI successfully indicate the tension periods.

Keywords: financial stress indicators; composite indicator of systemic stress; principal component analysis; Bayesian dynamic factor model; portfolio theory; aggregation methods

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Non-Technical Summary

Detecting and quantifying financial stress and its systemic risk channels have been one of the main concerns for regulatory authorities especially after the 2008 global financial crisis. The intensified search for viable early warning systems is justified by the length and depth of the recessions that are followed by financial stress. While most of emerging economies remained relatively stable during the 2008 global financial crisis and the global economic downturn afterwards, monitoring systemic stress via early warning practices and Financial Stress Indicators (FSIs) became indispensable tools for economic policymaking.

To evaluate financial stress, the formulation of stress episodes is critically important. A metric that solely accounts for banking, currency or debt market may not be appropriate, as the interaction among different segments of financial markets may intensify and lead to a systemic crisis afterwards. The development of stress indicators for various segments of financial markets and aggregating them into a composite indicator enable one to monitor the propagation of a systemic risk and its channels. In that framework, an FSI will be an invaluable tool to measure and monitor current state of financial stress and summarize it as a continuous time series.

This paper introduces an FSI for the Turkish financial system. We discuss various aggregation approaches to compute FSIs including equal-weighting, PCA, basic portfolio theory and Bayesian dynamic factor model, and eventually offer a single FSI averaging all different indicators via model averaging. Although there is some degree of disagreements between the variants of FSIs in terms of their forecasting power, all the variables quite effectively point to similar tension periods during the sample period. This result motivate us to benefit from the information content of all the indicators via a model averaging scheme. Therefore, we introduce a final FSI for Turkey by adopting a weighting scheme that computes rolling correlations between economic activity (industrial production index) and 15 different FSIs. This model averaging scheme, which employs weighting with respect to the industrial production allows us to include the information content of 15 different FSIs in proportion to its correlation with economic activity in a dynamic structure and increased accuracy.

The present paper is not the first one to discuss FSI for Turkey, but as far as we know, it is the first in the literature that discusses many FSIs and obtain a single FSI via model averaging. Although the papers in the literature generally propose a few methodologies to compute FSIs, we observe that the proposed methodologies may not overlap in quantifying the financial stress. We believe that aggregating various FSIs addresses this caveat. What is more encouraging is, we find that the final FSI for Turkey successfully indicates well accepted tension periods. Therefore, the most important strength of this paper is that it provides the opportunity for comparison across a variety of tools and techniques in the financial stress literature. Although many papers present successful results favoring financial stress indicators, they fail to provide convincing evidence how robust their indicators to alternative technique and tools.

1 Introduction

The burst of the 2008 global financial crisis has reignited interest toward systemic stress and early warning indicators. The financial stress that culminated from uncertainties in global financial markets and rippled through the real economy unravels the need for effective early warning systems. Despite its origin in advanced economies, the financial systemic stress has spillover effects without discriminating sound economies. While most of emerging economies remained relatively stable during the 2008 global financial crisis and the global economic downturn afterwards, monitoring systemic stress via early warning practices and FSIs became indispensable tools for economic policymaking.

Detecting and quantifying financial stress and its systemic risk conduits have been one of the main concerns for regulatory authorities especially after the 2008 global financial crisis. The intensified search for viable early warning systems is justified by the length and depth of the recessions that are followed by financial stress. As Claessens et al. (2012) and Claessens et al. (2010) empirically find, the recessions associated with financial disruptions are often deeper and more destructive. Financial stress is generally coupled with reduced wealth, constrained credit and reduction in firm's collateral. Borio (2014) argues that banking systems do not only provide real resources but also change the purchasing power and have a direct hit on real economy. During recessions coinciding with the episodes of busts, macroeconomy usually displays sharper downturns due partly to negative wealth effects, reduced credit and widespread uncertainties.

Empirical investigation on financial crises rests generally on the development of tools that enable their precise dating and quantification. Binary codification is generally employed for dating and is based on subjective evaluation. However, as argued by Danninger et al. (2009), binary codification does not provide a measure of the intensity of stress and ignore the ambiguity of the "crisis" definition, e.g. the existence of a pseudo-crisis, when it is very close to being defined as a crisis but is not considered as one actually. Foreseeing a crisis prior to a tolerable time period is a success measure for early warning systems. It is however of at least equal importance to have a measure of "stress" that may result in a financial crisis. In that case, just a binary indicator defining the time boundaries of a possible crisis may not be adequate, particularly for the policymaker who is mandated to formulate effective policies during the build-up of a possible crisis. To evaluate financial stress, the formulation of stress episodes is critically important too. A metric that solely accounts for banking, currency or debt market may not be appropriate, as the interaction among different segments of financial markets may intensify and lead to a systemic crisis afterwards. The development of stress indicators for various segments of financial markets and aggregating them into a composite indicator enable one to monitor the propagation of a crisis and its channels. In that framework, an FSI will be an invaluable tool to measure and monitor current state of financial stress and summarize it as a continuous time series.[1]

Although FSIs have an objective to foresee stress periods timely and accurately, data selection,

[1] As Holló et al. (2012) argue, it would be unrealistic to expect that such a concise indicator can sufficiently characterize a very complex systemic risk, yet FSIs may also improve the statistical power on the information content of macroprudential early warning models.

aggregation, and calibration schemes of each indicator vary substantially. Most of the studies conducted on FSIs develop high frequency indicators that utilize market data, while some employ a mixed data set and a few studies use balance sheet data.[2] Considering the aggregation schemes, the most popular scheme is equal-variance weights as it is easy to implement and comprehend.[3] Some others consider factor analysis or PCA that relies on extracting a common component among a number of variables. A recent approach employed by Holló et al. (2012) focuses on the correlations between various financial segments as indicating the likelihood of a systemic crisis, since, by definition, intensified interactions create greater damage on the real-economy. The mentioned approaches to FSIs are relatively easy to implement and comment, however, some studies quantify financial stress via more complex and sophisticated approaches like dynamic factor analysis.[4]

The endeavors of detecting a financial crisis and monitoring its build-up phase in a timely manner prompted academicians and policymakers to create FSIs for various countries. Several papers including Lall et al. (2009), Blix Grimaldi (2010) and Melvin and Taylor (2009) investigate FSIs for a set of advanced economies, and several others like Danninger et al. (2009) and Park and Mercado (2014) examine the transmission channels of financial stress between advanced and emerging economies. Although there exist many single country studies, most of them primarily focus on advanced economies.[5] Notable exceptions are those of Morales and Estrada (2010) and Cevik et al. (2013) who study Colombia and Turkey, respectively.[6] Our paper, which is one of the rare studies on the financial stress indicators on Turkey, differs from those studies in terms of the variety of model coverage, i.e. Camlica and Gunes (2016) and Cevik et al. (2013) use principal components and portfolio theory models to construct an FSI , while we use most of the models covered in the literature, make model comparison and finally come up with an aggregated FSI. Indeed, our paper is a first in the literature that compares many variety of aggregation methods and offers model averaging based on these methods. We illustrate that nearly every model captures basic global stress periods, yet they differ with respect to their representation of local stress periods, which we believe is related to weights given to different financial markets. In Turkey, local financial stress periods are conceived to be mostly related to volatility in foreign exchange markets by policy makers. However, our FSI covers five different markets, where high stress periods of foreign currency can be offset by low stress in other financial markets, i.e. stock market and banking sector.[7]

As emerging economies are rapidly integrating into global and regional markets, the cross-border effects of national crises are getting more destructive. The transmission of financial crises is often amplified by the co-movements in asset prices and capital flows. The economies which share similar fundamentals and have strong macroeconomic interdependence are more affected from peer

[2] See Lall et al. (2009), Holló et al. (2012), and Illing and Liu (2006) employing high frequency data. Hanschel and Monnin (2005) employ mixed data and (Morales and Estrada, 2010) use balance sheet data.

[3] See Lall et al. (2009), Hanschel and Monnin (2005) and Elekdag et al. (2010) for details.

[4] See Brave and Butters (2010) and Brave and Butters (2011).

[5] See Illing and Liu (2006) Hatzius et al. (2010) and Hanschel and Monnin (2005).

[6] See Kilimci et al. (2015) and Camlica and Gunes (2016), which are two other studies on financial stress indicators for Turkey.

[7] Some of the FSIs we form are smoother after mid-2016 where there were sharp increases and high volatility in exchange rates, that is related with the weighting structure of each model.

country crises. Herding behaviors also exacerbate the crisis effects as international investors present withdrawals without assessing the fundamentals of peer countries. In the past 30 years, the Turkish economy experienced several episodes of financial stress, some having national characteristics while others resulting from spillover effects of global or regional crises. The crises in 1994 and 2001 have been the major ones that led to successful restructuring of the economy. The successful implementation of various reforms has geared up the economy, and the country recovered from the crisis while achieving significant growth until the 2008 global financial crisis. However, the country has several linkages with its peer emerging countries and is a candidate country of the European Union. The instance of a possible financial stress in Turkey is also a credible threat for these countries. We thus argue that monitoring and foreseeing financial stress in Turkey is not a national regulatory concern solely but has potential cross-country impacts.

This paper introduces an FSI for the Turkish financial system. We discuss various aggregation approaches to compute FSIs including equal-weighting, PCA, basic portfolio theory and Bayesian dynamic factor model, and eventually offer a single FSI averaging all different indicators via model averaging. Although there is some degree of disagreements between the variants of FSIs in terms of their forecasting power, all the variables quite effectively point to similar tension periods during the sample period. This result motivate us to benefit from the information content of all the indicators via a model averaging scheme. Therefore, we introduce a final FSI for Turkey by adopting a weighting scheme that computes rolling correlations between economic activity (industrial production index) and 15 different FSIs. This model averaging scheme, which employs weighting with respect to the industrial production allows us to include the information content of 15 different FSIs in proportion to its correlation with economic activity in a dynamic structure and increased accuracy.

The present paper is not the first one to discuss FSI for Turkey, but as far as we know, it is the first in the literature that discusses many FSIs and obtain a single FSI via model averaging. Although the papers in the literature generally propose a few methodologies to compute FSIs, we observe that the proposed methodologies may not overlap in quantifying the financial stress. We believe that aggregating various FSIs addresses this caveat. What is more encouraging is, we find that the final FSI for Turkey successfully indicates well accepted tension periods.

This paper proceeds as follows: Section 2 introduces the variables and related transformation and aggregation techniques in computing the FSIs. Section 3 discusses the choice of FSIs by evaluating the performance of indicators in predicting economic activity. Section 4 presents a model averaging scheme based on weights with respect to industrial production index to compute a final FSI. The last section concludes.

2 Selection of markets and market specific variables

The construction of an FSI involves four specific steps. The first step is the inclusion of financial markets that will be represented by the composite indicators. The second step is the selection of

variables that should well speak for the specifics of the Turkish economy. The third step is the transformation and scaling of raw variables that will be included into the formation of FSI. Finally, the last step will be related to the aggregation of all the transformed variables into a composite indicator. The first two steps are determined mostly by the characteristics of the Turkish economy, data availability and the literature on which these kind of composite indicators are based upon. The last two steps, i.e. transformation of the variables and aggregation of the FSI are related to available methodologies employed in the literature. In this paper, we select a wide range of transformation and aggregation techniques to construct a variety of FSIs and obtain a final FSI via model averaging, which represents the financial stress of the Turkish economy.

