Graduate Institute of International and Development Studies
International Economics Department
Working Paper Series

Working Paper No. HEIDWP15-2020

A New Financial Stress Index for Ukraine

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August 2020

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Abstract

This study improves on the methodology for calculating the financial stress index (FSI) for Ukraine by introducing time-varying correlation into the aggregation of 5 sub-indices (representing the banking sector, households, the corporate sector, government securities, and the foreign exchange (FX) market). The index consists of 20 indicators selected from an initial list of 47 potential candidates. To check the performance of the indicators, sub-indices, and index, we use area under the receiver operating characteristic curve (AUROC) and logit tests. Each sub-index is assigned a weight that reflects the impact of each market on the financial system. This new FSI peaks during periods of crisis that are in line with the consensus of financial experts and performs better than the previous FSI, which makes it more attractive for policy decisions. In particular, the new FSI can be used as a monitoring tool for the macroprudential policy of the National Bank of Ukraine.

JEL Code: E44, G01, G18

Keywords: financial stability, financial stress index, indicator performance

[1] The author would like to thank Professor Jean-Guillaume Sahuc for his valuable guidance and comments. The author is also grateful to the BCC program, the Graduate Institute (Geneva), and the National Bank of Ukraine for providing the data and resources used in this study, as well as the Swiss State Secretariat for Economic Affairs (SECO) for funding this research. The views expressed are those of the author and do not necessarily reflect those of the National Bank of Ukraine.

1. Introduction

The objectives of modern central banks, and of the National Bank of Ukraine in particular, are to ensure price and financial stability. The connections between these two objectives become more pronounced during periods of stress; the crisis in 2008-2009 is an example of such mutual relation. That is why the identification and assessment of risks to financial stability are some of the key functions of the central bank. Financial institutions develop financial conditions indices (FCIs) or financial stress indices (FSIs) to identify such systemic risks. The first FCI developed in the 1990s consisted of a small number of indicators. As financial markets became more complex, FSIs began to appear. The first inclusive FSI was developed by the Central Bank of Canada in 2003. After the financial crisis of 2007-2008, institutions started to develop their own versions of the financial stress index (FSI) more actively. For instance, Bank of America developed the Global Financial Stress Index and domestic Financial Stress Indices. The Federal Reserve Banks in the U.S. constructed several local indices (the Federal Reserve Bank of Kansas City's FSI, the Federal Reserve Bank of St. Louis' FSI, and the Federal Reserve Bank of Cleveland's FSI). Moreover, the initial methodologies have been constantly updated in Sweden, Canada and other countries. Hence, the FSI is a basic monitoring tool for financial institutions in 2020.

In 2017, the National Bank of Ukraine developed its own FSI aimed at quantitatively measuring the degree of turbulence in the financial sector. This index comprised 4 sub-indices (a banking sector sub-index, corporate sector sub-index, government securities sub-index, and FX market sub-index). The weights of each sub-index were set to be constant according to the volume of each market compared to GDP. However, the fixed weights for the aggregation of the sub-indices have some methodological weaknesses. This design implies that a substantial change in one indicator could cause a material surge in the FSI. Consequently, the FSI could produce signals that are misleading to stakeholders and could even increase uncertainty in the market. In essence, fluctuations in one or several indicators do not necessarily indicate stress in the financial sector as a whole and may send a false signal of increasing turbulence. The high volatility of the FSI due to spikes in the values of individual indicators distorts its explanatory power and makes the FSI less relevant and applicable for policy decision making. For instance, the current FSI includes the indicator "Index of Ukrainian stocks on the Warsaw Stock Exchange". There are approximately 6 companies traded on the Warsaw Stock Exchange, and the majority of them are agricultural companies. This means that a sectoral crisis in agriculture can significantly increase the FSI, even if there are no shocks to the other markets.

Conversely, a relatively high index even in peaceful periods can lead to underestimation of the stress level. First, the current FSI disregards spill-over effects. During a real crisis, one sector's stress may spread to the whole economy due to the domino effect. However, the constant-weights approach does not incorporate this co-movement between markets.

The current list of indicators used in the FSI is also questionable. This list is selected by expert judgement without tests of the indicators' explanatory power. After 3 years, we have observed that some of the indicators do not perform as desired; moreover, there is often a strong negative correlation between indicators. The contribution of such indicators to the estimates of the overall level of financial stress remains to be determined. Ex-post analysis gives us the opportunity to select the best stress indicators, exclude less significant indicators and add new indicators. Moreover, there have been several structural changes in the Ukrainian economy during recent years. First, an inflation targeting policy was implemented 5 years ago. Hence, the key interest rate now plays a major role in central bank policy. Second, a new monetary regime provided for a flexible foreign exchange (FX) rate. Before 2017, the Ukrainian economy had a fixed FX rate and primarily experienced periods of rapid currency depreciation during crises. Now, we can observe periods of currency appreciation that might also be a source of risk.

In this paper, we propose a new FSI for Ukraine. We improve the selection of indicators based on quantitative metrics rather than expert judgement. Moreover, we revise the normalization process and group indicators into sub-indices. To reduce the frequency of false signals, we use time-varying correlations instead of fixed weights for the sub-indices. These updates significantly increase the explanatory power of the index, which makes it more useful for policymaking.

The paper is structured as follows. Section 2 describes the historical development of FSIs and the most relevant examples of FSIs. Section 3 outlines the selection of indicators. Section 4 describes the alternative methodologies for the aggregation of indicators. The results of the paper are discussed in Section 5. Section 6 consists of policy recommendations and overall conclusions.

2. Literature review

The era of FSI development is divided into 2 phases: before the publication of the Composite Indicator of Systemic Stress (CISS) and after. During the era before the CISS was published, the first composite indices, such as the Canadian FSI, were introduced, each of which has a completely different methodology. It was as though every team of authors built their own house and no one built a second floor for others. The CISS is the index developed by the European Central Bank. The methodology behind this index created a backdrop for the evolution of other domestic FSIs. First, the methodology sets daily frequency data as the standard, with minimal delays to publication. Second, the authors significantly improved the methodology for raw indicator transformation. Moreover, the main contribution of the CISS authors was the use of time-varying correlations among sub-indices. The paper “Portfolio-Theoretic Framework for the Construction of Composite Financial Stress Indices” by Holló et al. (2012) describes this approach in detail.

The Swedish FSI methodology also adopts a time-varying correlation. The first version of the Swedish FSI (2011) uses a simple average of sub-indices as its aggregation process. However, Johansson and Bonthron (2013) improve on this methodology and make the Swedish FSI 2.0 more advanced. They use a method parallel to portfolio theory and use an exponentially weighted moving average (EWMA) to build a correlation matrix. Their analysis shows that the new FSI is a better measure of financial stress. The authors claim that the correlation of the sub-indices reinforces the magnitude of the index during crises and more clearly highlights stress periods.

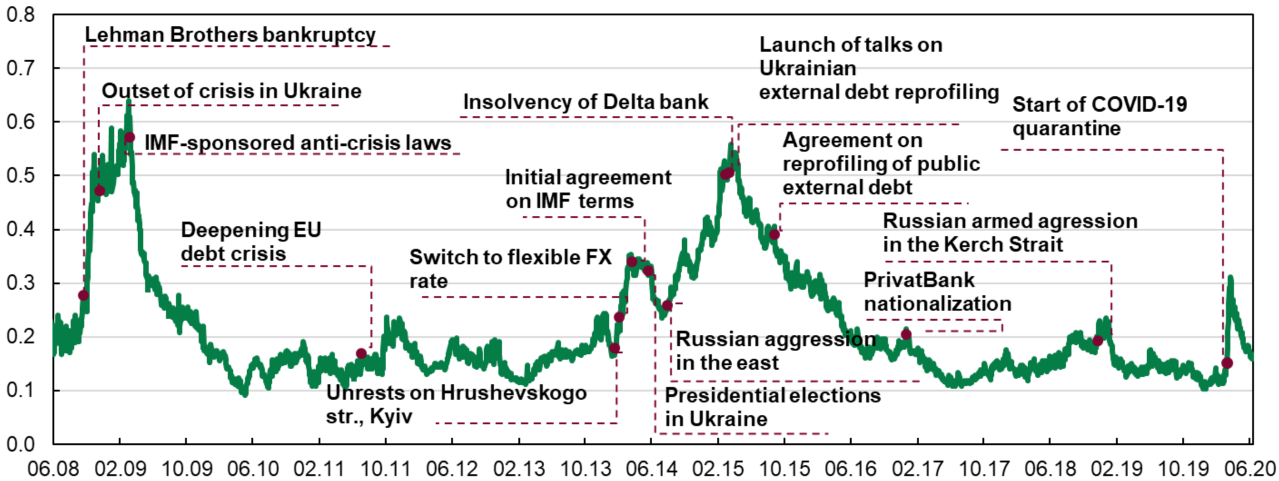
Chatterjee et al. (2017) use the basic ideas behind the CISS and improve the algorithm for indicator testing in the construction of the United Kingdom FSI. In particular, the authors use the area under the receiver operating characteristic curve (AUROC) and partial AUROC methodologies to test the indicators’ explanatory power. The dependent variable is a crisis dummy and the independent variables are normalized indicators. If an indicator has a high AUROC, it is a good crisis predictor. They test the EWMA and generalized autoregressive conditional heteroskedasticity (GARCH) approaches to construct the optimal dynamic correlation matrix to aggregate the sub-indices.