2.1 Financial markets and data

There does not exist an agreement on the number of markets to be represented or the number of variables to be added into each financial market. Yet, different researchers choose markets and variables that they believe reflect important aspects of the financial markets.[8] The markets which represent the economy are meticulously chosen to include economic and financial fundamentals of the country, i.e. yields, risk premiums, liquidity premium, stock and bond market indicators, exchange rate markets, and volatilities related to all these markets. The majority of the previous literature that measures financial stress employ five different markets, i.e. the money market, the bond market, the foreign exchange market, the banking sector and the equity market, not necessarily including all at the same time. Also, markets considered for a composite indicator should include stressful events that will create a fragility for the financial environment of the country that is studied.

In this study, the selection of the markets and variables is closely related to the systemic stress. There is also a trade-off between the candidate variables that will join the composite indicator. As discussed in Kliesen et al. (2012), composite indicators with longer samples could be constructed using stock prices, exchange rates and interest rates on Treasury bonds. The advantage of using long samples is related to testing the performance of constructed composite indicator over the couple of business cycles to observe its relationship with the macroeconomy. By contrast, using newer indicators like credit default swap spreads or the LIBOR might limit the span of the composite indicator, but sometimes newer measures might be better indicators of financial conditions especially after the 2008 global financial crisis. Another trade-off about the data is related to the frequency of the final composite indicator, i.e. the indicator can be monthly, weekly or daily. Using a high-frequency data has an advantage in real-time analysis and decision-making but high-frequency data can be very volatile and may give inaccurate signals.

[8] See Kliesen et al. (2012) for a detailed survey of different composite indicators.

Table 1: *Market specific stress indicators included in FSI*

Variable	Sector	Data start date	Data end day
Volatility of the 3 month LIBOR rate	money market	May 2005	December 2016
TED-spread	money market	April 2005	December 2016
Volatility of the benchmark bond index	bond market	May 2005	December 2016
EMBI+ sovereign spread	bond market	April 2005	December 2016
Volatility of the USD/TRY	foreign exchange market	May 2005	December 2016
CMAX of the USD/TRY	foreign exchange market	April 2006	December 2016
Volatility of the EUR/TRY	foreign exchange market	May 2005	December 2016
CMAX of the EUR/TRY	foreign exchange market	April 2006	December 2016
Volatility of the BIST100 equity index	equity market	May 2005	December 2016
CMAX of the BIST100 equity index	equity market	April 2006	December 2016
Correlation of the benchmark bond index and the BIST100 equity index	equity market	May 2005	December 2016
Volatility of the XBANK banking sector equity index	banking	May 2005	December 2016
CMAX of the XBANK banking sector equity index	banking	April 2006	December 2016
Banking sector beta	banking	May 2005	December 2016

Table 1 presents the data that we choose to represent five different markets based on data availability and their relations with the real economy. As the composite indicator concerns the systemic risk, the employed variables should be related in some way to the dynamics of the real economy. Therefore, we checked the correlation of the variables to be included in the analysis with the monthly industrial production indicator to see whether they have a relative high correlation. The industrial production index is better than many other indicators, e.g. GDP, in showing high frequency economic activity. In line with the discussion presented above, we decided to include 14 different variables that represent five different markets to compute the composite indicator. The closest approach to our data selection building blocks of FSI is the financial stress index of Huotari (2015). All the data employed in this study is weekly data collected from Bloomberg.

2.1.1 Money market

The money market is the primary source of liquidity among financial markets. The inclusion of variables related to the money market will enhance the ability of the composite indicator to identify financial stresses. In this respect, we include two variables that will represent the money market of the Turkish economy, i.e. volatility of the 3 month LIBOR rate and TED-spread. These two variables will capture the flight to quality, flight to liquidity, and uncertainty about macroeconomic fundamentals. Our whole dataset is restricted by the availability of LIBOR rate as it starts from 2005.

2.1.2 Bond market

The degree of uncertainty in the bond market and the sovereign debt risk are represented by the volatility of a benchmark bond index for Turkey and EMBI+ sovereign spread. The volatility of the benchmark bond index will capture the overall country risk, whereas the EMBI+ sovereign spread also reflects the overall country risk premium as it roughly reflects a country's creditworthiness. As argued by Cevik et al. (2013), short term capital flows that are driven by investors' risk perceptions are poised to be a useful indicator during financial stresses in developing countries. Both Illing and

Liu (2006) and Park and Mercado (2014) define the debt crisis as the inability of sovereign nations or the private sector to service its foreign debt. The earlier literature on debt crises deals with a group of emerging economies that were exposed to severe external indebtedness in the early 1980s. Therefore, the selected indicators are capable of revealing the tension in the debt markets as they generally show the spread between risky and risk-free bond yields.

2.1.3 Equity market

Stress in the equity market impairs the availability of funds to firms as well as returns to investors, impinging both on the supply and the demand dynamics of the real economy. More severely, it spreads easily to the rest of the financial system and is often the trigger of financial crises. Most of the studies in the literature define equity crisis as a sharp decline in the overall stock price index. The decline can be indicative of greater expected loss, higher dispersion of probable loss (higher risk), or increased uncertainty about the return of firms. Patel and Sarkar (1998) identify periods of significant decline in 8 developed countries and 14 emerging market countries using the ratio of the regional equity index level at time t to the maximum regional index level for the period up to time t and defined this ratio as $CMAX_t$.[9] We include three different variables to our analysis to capture the abnormalities in the equity market. We include the volatility of the Borsa Istanbul (BIST100) equity index, $CMAX_t$ of the BIST100 equity index and lastly the correlation between the benchmark bond index and the BIST100 equity index. The correlation will serve as a prominent measure for flight to quality, because stocks are usually viewed by investors as much riskier than government bonds. Therefore, the opposite movement of the two asset classes will represent periods of financial stress.[10]

2.1.4 Foreign exchange market

The movements in the TL/USD and the TL/EUR exchange rates are very important benchmarks for both the Turkey's financial sector and its real economy. The Euro Area is the largest trading partner of Turkey, whereas the significant portion of foreign trade activity take place in US dollars. Moreover, many Turkish banks and large enterprises are increasingly financing themselves from international debt markets.[11] In this respect, higher volatility in the exchange rates will also add to systemic stress. As discussed by Illing and Liu (2006), in a fixed exchange rate regime, losses in foreign exchange reserves and increases in interest rates often cause financial stress. For a floating currency, like the TL, both the depreciation of the currency and unexpected volatility may signal stress in the foreign exchange markets. Thus, both the volatility and the depreciation are taken into consideration for the foreign exchange market. In this framework, we include four different variables related to foreign exchange market to compute FSI. These are: volatility of the TL/USD,

[9] $CMAX_t$ measure is a hybrid volatility-loss measure and used extensively in the financial stress indicator literature and can be defined by $CMAX_t = \frac{y_t}{max[y \in (y_{t-j} | j=0,1,\ldots,T)]}$, where y_t is the equity index.

[10] The stock bond correlation is calculated over rolling three month periods.

[11] According to Financial Stability Report 2016 of the Central Bank of the Republic of Turkey, of approximately 27 thousand firms with FX loan balances, 100 thousand firms with FX liabilities of over 100 million TL hold 75 percent of total FX debt.

volatility of the TL/EUR and $CMAX_t$ for these two exchange rates.

2.1.5 Banking sector

Market-driven data for the banking sector reflects expectations toward the prospects of the banking sector. Since the banking sector is a primary component of the financial system in Turkey, a composite index that will reflect financial stress should definitely include a measure that captures the stress in the banking sector. We will use the most common three variables employed within the FSI literature that represent banking stress. The first variable is the volatility of the banking sector equity index (XBANK). The second variable will be the $CMAX_t$ of the XBANK. Lastly, we use banking sectors' beta (β). This measure involves the ratio of bank share prices to total share prices. It provides a stationary measure of relative equity-return volatility and isolates banking sector specific shocks. Indeed, β is simply the linear regression coefficient of XBANK return on BIST100. If β is greater than one, then the banking sector is relatively risky than the overall market.[12]

2.2 Transformation of raw data

The individual variables, as defined in detail above, should be transformed before we combine them as a composite indicator. We employ two basic transformations in this paper. The first transformation is related to scaling of each raw variable before we aggregate them with different methods to get a single composite indicator. The second transformation of the raw data is related to obtaining the volatilities and correlations.

2.2.1 Scaling raw data

Before aggregating the raw data, we need to transform them on a common scale in order to make them comparable.[13] We use two different scaling methods to scale the raw indicators and convert them into a common unit. The most common and preferred conversion method, due to its simplicity and parsimony, is standardizing each variable, which is usually done by subtracting its sample mean and dividing by its standard deviation.[14] With this approach, fluctuations across variables are on the same scale. It is assumed that the raw data is distributed normal when employing this type of scaling. The main drawback of this approach is thus the normality assumption, as it is kind of a common knowledge that high frequency financial data has fat tails. Another popular approach to scale the raw variables is standardization based on each indicator's empirical cumulative density function (CDF).[15] In this approach, raw stress indicators are normalized by transforming the values

[12] $\beta = \frac{cov(return_{BIST100} return_{XBANK})}{var(return_{BIST100})}$.

[13] Some aggregation methods does not require the data to be scaled. For example non-Gaussian dynamic factor model do not require the data to be scaled as they are clear from the normality assumption.

[14] Given that y_t is the raw data, then the standardization can be defined as $\frac{y_t - y_\mu}{\sigma_{y_t}}$.

[15] The difference between the two types of standardization can be visually seen in Appendix B for only one variable,i.e. TED-spread, we include into the composite index.

of each series into the corresponding value of their empirical CDF. This method is employed by Holló et al. (2012) in the literature.[16]

2.2.2 Measures of volatility

We use three different measures for volatility. The simplest and the most common measure to illustrate the time-varying movement of the variance is the realized volatility. Realized volatility is calculated as the square root of the monthly sum of squared weekly log returns. Second volatility measure we employ is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model of Bollerslev (1986) and the GARCH(1,1) process can be illustrated as:

$$\begin{cases} y_t = AR(k) + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} z_t \\ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \end{cases} \tag{1}$$

where y_t is the variable that will be included in the aggregation of FSI and h_t is the conditional variance. y_t, the mean equation, is modeled as a combination of an autoregressive $AR(k)$ process to get rid of the serially correlated errors and GARCH(1,1) process takes into account the time-varying characteristics of movements in related variables.

Similarly, we use a linear stochastic volatility model as the last volatility method we employ.[17] A linear stochastic volatility model can be illustrated as:

$$\begin{cases} y_t = AR(k) + \varepsilon_t \\ \varepsilon_t = \sqrt{h_t} z_t \\ h_t = \omega + \alpha h_{t-1} + u_t - \beta u_{t-1}. \end{cases} \tag{2}$$

2.2.3 Measures of covariance and correlation

We use two different measures for correlation. The first measure is the realized correlation that is calculated over three-month rolling windows. The second measure is the Dynamic Conditional Correlation - Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model of Engle (2002), which provides a convenient way to model the dynamic processes of conditional variances, conditional covariances and conditional correlations simultaneously. Similar to GARCH-type processes for modeling conditional variances, the current values of conditional covariances are related to their lagged values and lagged squared innovations in the model. However, in DCC-GARCH model, conditional covariances are modeled as nonlinear functions of the conditional variances.

The most important advantage of using DCC-GARCH model is that it enables us to detect the

[16] Empirical CDF transformation is given by: $z_t = \begin{cases} \frac{r}{T} & \text{for } y_{[r]} \leq y_t, r = 1, 2, ..., T-1 \\ 1 & \text{for } y_t \geq y_{[T]} \end{cases}$, where $y_{[T]}$ is the sample maximum, y_1 represents the sample minimum, z_t is the standardized series, r the ranking number of y_t and T the total number of observations in the sample.

[17] The difference between three types of volatility measure we use can be visually observed in Appendix C, for only one variable, the USD/TL exchange rate, we include into the composite index.

possible changes in conditional correlations over time between two variables.[18] To get the dynamic conditional correlation between two series, we will employ the following DCC-GARCH(1,1) model:

$$\begin{aligned}
\Delta Y_t &= \Theta \Delta X_t + \varepsilon_t \qquad (3)\\
\varepsilon_t &\sim N(0, H_t) \quad t = 1, ..., T\\
\varepsilon_t &= H_t^{\frac{1}{2}} \upsilon_t\\
\upsilon_t &\sim N(0,1)\\
H_t &= D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}}\\
R_t &= diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}\\
Q_t &= (1-\lambda_1-\lambda_2)R + \lambda_1 \varepsilon_{t-1}\varepsilon_{t-1}^{'} + \lambda_2 Q_{t-1}
\end{aligned}$$

where Equation 3 is a reduced-form Vector Autoregression process (VAR), $D_t = diag(h_{it})$ is a 2×2 matrix containing the time varying standard deviations from univariate GARCH(1,1) models and $R_t = \{\rho_{ij}\}_t$ is a correlation matrix containing conditional quasicorrelations for $i, j = 1, 2$.

Table 1 lists the indicators used in the FSIs for Turkey. All the variables are grouped according to the market they belong to. We also represent the data availability related to each weekly indicator we employ. 3 month LIBOR rates and the calculation of $CMAX_t$ restricts our data availability to April 2006. Among the aggregation methods that will be used to form FSI, Bayesian dynamic factor model is robust to missing data. FSIs computed using basic portfolio theorem and PCA starts from April 2006 and the other FSIs start from April 2006.

2.3 Aggregation of the transformed variables

The choice of how to combine the variables, i.e. the weighting method, is one of the most challenging aspect of constructing a composite indicator. The importance of it reveals itself as a variety of different combination schemes appearing in the literature and there does not exist an agreement upon which combination method serves its purpose best. Indeed, we propose this difficulty as the major strength of the present paper, as we offer a wide array of methods that finalize at a single indicator via model averaging.

2.3.1 Variance equal weights

The most common weighting method used in the literature for a composite indicator is the variance equal weights (VEW). With this approach, a common index is generated by simply giving equal importance to each component variable. The variables are assumed to be normally distributed, which could be regarded as the primary drawback of this approach. The mean is subtracted from each variable before it is divided by its standard deviation. The advantage of this approach is that it is easy to understand and implement.[19] We obtain six different composite indicators when we

[18] A visual comparison of realized correlation and the dynamic correlation we extract using a DCC-GARCH(1,1) model for BIST100 equity index and benchmark government index takes place in Appendix D.

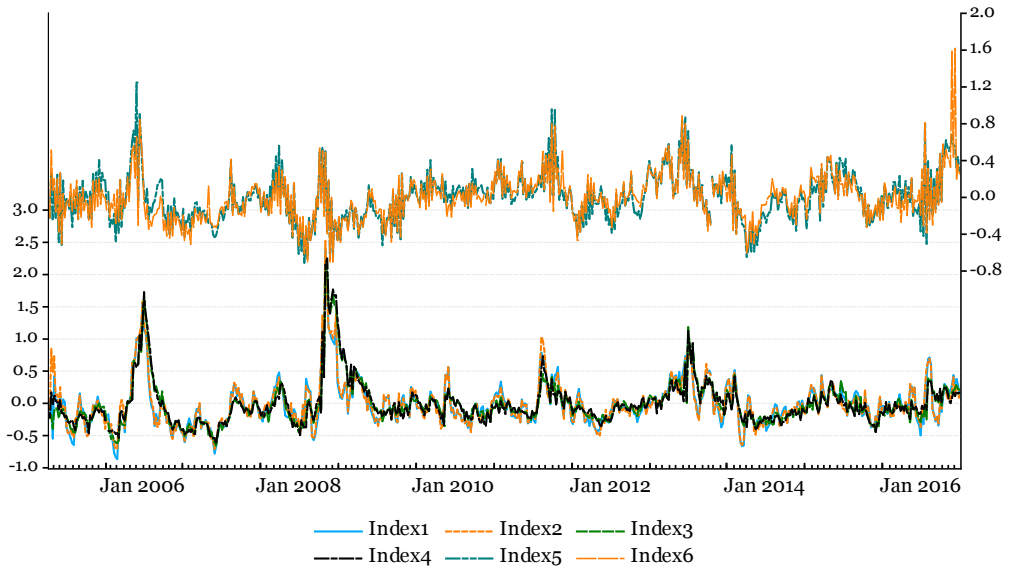
[19] Next to these merits, it is also applicable for cross-country comparisons, that is why it is the most popular technique employed in the literature.

diversify our volatility and correlation measures. Table 2 lists six different composite indicators with the related transformed variable employed during aggregation and their basic descriptive statistics. Figure 1 shows six variance equal weights FSIs. On the right axis and on top of Figure 1, we can see two FSIs that seem a bit different than the other four. These two composite indicators that exhibit a degree of fluctuation uses stochastic volatility for the transformed variables. Although in Figure 1 the composite indicators which are aggregated via stochastic volatility measure seem more volatile compared to the indicators which are aggregated via GARCH(1,1) and realized volatility, the descriptive statistics in Table 2 reveal that the standard errors of those indicators which are aggregated through stochastic volatility are smaller.

Table 2: *FSI based on variance equal weights*

FSI from VEW	transformation measures	mean	std. dev.
Index1	realized volatility and realized correlation	-0.006	0.350
Index2	realized volatility and correlation with DCC-GARCH(1,1)	-0.003	0.354
Index3	volatility with GARCH(1,1) and realized correlation	-0.007	0.349
Index4	volatility with GARCH(1,1) and correlation with DCC-GARCH(1,1)	-0.005	0.354
Index5	stochastic volatility and realized correlation	-0.001	0.269
Index6	stochastic volatility and correlation with DCC-GARCH(1,1)	-0.001	0.261

Figure 1: *FSI based on variance equal weights*



2.3.2 Principal component analysis

PCA is another commonly employed weighting method within the FSI literature. PCA uses an orthogonal transformation to convert a set of observations of potentially correlated variables into a set of values of uncorrelated variables. In other words, the principal components are assumed to be uncorrelated (orthogonal).[20] For each principal component, the analysis determines a weighted

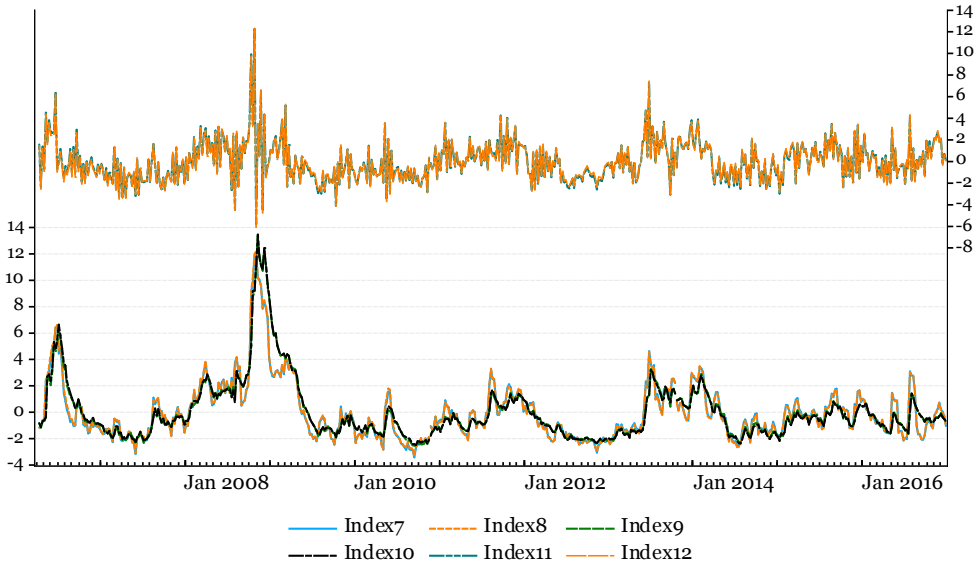
[20] In PCA the most number of principal components one can get is equal to the number of variables. In studies involving coincidence and composite indicators, researchers usually assume that there exist one component that derives the markets, in our case we expect to have one common component deriving the financial stress among five different markets. This common component will be our FSI.

linear combination of the variables that maximizes the percentage of the total variance of each series. The first principal component explains the largest percentage of the variance, the second principal component the next most and so on. The variables are also standardized within the framework of PCA weighting scheme, and as the variables are standardized, the principal component loadings have a natural interpretation. The coefficient of each variable represents the effect on the composite stress indicator of a one-standard deviation change in the corresponding variable. Table 3 lists the six different composite indicators with the related transformed variable employed during aggregation and their basic descriptive statistics. Figure 2 shows six composite indicators aggregated with PCA.

Table 3: *FSI based on principal component analysis*

FSI from PCA	transformation measures	mean	std. dev.
Index7	realized volatility and realized correlation	0.000	2.187
Index8	realized volatility and correlation with DCC-GARCH(1,1)	0.000	2.207
Index9	volatility with GARCH(1,1) and realized correlation	0.000	2.259
Index10	volatility with GARCH(1,1) and correlation with DCC-GARCH(1,1)	0.000	2.282
Index11	stochastic volatility and realized correlation	0.000	1.879
Index12	stochastic volatility and correlation with DCC-GARCH(1,1)	0.000	1.869

Figure 2: *FSI based on principal component analysis*



2.3.3 Portfolio theory

An aggregation scheme that is gaining wider acceptance in the FSI literature is the one that is based on the portfolio theory. As the main intention of a stress indicator is to raise awareness about the joint destruction capacity of each subsector on real economic activity, i.e. systemic risk, a weighting scheme relied on the portfolio theory is adopted. This theory suggests that the portfolio weights for the sub-indexes can be computed on the basis of cross-correlations across each sub-sectors. In

doing so, the contribution of changes in the sub-indexes are higher once the correlations between each sector is higher. The proposed scheme is defined as,

$$FSI_t = (\omega \circ s_t) C_t (\omega \circ s_t)'$$

where ω is the vector of constant sub-index weights, s_t is the vector of sub-indexes, $\omega \circ s_t$ is the Hadamard-product, and the matrix of time-varying cross-correlation coefficients,

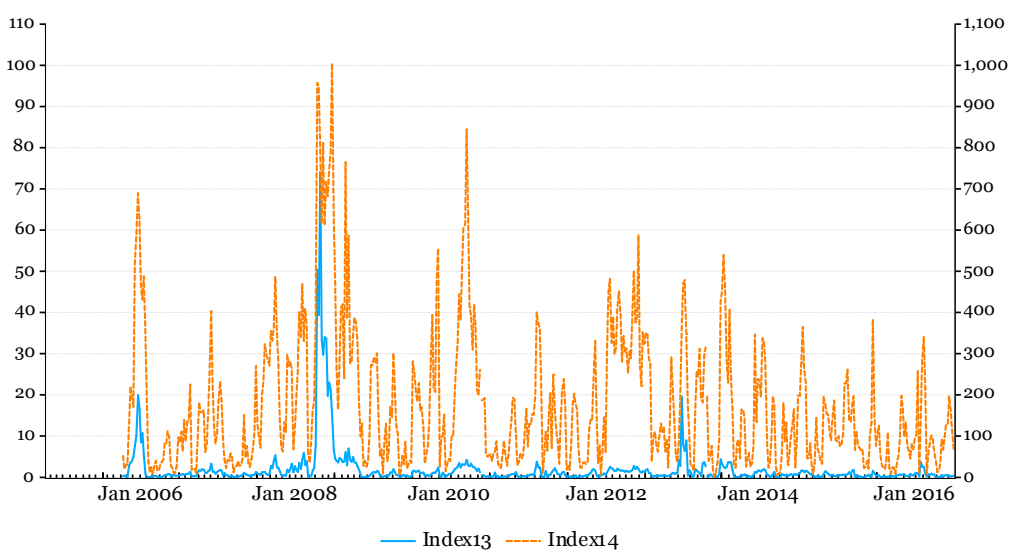
$$C_t = \begin{pmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{14,t} & \rho_{24,t} & \rho_{34,t} & 1 & \rho_{45,t} \\ \rho_{15,t} & \rho_{25,t} & \rho_{35,t}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

is composed of the $\rho_{ij,t}$ which denotes for dynamic cross-correlations between sub-indexes i and j which are estimated via DCC-GARCH(1,1) model. Table 4 lists the descriptive statistics of two FSIs that are constructed using the portfolio theory, and Figure 3 illustrates these two FSIs as time-series.