Duprey (2020) uses the Canadian FSI to estimate the relation between financial stress and GDP. The author suggests that a combination of economic decline and financial stress has the greatest negative impact on GDP. Duprey is also the co-author of the (2017) paper “Dating systemic financial stress episodes in the EU countries” that uses a methodology that is parallel to that of the CISS. Duprey et al. (2017) describe the general algorithm for FSI construction. On the one hand, their method is a substitute for the CISS because it describes different approaches to fix the same issue. The authors perform a more detailed robustness check of the index and deeply analyse the normalization of the indicators. On the other hand, their method is complementary to the CISS because they use the basic principle of the CISS, and in particular, their approach to sub-index aggregation is parallel to portfolio theory.

Vdovychenko and Oros (2015) suggested the first draft of the Ukrainian FSI. They use 4 sub-indices: banking, foreign exchange, the stock market and government debt. Each sub-index has only one indicator. On the one hand, the authors play with different specifications for the indicators, which may increase their explanatory power. For instance, for the banking sector, they use the first difference in log-transformed variables, and for the stock market, they use the GARCH model. On the other hand, the small number of indicators makes the index more volatile and less resilient to local shocks. Tyschenko and Csajbok (2017) go further and develop a modern version of the FSI in line with the practice of central banks all over the world. They follow Vdovychenko and Oros (2015) and also take 4 sub-indices: a banking sector sub-index, corporate sector sub-index, government securities sub-index, and FX market sub-index. To aggregate indicators within the sub-indices, the authors use a simple average, and to aggregate the sub-indices they use an average with constant weights. The authors test different methods of normalization such as the MINMAX range, cumulative distribution function, equal variance methods, and eventually choose the MINMAX range as their basis.

The graph of the Ukrainian FSI 1.0 by Tyschenko and Csajbok is provided below. In recent years, Ukraine has experienced several crises, such as the financial crisis of 2008-2009, the crisis in 2014-2015 caused by the war in the Donbas and the ongoing COVID-19 crisis in 2020. The FSI reacts to these periods with spikes. The highest level is 0.65; however, the crises in 2008-2009 and 2014-2015 are deep and comprehensive. Nevertheless, in Graph 1, we observe some volatility in the non-crisis periods, which is often driven by one factor. The average level of the index is approximately 0.22, even in periods of macroeconomic stability. These are the main weaknesses of the FSI performance we will overcome in this paper.

Graph 1. FSI for Ukraine, version 1.0



3. Data preparation and selection of indicators

In this section, we describe several steps. First, we determine the crisis periods. For this purpose, we use a dummy for GDP growth as a proxy for real economy developments and a survey of experts as a proxy for financial sentiments. After that, we test the ability of 47 candidate indicators to identify these crisis periods. Finally, we select the final list of the indicators that best identify the crisis events and group them into sub-indices.

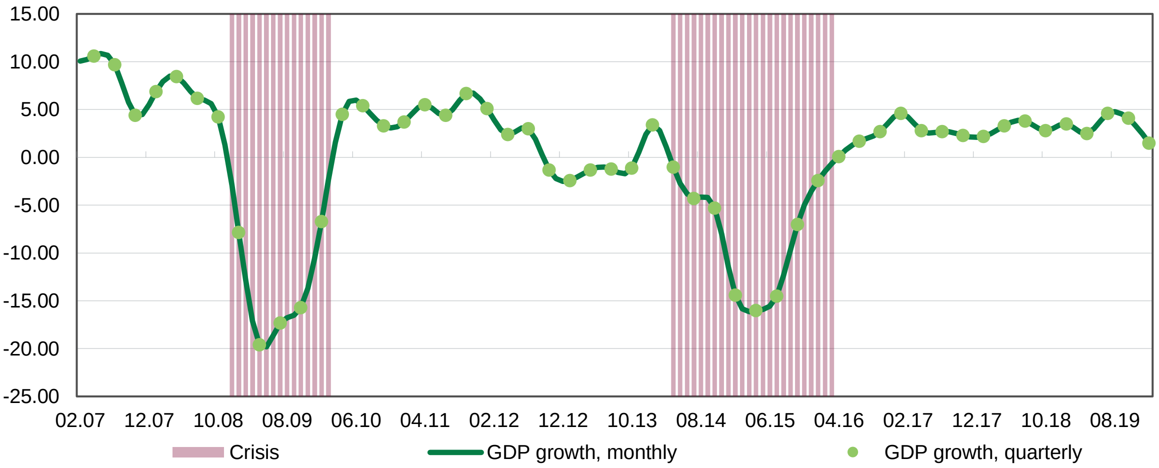
3.1. Determination of the crisis periods

The performance of FSI 1.0 has not been measured, which is one of its main problems. The index shows both upturns and downturns, but there is no evidence of a correlation between real stress and the FSI. To solve this problem, we create several crisis dummies. One is based on GDP growth data, and the other two are derived from a survey of financial experts. This creates a good tool to measure the performance of the index and makes us more confident in our final estimation.

3.1.1. GDP-growth crisis dummy

GDP growth is a worldwide indicator of economic performance. However, GDP growth data are quarterly, which is too infrequent to create a dummy. Therefore, we use cubic spline interpolation to convert quarterly data to monthly data. A GDP decline (y-o-y) that lasts for more than 4 quarters indicates a crisis. In Graph 2, we can observe the monthly interpolation of GDP growth.

Graph 2. Cubic spline interpolation of GDP growth in Ukraine



3.1.2. Expert survey dummies

Using only the GDP growth dummy, one obtains some controversial results. In general, financial stress correlates with GDP growth; however, there are also sometimes lags between financial and economic crises. In fact, financial markets react to shocks and start to recover from them earlier than economic markets. Therefore, additional dummies were developed based on experts' judgements on the periods of financial stress.

Eight Ukrainian financial experts from investment institutions, banks, analytical centres, universities and government institutions were surveyed about periods of crisis, particularly regarding the month in which the crises began and ended. We also asked about the worst months during the crisis. The value 1 was assigned to a dummy variable for any month that was marked as a crisis or crisis peak by more than three experts. As a result, we obtain a GDP growth dummy, survey crisis dummy and survey crisis peaks dummy. More details about the dummies are in Appendix C.

3.2. Selection and grouping of indicators

The selection of indicators is the basis for index development. If indicators are selected in the wrong way, the subsequent steps will not make practical sense. That is why this step is the most time-consuming and important. According to the current methodology and common practice for the majority of domestic FSI, indicators are selected by a rule of thumb. Riksbank and ECB selection methodologies are also based on expert judgements. However, in the UK's FSI, the authors introduce an econometric approach to verify whether the selected indicators are statistically relevant or not. They proposed using a partial AUROC methodology to measure the explanatory power of each indicator.