Table 4: *FSI based on portfolio theory*

FSI from portfolio theory	transformation measures	mean	std. dev.
Index13	empirical cdf transformation	19.298	54.226
Index14	standardizing assuming normal distribution	17.684	16.869

Figure 3: *FSI based on portfolio theory*



2.3.4 Dynamic factor analysis

This part of the paper presents the last method of aggregation that takes into consideration of the dynamic nature of the final composite indicator.[21] We use the Bayesian dynamic latent factor

[21] See Matheson (2012) and Van Roye (2014).

model of Otrok et al. (1998) to aggregate the variables. For simplicity, we will use the same notation as in Otrok et al. (1998) to describe the model. The model is patterned after the "new indexes of coincident and leading indicators" of Stock and Watson (1989) and Stock and Watson (1993).[22] Accordingly, there are n variables, i.e. 14 variables for our case, denoted y_i, on which observations have been collected for periods $t = 1, ..., T$. There is a single common factor, y_0, which accounts for all comovement among the n variables. Thus:

$$y_{it} = a_i + b_i y_{0t} + \varepsilon_{it} \qquad E\varepsilon_{it}\varepsilon_{jt-s} = 0 \text{ for } i \neq j \tag{4}$$

The idiosyncratic errors ε_{it} may be serially correlated, and are modeled as p_i-order autoregressions:

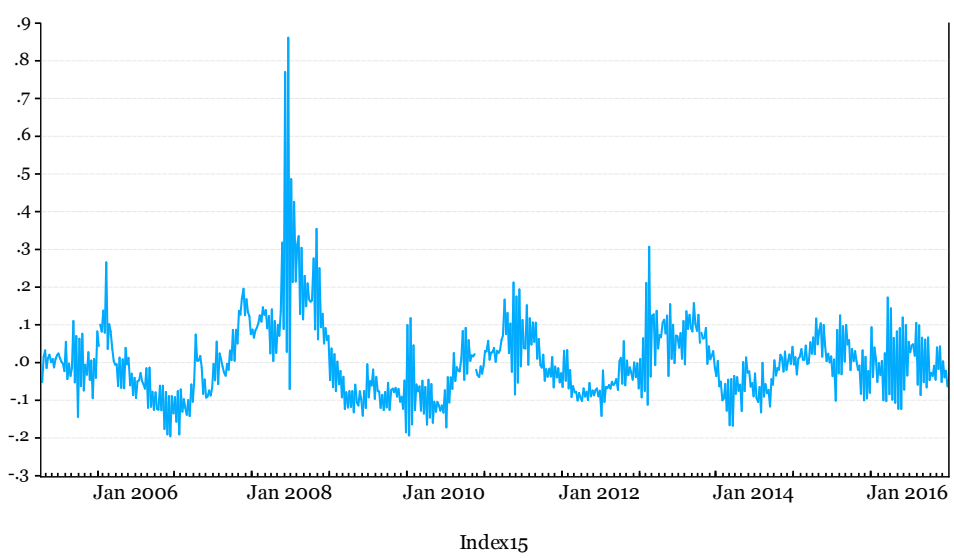
$$\varepsilon_{it} = \phi_{i1}\varepsilon_{it-1} + \phi_{i2}\varepsilon_{it-2} + \cdots + \phi_{ip_i}\varepsilon_{it-p_i} + u_{it} \tag{5}$$
$$Eu_{it}u_{jt-s} = \sigma_i^2 \text{ for } i = j, s = 0; \qquad 0 \text{ otherwise}$$

The evolution of the factor is likewise governed by an autoregression, of order q:

$$y_{0t} = \varepsilon 0t \tag{6}$$
$$\varepsilon_{0t} = \phi_{01}\varepsilon_{0t-1} + \phi_{02}\varepsilon_{0t-2} + \cdots + \phi_{0q}\varepsilon_{0t-q} + u_{0t}$$
$$Eu_{0t}u_{0t-s} = \sigma_0^2 \text{ for } s = 0; 0 \text{ otherwise}, \qquad Eu_{0t}u_{it-s*} = 0, \ \forall i, s$$

The innovations u_{it}, $i = 0, ..., n$ are assumed to be zero mean, independent normal random variables; that is, $u_{it} \sim N(0, \sigma_i^2)$.[23] Table 5 and Figure 4 represents the FSI extracted by employing Bayesian dynamic factor model.

Figure 4: *FSI based on Bayesian dynamic factor model*



[22] See all the details related to the Bayesian dynamic latent factor model in Otrok et al. (1998).
[23] For all the other details about the model, see Otrok et al. (1998).

Table 5: *FSI based on Bayesian dynamic factor model*

FSI from BDFM	transformation measures	mean	std. dev.
Index15	standardizing assuming normal distribution	0.001	0.104

3 Choice of the FSI: Evaluation through different methodologies

In general, the usefulness of an indicator lies in its ability to measure what it was designed to measure. In addition to that, one of the main objectives of constructing a composite indicator for financial stress is to help policymakers identify stress levels in the financial system that may cause series concern and affect the working of the whole macroeconomy. Within this framework, we will try to address some basic questions, e.g. can constructed indexes measure systemic stress successfully? Do changes in the constructed indexes are good leading indicators for financial crisis? Can the composite indicators predict economic conditions?

To answer these questions, first, we will examine the correlations between constructed indicators with monthly industrial production cycle and business conditions index.[24] We will, then, conduct an out-of-sample forecasting exercise using our indicators, industrial production growth rate and business conditions index. Lastly, we will perform a probit model to see if the indicators can identify stress periods. To pick up stress periods, we use expert judgments and the turning points of economic activity as appropriate references. As a final attempt, we compute a final FSI for Turkey through averaging all the FSIs via rolling correlation scheme. VAR and Probit methods are the most common performance evaluation in the literature. VAR model is one of the most successful, flexible and easy to use models for the analysis of multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series and forecasting. On the other hand, probit/logit types of models are frequently used in early indicator literature.[25]

3.1 Correlation with industrial production

We first discuss the simple correlations between the 15 FSIs, the industrial production cycle and the BCI, respectively. Table 6 lists the correlations of all the FSIs with the industrial production cycle and with the BCI.[26] Overall, the results suggest that the correlation metrics are offering high close association between the indicators and mentioned economic activity indicators. The correlations are within [-0.10,-0.38] and [-0.10,-0.73] range, for the industrial production cycle and

[24]The business conditions index (BCI) of OECD is based on enterprises' assessment of production, orders and stocks, as well as its current position and expectations for the immediate future. Opinions compared to a "normal" state are collected and the difference between positive and negative answers provides a qualitative index on economic conditions.

[25]See Kliesen et al. (2012) and Illing and Liu (2006) for more details on the usage of these two models.

[26]We calculate the cycle of the industrial production with HP filter.

the BCI, respectively. The correlations with the BCI are generally higher, which may be due to better performance of the BCI measure in reflecting economic activity.

Table 6: *Correlation with Industrial Production Cycle and Business Condition Index*

	IP	BCI	Ind.1	Ind.2	Ind.3	Ind.4	Ind.5	Ind.6	Ind.7	Ind.8	Ind.9	Ind.10	Ind.11	Ind.12	Ind.13	Ind.14	Ind.15
IP	1.000	0.492	-0.100	-0.121	-0.229	-0.244	0.215	-0.263	-0.209	-0.225	-0.313	-0.327	0.112	0.142	-0.285	-0.262	0.118
BCI	0.492	1.000	-0.392	-0.416	-0.573	-0.586	0.247	-0.102	-0.607	-0.606	-0.734	-0.730	-0.252	-0.255	-0.528	-0.582	-0.107
Ind.1	-0.100	-0.392	1.000	0.990	0.867	0.849	0.431	0.032	0.773	0.775	0.669	0.673	0.510	0.493	0.501	0.625	0.249
Ind.2	-0.121	-0.416	0.990	1.000	0.874	0.873	0.388	0.033	0.790	0.793	0.696	0.702	0.509	0.493	0.518	0.649	0.256
Ind.3	-0.229	-0.573	0.867	0.874	1.000	0.992	0.277	0.038	0.735	0.742	0.806	0.812	0.456	0.431	0.549	0.614	0.158
Ind.4	-0.244	-0.586	0.849	0.873	0.992	1.000	0.235	0.038	0.742	0.750	0.820	0.827	0.449	0.426	0.557	0.629	0.164
Ind.5	0.215	0.247	0.431	0.388	0.277	0.235	1.000	0.067	0.044	0.047	-0.075	-0.069	0.492	0.471	-0.032	0.059	0.106
Ind.6	-0.263	-0.102	0.032	0.033	0.038	0.038	0.067	1.000	0.016	0.024	0.029	0.036	-0.035	-0.060	-0.134	-0.012	-0.122
Ind.7	-0.209	-0.607	0.773	0.790	0.735	0.742	0.044	0.016	1.000	0.999	0.938	0.936	0.705	0.694	0.498	0.726	0.391
Ind.8	-0.225	-0.606	0.775	0.793	0.742	0.750	0.047	0.024	0.999	1.000	0.940	0.940	0.700	0.686	0.506	0.730	0.382
Ind.9	-0.313	-0.734	0.669	0.696	0.806	0.820	-0.075	0.029	0.938	0.940	1.000	0.999	0.609	0.593	0.535	0.706	0.313
Ind.10	-0.327	-0.730	0.673	0.702	0.812	0.827	-0.069	0.036	0.936	0.940	0.999	1.000	0.605	0.587	0.542	0.709	0.304
Ind.11	0.112	-0.252	0.510	0.509	0.456	0.449	0.492	-0.035	0.705	0.700	0.609	0.605	1.000	0.995	0.178	0.420	0.408
Ind.12	0.142	-0.255	0.493	0.493	0.431	0.426	0.471	-0.060	0.694	0.686	0.593	0.587	0.995	1.000	0.181	0.417	0.425
Ind.13	-0.285	-0.528	0.501	0.518	0.549	0.557	-0.032	-0.134	0.498	0.506	0.535	0.542	0.178	0.181	1.000	0.707	0.198
Ind.14	-0.262	-0.582	0.625	0.649	0.614	0.629	0.059	-0.012	0.726	0.730	0.706	0.709	0.420	0.417	0.707	1.000	0.276
Ind.15	0.118	-0.107	0.249	0.256	0.158	0.164	0.106	-0.122	0.391	0.382	0.313	0.304	0.408	0.425	0.198	0.276	1.000

3.2 Forecasting with a simple VAR model

In this part of the paper, we investigate whether our 15 different composite indicators can forecast economic growth. To do this experiment, we conduct a series of simple out-of-sample forecasting exercises. The forecasting model is a simple bivariate vector autoregression (VAR) of the form:

$$Y_t = \Phi + \Gamma_1 Y_{t-1} + \Gamma_2 Y_{t-2} + \cdots + \Gamma_p Y_{t-p} + \Psi_t \tag{7}$$

where Y_t is a vector consisting of the period t values of the economic indicator that we would like to forecast, i.e. the industrial production growth rate or the BCI along with one of the 15 FSIs. Φ is the vector including constant coefficients. $\Gamma(L)$ is a matrix polynomial in the lag operator and Ψ_t is the reduced form residuals.[27] The 1-step forecast based on information available at time T is:

$$Y_{T+1|T} = \Phi + \Gamma_1 Y_T + \cdots + \Gamma_p Y_{T-p+1} \tag{8}$$

Forecasts for longer horizons h can be obtained using the chain rule of forecasting as:

$$Y_{T+h|T} = \Phi + \Gamma_1 Y_{T+h-1|T} + \cdots + \Gamma_p Y_{T+h-p|T} \tag{9}$$

and when we know the parameters of the estimated $VAR(p)$, the best linear predictor of $Y_{T+h|T}$ will be:

$$\widehat{Y}_{T+h|T} = \Phi + \widehat{\Gamma}_1 \widehat{Y}_{T+h-1|T} + \cdots + \widehat{\Gamma}_p \widehat{Y}_{T+h-p|T} \tag{10}$$

[27] We determine the lag order p of $VAR(p)$ using Akaike information criterion. For each bivariate model we estimate $VAR(p)$, where we decide on p with respect to the lag length criteria. See Appendix A.

where $\widehat{\Gamma}$ are the estimated parameter matrices.

Our out-of-sample forecasting experiments are conducted for $h = 1, \ldots, 12$ along with estimated forecast standard errors from the bivariate $VAR(p)$ model for each of our composite indices. Accordingly, we estimate the models for the time period March 2005 and October 2015 for both the industrial production growth and the BCI. After getting the estimated parameters $\widehat{\Gamma}$ we calculate the h-step forecast errors and find root mean squared error (RMSE), by comparing the forecasts and the realized values. [28]

Table 7: *Out of Sample Forecasts of FSIs-VAR Results with Industrial Production Index*

RMSE*	Ind.1	Ind.2	Ind.3	Ind.4	Ind.5	Ind.6	Ind.7	Ind.8	Ind.9	Ind.10	Ind.11	Ind.12	Ind.13	Ind.14	Ind.15
t+1	0.01008	0.01006	0.01229	0.01141	0.00552	0.02107	0.00840	0.00841	0.01137	0.01148	0.00291	0.00395	0.01450	0.01241	0.00691
t+2	0.00779	0.00777	0.00930	0.00889	0.00540	0.00670	0.00719	0.00720	0.00809	0.00822	0.00345	0.00450	0.01062	0.00937	0.00728
t+3	0.00737	0.00732	0.00827	0.00810	0.00584	0.00702	0.00725	0.00725	0.00713	0.00727	0.00479	0.00558	0.00928	0.00844	0.00725
t+4	0.00640	0.00636	0.00721	0.00708	0.00508	0.00543	0.00635	0.00635	0.00619	0.00631	0.00416	0.00497	0.00806	0.00734	0.00639
t+5	0.00697	0.00697	0.00754	0.00740	0.00609	0.00638	0.00674	0.00674	0.00685	0.00695	0.00540	0.00567	0.00819	0.00761	0.00674
t+6	0.00826	0.00830	0.00859	0.00848	0.00770	0.00826	0.00792	0.00792	0.00828	0.00834	0.00722	0.00720	0.00908	0.00863	0.00792
t+7	0.00900	0.00901	0.00928	0.00920	0.00855	0.00932	0.00888	0.00888	0.00892	0.00898	0.00824	0.00830	0.00973	0.00937	0.00884
t+8	0.01042	0.01046	0.01062	0.01057	0.01009	0.01108	0.01019	0.01019	0.01044	0.01048	0.00983	0.00980	0.01089	0.01062	0.01022
t+9	0.02598	0.02605	0.02608	0.02606	0.02588	0.02600	0.02571	0.02571	0.02608	0.02608	0.02572	0.02564	0.02602	0.02592	0.02582
t+10	0.03543	0.03544	0.03547	0.03546	0.03536	0.03548	0.03539	0.03539	0.03544	0.03545	0.03530	0.03528	0.03556	0.03549	0.03538
t+11	0.03595	0.03597	0.03599	0.03598	0.03588	0.03589	0.03585	0.03585	0.03598	0.03598	0.03581	0.03578	0.03601	0.03595	0.03588
t+12	0.03574	0.03575	0.03578	0.03577	0.03568	0.03572	0.03570	0.03570	0.03576	0.03576	0.03563	0.03561	0.03584	0.03578	0.03569

Note: This table presents the performance of the FSIs in forecasting economic activity (industrial production index). The forecasting model is a simple bivariate vector autoregression (VAR) through twelve month periods. * indicates RMSE. The shaded cell in each row of the table represents the model with a minimum RMSE.

Table 8: *Out of Sample Forecasts of FSIs-VAR Results with Business Condition Index*

RMSE*	Ind.1	Ind.2	Ind.3	Ind.4	Ind.5	Ind.6	Ind.7	Ind.8	Ind.9	Ind.10	Ind.11	Ind.12	Ind.13	Ind.14	Ind.15
t+1	0.29978	0.85921	1.11353	1.08076	0.46311	0.85608	0.62318	0.64443	0.86647	0.89237	0.12522	0.11669	1.36828	1.10344	0.60867
t+2	0.76566	0.60820	0.81840	0.78081	0.40959	0.60549	0.47595	0.48696	0.61818	0.63558	0.28796	0.28541	1.03551	0.80692	0.45747
t+3	1.34957	0.84779	0.80790	0.82359	0.90169	0.83516	0.91724	0.91447	0.77204	0.78631	0.87215	0.87471	0.91510	0.82623	0.86941
t+4	1.68424	1.11137	0.95496	1.00844	1.21497	1.09442	1.24547	1.24000	1.02889	1.03809	1.18301	1.18748	0.97932	1.00407	1.17726
t+5	1.65144	1.06646	0.89004	0.95152	1.17738	1.04843	1.22115	1.21497	0.99310	0.99929	1.14117	1.14660	0.89573	0.94807	1.14258
t+6	1.50811	0.99107	0.85942	0.90059	1.08363	0.97666	1.11777	1.11240	0.92350	0.92990	1.05484	1.05901	0.88341	0.89553	1.05194
t+7	1.57514	1.06979	0.93235	0.98207	1.16137	1.05453	1.21921	1.21351	1.03021	1.03282	1.12499	1.13060	0.92866	0.98538	1.14109
t+8	1.47349	1.01313	0.89512	0.93534	1.09434	1.00002	1.14275	1.13758	0.97091	0.97391	1.06388	1.06845	0.90083	0.93502	1.07368
t+9	3.19308	3.13912	3.13589	3.12697	3.14423	3.14006	3.10518	3.10545	3.07593	3.08226	3.15564	3.15320	3.16397	3.10478	3.11828
t+10	3.06611	3.00226	2.99658	2.99016	3.00909	3.00265	2.98012	2.98009	2.95169	2.95664	3.01734	3.01551	3.02082	2.97266	2.98802
t+11	3.09618	3.06523	3.06584	3.05538	3.06692	3.06665	3.02358	3.02414	2.99612	3.00295	3.08041	3.07756	3.09168	3.03009	3.03869
t+12	2.98011	2.94480	2.94444	2.93534	2.94725	2.94597	2.91021	2.91059	2.88556	2.89131	2.95883	2.95636	2.96862	2.91360	2.92292

Note: This table presents the performance of the FSIs in forecasting economic activity (BCI). The forecasting model is a simple bivariate vector autoregression (VAR) through twelve month periods. * indicates RMSE. The shaded cell in each row of the table represents the model with a minimum RMSE.

Table 7 presents RMSEs out of our forecasting exercise conducted using the industrial production index and Table 8 presents the RMSEs for the bivariate VARs estimated using BCI. The shaded cells in Table 7 and 7 represent the minimum RMSE and the results regarding the out-of-sample forecasts also indicate different forecasting performances for the FSIs. Although the disagreement between the performance of the models seems to be a caveat, the choice of economic activity measure emerges to be an important culprit, since the conflict between the FSIs mainly arises from the economic activity measures.[29]

[28] $RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$.

[29] FSI employs timely and high frequency data which is by nature should be a leading indicator for growth (the growth series are not timely), therefore we think there is no need to go further for a detailed Granger causality analysis. Saying that, we include a Granger Causality table (Table A3 in Appendix A) which proves our point.

3.3 Predicting stress times with a probit model

One of the objectives of the FSI, as a leading indicator, is to predict material changes in economic activity.[30] We would therefore expect that increases in the FSI, which can be translated as heightened stress in financial markets, would subsequently result in deterioration in economic activity. To test this conjecture, we estimate a probit model in which the binary index is first derived from expert judgment and second using the turning points in Composite Leading Indicator CLI produced by the OECD. The probit model we estimate is,

$$Pr(Tension_t) \quad = \quad \phi(c + \alpha x_t + \sum_{k=0}^{1} b_k \Delta x_{t-k} + e_t)$$

where $Tension_t$ is the binary index derived by expert judgment and using the turning points in CLI produced by the OECD respectively, and ϕ is normal cumulative distribution function and x_t is the FSI that is computed with alternative transformations and techniques.

Table 9: *Probit Regression Results with Expert Judgement*

	Ind.1	Ind.2	Ind.3	Ind.4	Ind.5	Ind.6	Ind.7	Ind.8	Ind.9	Ind.10	Ind.11	Ind.12	Ind.13	Ind.14	Ind.15
constant	**-1.065**	**-1.105**	**-1.084**	**-1.101**	**-0.866**	**-0.870**	**-1.034**	**-1.033**	**-0.987**	**-0.988**	**-1.193**	**-1.164**	**-1.583**	**-1.770**	**-0.982**
	(0.159)	(0.167)	(0.171)	(0.179)	(0.128)	(0.139)	(0.161)	(0.161)	(0.158)	(0.159)	(0.197)	(0.191)	(0.260)	(0.247)	(0.142)
x_t	**4.496**	**5.017**	**4.885**	**5.591**	**2.498**	-0.477	**0.537**	**0.538**	**0.518**	**0.525**	**0.996**	**0.996**	**0.039**	**0.058**	**4.672**
	(0.807)	0.(902)	(0.882)	(1.026)	(0.735)	(0.718)	(0.109)	(0.109)	(0.106)	(0.107)	(0.193)	(0.195)	(0.011)	(0.014)	(1.734)
Δx_t	**-2.205**	**-2.556**	-0.286	-0.571	**-0.789**	0.539	**-0.213**	-0.204	0.014	**0.027**	**-0.397**	**-0.427**	**-0.021**	**-0.032**	**-10.103**
	(0.660)	(0.733)	(0.843)	(0.949)	(0.740)	(0.908)	(0.117)	(0.116)	(0.167)	(0.166)	(0.161)	(0.164)	(0.011)	(0.012)	(3.585)
Δx_{t-1}	**-1.481**	**-1.600**	-0.402	-0.477	-1.025	0.331	-0.179	-0.172	0.016	0.014	**-0.378**	**-0.391**	-0.014	**-0.024**	**-10.619**
	(0.538)	(0.579)	(0.791)	(0.835)	(0.731)	(0.750)	(0.109)	(0.109)	(0.163)	(0.161)	(0.169)	(0.169)	(0.010)	(0.010)	(3.432)
McFadden's															
$R-square$	0.394	0.438	0.465	0.510	0.095	0.003	0.317	0.323	0.340	0.349	0.337	0.318	0.111	0.313	0.185

Note: This table estimates a probit model to observe how the FSI is associated with the tension periods. Values in brackets are standard errors. The bold values are significant at conventional levels. The dependent variable is a dummy variable taking the value of one for the periods where it is deemed as tension periods. The tension periods are identified in correspondence with expert judgments.

Table 10: *Probit Regression Results with CLI Reference Turning Points*

	Ind.1	Ind.2	Ind.3	Ind.4	Ind.5	Ind.6	Ind.7	Ind.8	Ind.9	Ind.10	Ind.11	Ind.12	Ind.13	Ind.14	Ind.15
constant	**-0.592**	**-0.596**	**-0.588**	**-0.590**	**-0.614**	**-0.640**	**-0.576**	**-0.574**	**-0.544**	**-0.544**	**-0.583**	**-0.584**	**-0.816**	**-0.714**	**-0.658**
	(0.116)	(0.117)	(0.116)	(0.116)	(0.117)	(0.131)	(0.130)	(0.130)	(0.128)	(0.128)	(0.130)	(0.130)	(0.215)	(0.145)	(0.124)
x_t	**1.008**	**1.086**	**0.831**	**0.893**	**-1.130**	-0.608	**0.403**	**0.395**	**0.364**	**0.353**	**0.573**	**0.596**	**0.017**	**0.011**	**6.990**
	(0.465)	(0.458)	(0.405)	(0.401)	(0.696)	(0.676)	(0.088)	(0.087)	(0.0878)	(0.085)	(0.129)	(0.134)	(0.010)	(0.005)	(1.782)
Δx_t	-0.726	**-0.784**	-0.412	-0.466	0.031	0.636	**-0.253**	-0.247	-0.125	-0.127	**-0.357**	**-0.369**	-0.011	-0.006	**-8.113**
	(0.462)	(0.462)	(0.546)	(0.546)	(0.731)	(0.853)	(0.104)	(0.103)	(0.147)	(0.143)	(0.137)	(0.141)	(0.010)	(0.005)	(2.910)
Δx_{t-1}	-0.400	-0.412	-0.271	-0.316	0.212	0.308	-0.154	-0.148	-0.143	-0.135	**-0.289**	**-0.297**	-0.004	-0.004	**-8.897**
	(0.429)	(0.434)	(0.591)	(0.592)	(0.732)	(0.703)	(0.099)	(0.097)	(0.151)	(0.148)	(0.136)	(0.138)	(0.009)	(0.004)	(3.060)
McFadden's															
$R-square$	0.031	0.038	0.029	0.034	0.023	0.006	0.187	0.185	0.174	0.171	0.148	0.147	0.021	0.056	0.152

Note: This table estimates a probit model to observe how the FSI is associated with the tension periods. Values in brackets are standard errors. The bold values are significant at conventional levels. The dependent variable is a dummy variable taking the value of one for the periods where it is deemed as tension periods. The tension periods are the CLI reference turning points.

The fitted probability values pertaining to both models provide intuitive chronology for the deterioration in economic activity.[32] We report here the probit models in Table 9 and 10 to show the predictive significance (power) of the models. Both models, where the dependent crisis variables

[30] By definition, the FSI captures the contemporaneous level of stress and is not expected to have strong predictive power for future stresses or crises (Illing and Liu (2006)). The implicit assumption behind the probit regression is that a crisis should not be defined only as a function of the FSI level. This is due to the fact that the level of FSI which corresponds to a crisis is variable through time, due to policy regime switching or other structural changes. A crisis should be linked to both an intensification of stress (expressed in the sum of past FSI changes) and the absolute level of the index.[31]

[32] The results for the probability values are available on request.

either depend on expert judgments or the turning points in CLI, exhibit high predictive power. We propose the two best models given the McFadden's R-square in Figure 5 and Figure6.

Figure 5: *Probit Regression Forecast with Expert Judgement*

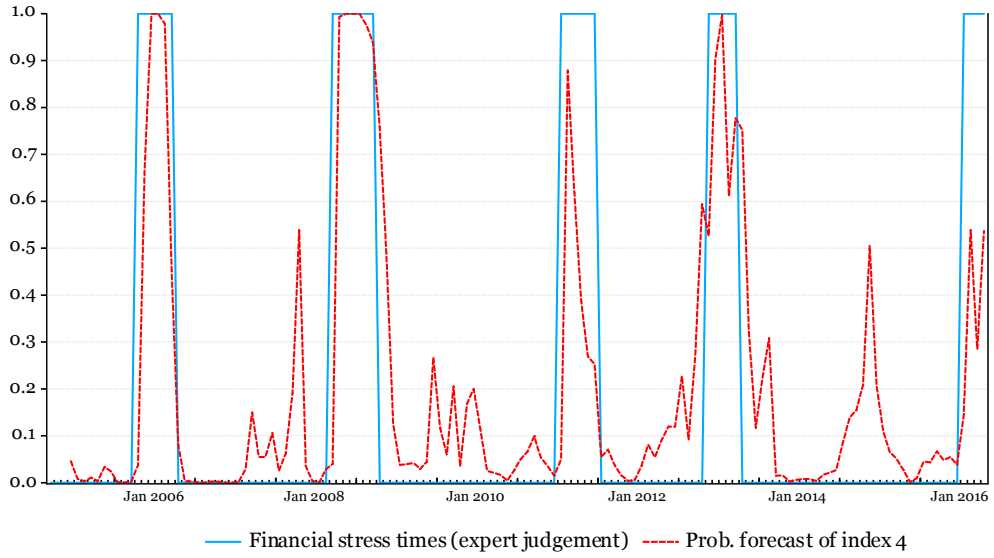
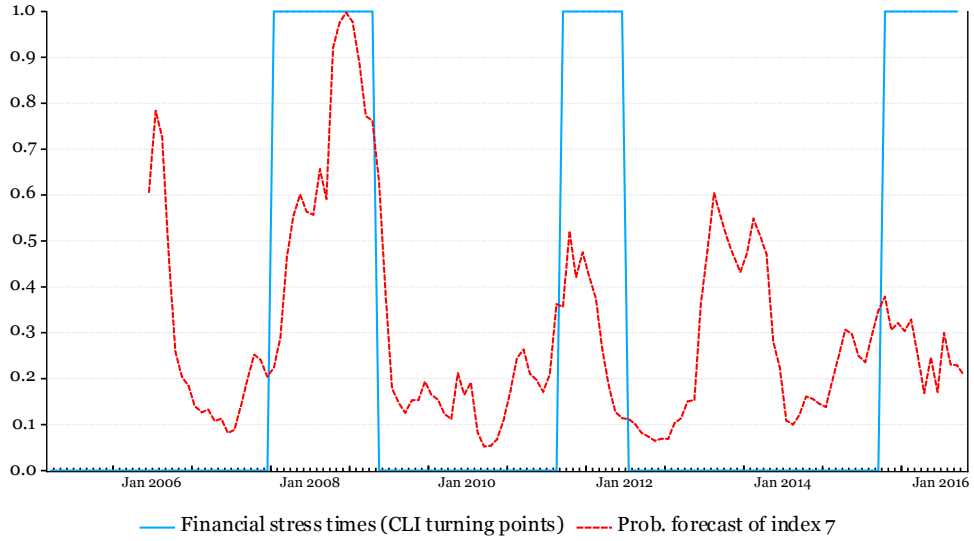


Figure 6: *Probit Regression Forecast with CLI Reference Turning Points*



The results for the performance of FSIs highlight that, besides their agreement on indicating the tension periods in financial markets, they also provide highly promising predictions for economic activity. Overall, these can be interpreted that, regardless of the technique and transformation, the FSIs serve quite reliable monitoring tools for the policymakers.

4 Aggregation Through Rolling Correlation

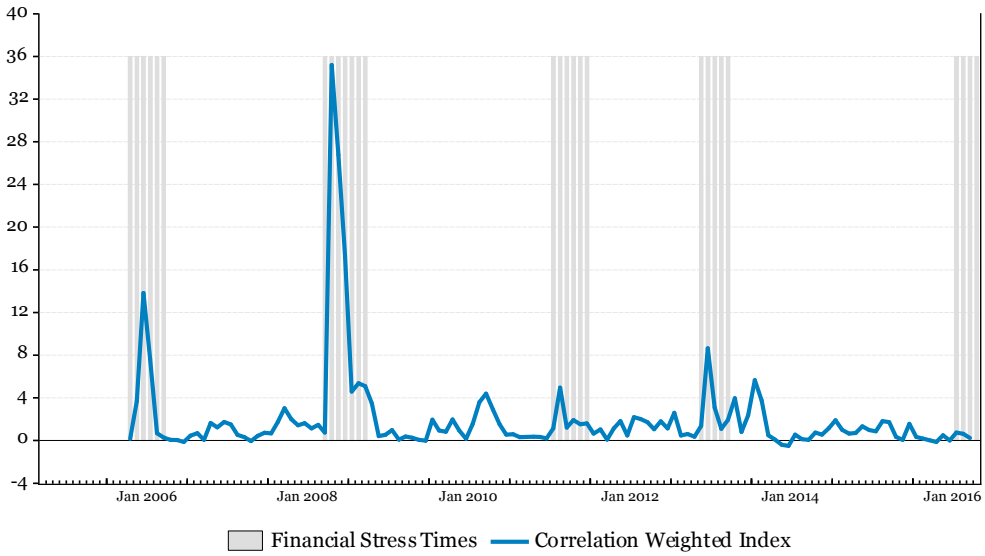
The discussions in the previous subsections show that all of the computed FSIs are performing good in terms of different computational approaches with respect to capturing financial stress periods. This result motivates us to benefit from all the FSIs via model averaging with an appropriate weighting scheme. As the measurement of the negative impact of a financial stress on economic activity is the key point in this research, we compute time-varying weights via rolling correlations of each FSI with industrial production index. To do so, we select a three-month window. We first compute correlations of each FSI with industrial production in a rolling three-month window. The rolling windows can be represented as, $[t; t+3], [t+4; t+6], ...[t+n-3; t+n]$, where the beginning of a window is the following month of the previous window's end month.[33]

The final weight of FSI i at a rolling window $[t; t+3]$ is:

$$W_{i,t} = \frac{Abs(corr_{FSI_{i,t-t+3}, IP_{t-t+3}})}{\sum_{i=1}^{n} Abs(corr_{FSI_{i,t-t+3}, IP_{t-t+3})}}.$$

The computation of FSI i at a rolling window $[t; t+3]$ thus allows each FSI to contribute to final FSI at a rate of its association with industrial production index. Figure 7 plots the final FSI and the tension periods. The performance of the final index in terms of detecting stress periods is also remarkable. During the analysis period, the FED's monetary tightening in May 2006, Lehman Brother's bankruptcy and subsequent financial crisis in 2008, the Euro Zone crisis in Greece in May 2010 and the FED tapering and domestic shocks in 2013 is accepted as the main stress episodes and it is observed that the aggregated FSI shows the mentioned stress periods successfully

Figure 7: *Final FSI with Rolling-Correlation Based Weighting*



[33] We choose three months as the window, because we calculate all the realized volatilities and correlations in the previous sections with a three month window.

Table 11: *Lag Selection for VAR with Industrial Production*

RMSE*	Best VAR model IP	Index16
t+1	0.00291	0.012468
t+2	0.00345	0.008600
t+3	0.00479	0.007914
t+4	0.00416	0.007270
t+5	0.00540	0.007957
t+6	0.00720	0.009457
t+7	0.00824	0.009235
t+8	0.00980	0.015910
t+9	0.02572	0.039016
t+10	0.03528	0.047761
t+11	0.03578	0.039810
t+12	0.03561	0.687091

Note: * indicates Root Mean Squared Error.

Table 11 illustrates the forecasting performance of the aggregated final FSI with respect to the simple bivariate VAR defined in the previous section. As can be observed, final FSI cannot beat the best performing composite indicators at each forecast horizon. Yet, if we compare the forecast performance of the aggregate FSI with all of the other models' performances that is listed in Table 7 and 8 with respect to their RMSEs, we can see that the aggregation offers a pretty good improvement over many models.

As can be observed from Figure 7 the final FSI proposed in this study responds prominently to the uncertainties that emerged during and after Lehman Brother's bankruptcy in 2008 and reached its highest level during this period. In 2006, 2010 and 2013, financial stress has also increased markedly. However, the recent low levels of FSI may be considered surprising at first glance, given the exchange rate movements within this period. Considering that FSI takes 5 different financial segments into account, and despite recent exchange rate movements, the high performance of equity markets in developing countries and the soundness of the banking sector in Turkey, it is evaluated that the developments in the exchange rate market did not alone significantly increased the stress.

5 Conclusion

The 2008 global financial crisis that erupted in the US and affected many advanced and emerging economies had severe spillovers. The recent global financial crisis was different from many of the past crises in the sense that the impact of it had significant and long-lived economic repercussions. It is now widely accepted that financial crises coupled with economic downturns create more severe affects in national economies.

The past literature on economic crises mainly focused on early warning systems. Early warning systems literature, in general, proposes that the likelihood of a crisis is closely associated with several related macroeconomic, fiscal and financial indicators. The monitoring of these indicators can be used effectively to avoid such devastating crisis. However, one of the main weaknesses of the early warning indicators is that the variables used for the models are low frequency in nature, which hinders an active and timely monitoring.

The necessity for financial stress indicators originates mainly from the caveats of the early warning systems. Devising indicators that are composed of high frequency data which have also close association with real economic activity is of crucial importance since the latest regulatory proposals suggest that timely detecting fragilities in financial markets is one of the top priorities. In this framework, this paper investigates how effectively the financial stress periods can be detected by financial stress indicators. Devising a number of stress indicators (FSIs) for Turkey, we propose that there is not a single best FSI for the financial system of Turkey in terms of different evaluation measures. However, regardless of the techniques and tools, the indicators successfully indicate past stress periods. The association of these FSIs with economic activity indicators are also robust. When the relationship between these FSIs and a number of economic activity indicators are analyzed, the results suggest that all the 15 FSIs can be effectively used for predicting the changes in economic activity.

One of the main strengths of this paper is that it provides the opportunity for comparison across a variety of tools and techniques in the financial stress literature. Although many papers present successful results favoring financial stress indicators, they fail to provide convincing evidence how robust their indicators to alternative technique and tools. The present paper fills this gap by presenting a variety of tools and techniques in computing variety of FSIs and their usefulness in detecting the stress periods. The performance measures with respect to different FSIs we compute with the combination of different approaches and techniques, do not single out a specific approach or technique. This motivates us to benefit from all the FSIs in relation to their association with economic activity. We obtain a final FSI from all the composite indicators via model averaging with a weighting scheme where the weights are computed through rolling correlations of each FSI with the industrial production index. This weighting scheme proves to be a good smoother as the final FSI, resulting from the model averaging, is remarkable in capturing the stress episodes.

Although this paper presents a variety of research points with respect to the FSI literature, we leave a number of research themes unexplored. For instance, disentangling the external and internal drivers of the FSI will be the topic of a separate research. The results of that research will highlight the degree of vulnerability of stress indicators to external and internal shocks. The response of FSI to different shocks is specifically important for a national policymaker who is mandated to effectively contain the adverse spillovers in global financial markets.

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Appendices

A Tests related to VAR's

Table A1: *Lag Selection for VAR with Industrial Production*

AIC*	Ind.1	Ind.2	Ind.3	Ind.4	Ind.5	Ind.6	Ind.7	Ind.8	Ind.9	Ind.10	Ind.11	Ind.12	Ind.13	Ind.14	Ind.15	Ind.16
Lag 0	-4.305282	-4.28432	-4.218127	-4.177244	-5.043467	-4.929165	-0.557827	-0.547307	-0.441523	-0.431884	-1.510518	-1.590524	3.41125	5.694909	-6.886458	5.07471
Lag 1	-4.736368*	-4.751083*	-5.247831	-5.233845	-5.623437	-5.185218	-1.582293*	-1.570863*	-2.206687	-2.198377	-2.215518	-2.25961	2.901777*	5.117277	-8.372378	1.865554
Lag 2	-4.714499	-4.722562	-5.402383*	-5.393497*	-5.675433*	-5.567199*	-1.540616	-1.527154	-2.390175	-2.384314	-2.262110*	-2.305374	2.924804	5.098166*	-8.370772	0.46643
Lag 3	-4.681816	-4.688058	-5.376728	-5.360545	-5.640222	-5.542489	-1.518477	-1.501739	-2.441414*	-2.419313*	-2.257296	-2.314730*	2.964075	5.133867	-8.380574*	0.126888*
Lag 4	-4.62307	-4.631132	-5.349239	-5.34866	-5.592989	-5.498247	-1.458823	-1.441595	-2.397408	-2.373683	-2.191572	-2.249572	2.995476	5.173514	-8.324404	0.154776
Lag 5	-4.632037	-4.638045	-5.399026	-5.388461	-5.543219	-5.442407	-1.417981	-1.400943	-2.386613	-2.35736	-2.142358	-2.200214	3.039892	5.222551	-8.33085	0.200513
Lag 6	-4.647537	-4.641609	-5.396177	-5.364921	-5.524773	-5.420803	-1.38827	-1.370196	-2.337334	-2.307583	-2.103121	-2.161298	3.079263	5.211879	-8.310359	0.247771
Lag 7	-4.601625	-4.597462	-5.349454	-5.307361	-5.484734	-5.369349	-1.342536	-1.324279	-2.291819	-2.260403	-2.097932	-2.154458	3.145896	5.214601	-8.288075	0.24203
Lag 8	-4.567527	-4.573469	-5.31342	-5.282446	-5.468792	-5.32153	-1.307378	-1.290123	-2.261683	-2.227909	-2.039708	-2.093195	3.184987	5.268433	-8.251439	0.266285
Lag 9	-4.565235	-4.585469	-5.290629	-5.270534	-5.466403	-5.337121	-1.333376	-1.315316	-2.268638	-2.237036	-2.029964	-2.07674	3.252038	5.326923	-8.225627	0.288853
Lag 10	-4.531596	-4.544406	-5.24895	-5.224456	-5.456166	-5.301485	-1.292649	-1.277428	-2.231078	-2.205794	-2.085235	-2.129643	3.299288	5.376581	-8.182857	0.300413
Lag 11	-4.48806	-4.497266	-5.197242	-5.169538	-5.412256	-5.289338	-1.284688	-1.268989	-2.186763	-2.154876	-2.069651	-2.116103	3.316599	5.415163	-8.139774	0.258764
Lag 12	-4.453851	-4.465287	-5.148117	-5.125184	-5.369201	-5.236677	-1.25135	-1.236162	-2.153338	-2.117452	-2.062501	-2.105951	3.380031	5.468002	-8.203413	0.228434

Note: * indicates lag order selected by the criterion . AIC is Akaike Information Criterion.

Table A2: *Lag Selection for VAR with Business Conditions Index*

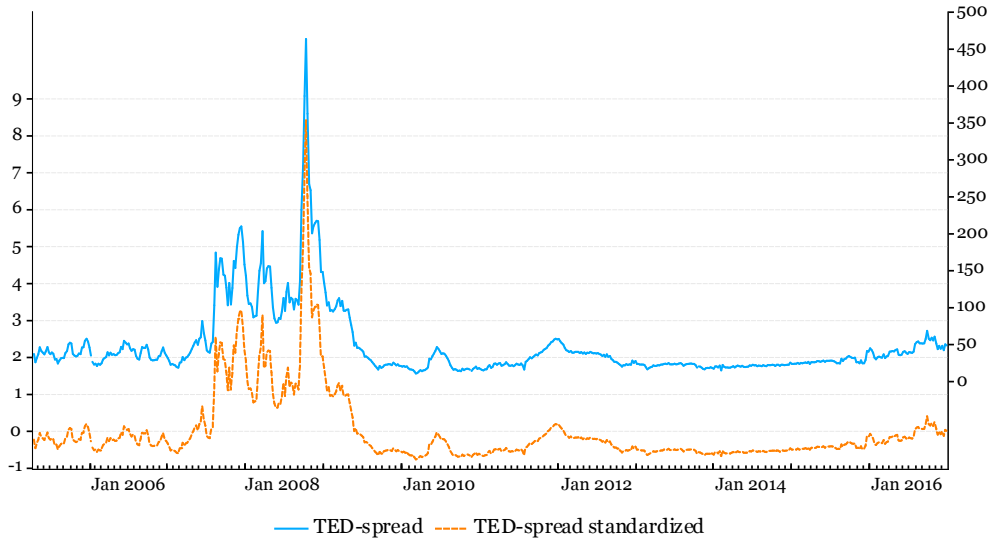
AIC*	Ind.1	Ind.2	Ind.3	Ind.4	Ind.5	Ind.6	Ind.7	Ind.8	Ind.9	Ind.10	Ind.11	Ind.12	Ind.13	Ind.14	Ind.15	Ind.16
Lag 0	5.614214	5.63668	5.613628	5.659901	4.886279	5.01799	9.469997	9.479931	9.568978	9.577662	8.470134	8.392308	13.36525	15.75016	2.952673	12.45023
Lag 1	4.57447	4.566009	4.027525	4.040769	3.671733	4.144028	7.823368	7.836416	7.111693	7.120978	7.117561	7.074323	12.25464	14.54308	0.919544	11.48611
Lag 2	4.451169*	4.441664*	3.734560*	3.750998*	3.557597*	3.670695	7.663928*	7.678191*	6.851084	6.857975	6.948595*	6.906203*	12.13968*	14.33359*	0.813042*	11.39093*
Lag 3	4.504313	4.496032	3.786407	3.796263	3.567477	3.663354*	7.698899	7.714916	6.774175*	6.798643*	6.967917	6.910493	12.16924	14.33973	0.825637	11.39492
Lag 4	4.521845	4.517698	3.798078	3.810371	3.588196	3.674935	7.71702	7.737132	6.827447	6.85422	6.973136	6.911897	12.19073	14.37589	0.860617	11.42962
Lag 5	4.563803	4.563827	3.826632	3.842217	3.636099	3.729183	7.777904	7.798214	6.867501	6.897427	7.024625	6.962659	12.2397	14.43817	0.85235	11.45993
Lag 6	4.560993	4.569578	3.822271	3.85759	3.627656	3.760711	7.83106	7.849354	6.907364	6.93441	7.074033	7.012983	12.28212	14.48372	0.86558	11.50264
Lag 7	4.592695	4.598319	3.858031	3.902449	3.685926	3.799712	7.886736	7.905668	6.959927	6.990936	7.075858	7.014546	12.33156	14.50609	0.912159	11.50906
Lag 8	4.633948	4.63667	3.887803	3.926227	3.705695	3.833411	7.924686	7.943101	6.974042	7.007789	7.13349	7.076332	12.39907	14.56533	0.96031	11.53444
Lag 9	4.62369	4.609032	3.867419	3.894906	3.742941	3.832735	7.886565	7.905325	6.944034	6.975211	7.142565	7.089236	12.43241	14.61979	0.988193	11.59663
Lag 10	4.631103	4.627179	3.907037	3.945256	3.739577	3.867175	7.918055	7.936777	7.009987	7.043762	7.066004	7.014485	12.4594	14.67155	1.028117	11.65948
Lag 11	4.657153	4.650212	3.94275	3.969354	3.766354	3.882443	7.959526	7.976328	7.0685	7.099505	7.104852	7.053869	12.49864	14.71473	1.068369	11.70183
Lag 12	4.702554	4.695255	3.990927	4.026169	3.81727	3.937981	8.007357	8.020772	7.10605	7.143801	7.137487	7.086142	12.55755	14.77532	1.111892	11.75101

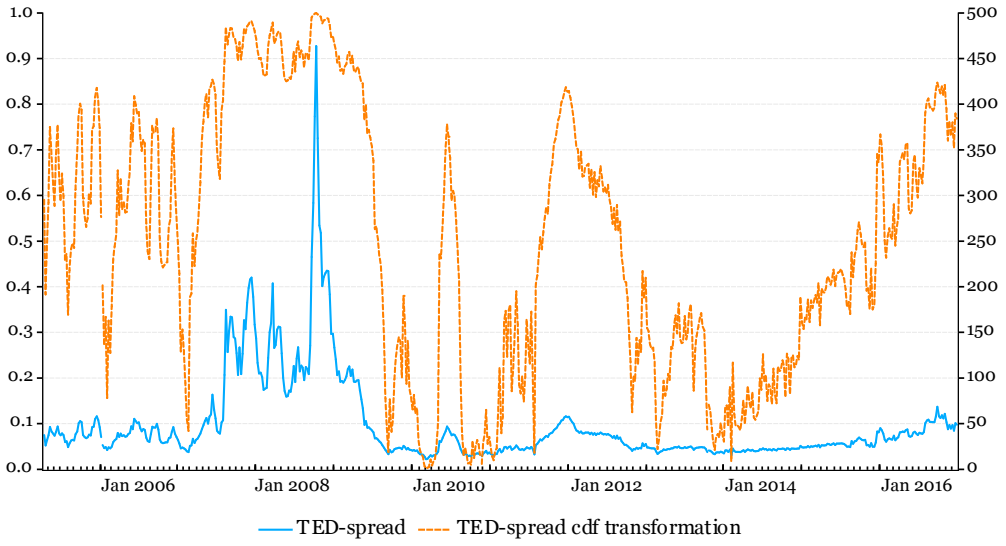
Note: * indicates lag order selected by the criterion . AIC is Akaike Information Criterion.

Table A3: *VAR Granger Causality under Block Exogeneity Wald Tests*

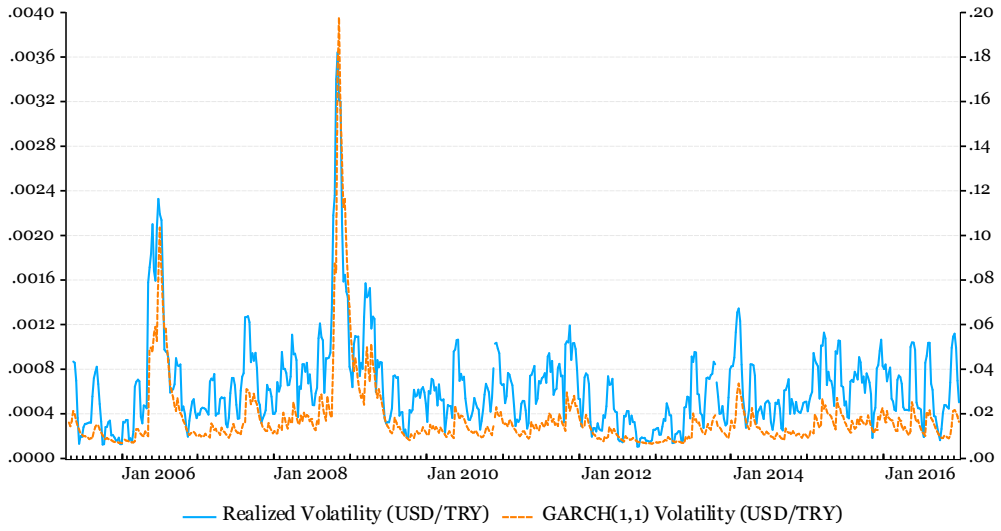
χ^2-Statistics / df [probability value]				
Dependent Variable	DIP		BCI	
Excluded				
Ind.1	10.80/[0.001]	0.33/[0.564]	12.40/2[0.002]	0.35/2[0.840]
Ind.2	13.01/[0.000]	0.40/[0.529]	14.69/2[0.001]	0.36/2[0.833]
Ind.3	13.23/[0.001]	2.21/[0.330]	22.96/2[0.000]	0.27/2[0.875]
Ind.4	15.75/[0.000]	2.93/[0.231]	22.75/2[0.000]	1.75/2[0.417]
Ind.5	1.52/[0.469]	2.44/[0.295]	5.26/2[0.072]	0.17/2[0.920]
Ind.6	11.75/[0.001]	0.31/[0.474]	11.29/2[0.004]	2.82/2[0.244]
Ind.7	25.95/[0.000]	0.55/[0.459]	20.79/2[0.000]	2.29/2[0.318]
Ind.8	25.86/[0.000]	0.61/[0.436]	20.29/2[0.000]	4.53/2[0.104]
Ind.9	24.51/[0.000]	6.29/[0.099]	20.04/2[0.000]	4.23/2[0.121]
Ind.10	24.48/[0.000]	6.47/[0.091]	23.70/2[0.000]	4.59/2[0.101]
Ind.11	9.25/[0.010]	2.64/[0.267]	11.91/2[0.000]	2.30/2[0.317]
Ind.12	9.10/[0.028]	1.91/[0.591]	12.35/2[0.002]	2.16/2[0.340]
Ind.13	17.62/[0.000]	2.52/[0.112]	16.51/2[0.000]	1.68/2[0.432]
Ind.14	26.30/[0.000]	0.06/[0.813]	30.17/2[0.000]	1.01/2[0.602]
Ind.15	12.16/[0.007]	4.86/[0.182]	3.60/2[0.000]	11.34/2[0.003]
Ind.16	22.50/[0.000]	4.38/[0.199]	16.33/2[0.000]	5.07/2[0.079]

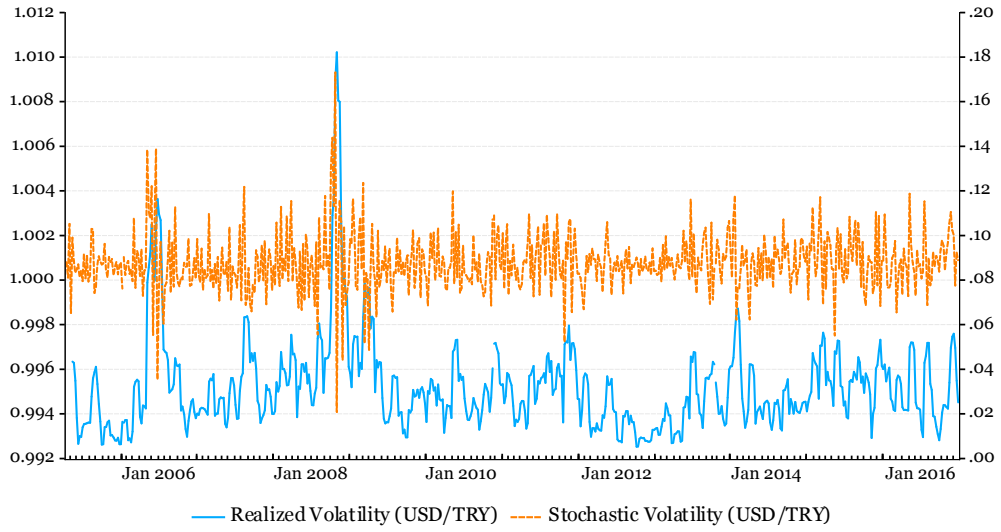
B Difference with respect to scaling



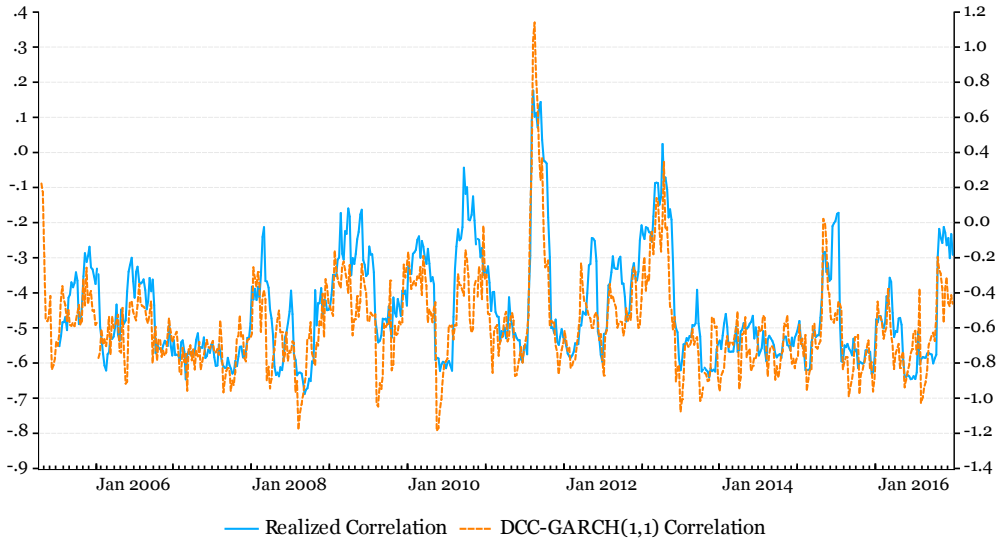


C Difference with respect to volatility measure





D Difference with respect to correlation measure–stock-bond correlation



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