Our selection process consists of several steps:

1) Form a pool of all potential indicators.
First, we take all the indicators from FSI 1.0. Second, we add all the relevant indicators from other countries' FSIs. As a result, there are both classical financial stress indicators as well as the retail price for gasoline and price of Brent crude oil in the pool of potential indicators. At this step, we reject indicators only in the case of missing data. Third, we add different terms for each indicator when possible. For instance, we include the price of Ukrainian Eurobonds credit default swaps for 6 months, 1 year, 2 years, 5 years, and 7 years. As a result, the pool of potential indicators consists of 47 items. Then, we consider the different specifications of the indicators. For example, we add both the value of the indicator and its simple 30-day moving average.
2) Estimate logistic regressions (logit) using the GDP crisis dummy and the indicators.
We construct a single-factor logit with the GDP growth dummy variable as the dependent variable and the potential indicators as the independent variables. Indicators were preliminarily transformed into monthly data by averaging the daily data.
We use binary logistic regression with one predictor:

$$log\frac{p}{1-p} = \beta_0 + \beta_1 x_1, \tag{1}$$

where p is the probability of a crisis (crisis=1), $\beta_{0,1}$ are parameters, and x_1 is an indicator.
For each logit regression, we recorded the p-values and group together the indicators that were highly significant (P-value $\leq$ 1%), significant (1% < P-value $\leq$ 10%) and insignificant (P-value > 10%).

3) Estimate the AUROC of the indicators for each dummy.
There are three dummies in our list: the GDP growth dummy, survey crisis dummy, and survey crisis peaks dummy. We estimated the AUROC of each indicator for each dummy. A high AUROC value means that the indicator explains the crisis well and produces minimal false signals in normal times. Chatterjee et al. (2017) use a loss function based on AUROC metrics in the UK's FSI.

$$L(\theta) = \theta T_1 + (1-\theta)T_2, \tag{2}$$

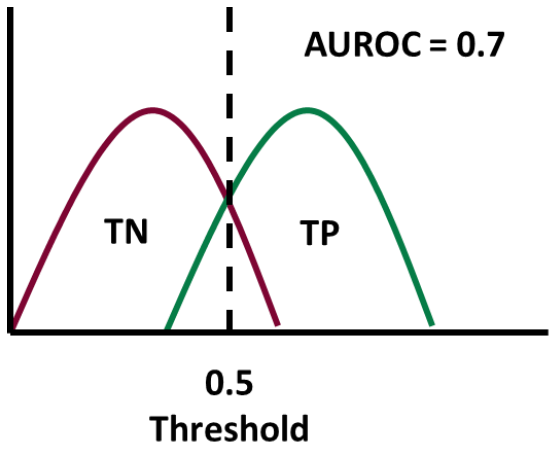
where T_1 is the Type I error rate and is given by C/(A+C). Similarly, T_2 is the share of Type II errors B/(B + D).
Values for A, B, C, and D:

	crisis	no crisis
above threshold	A	B
below threshold	C	D

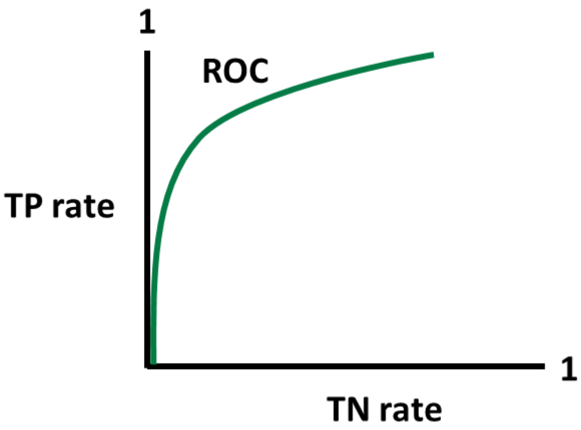
where A is a true positive (TP), and D is a true negative (TN).

Graphs 2 and 3 show the overlap in true positive signals and true negative signals. An AUROC value of 0.7 means that there is 70% chance that the model correctly distinguishes between crisis events and no crisis events.

Graph 3. Overlap of true negative and true positive in an AUROC analysis



Graph 4. AUROC curve example



We obtain an AUROC estimate for all potential indicators with the full data available. Table 1 presents the results of the AUROC estimations.

Table 1. Minimum, maximum and average values of the AUROC

	GDP growth	Survey Crisis	Survey Crisis Peaks
MEAN	0.8232	0.786	0.836
MIN	0.3575	0.44	0.56
MAX	0.9922	0.967	0.97

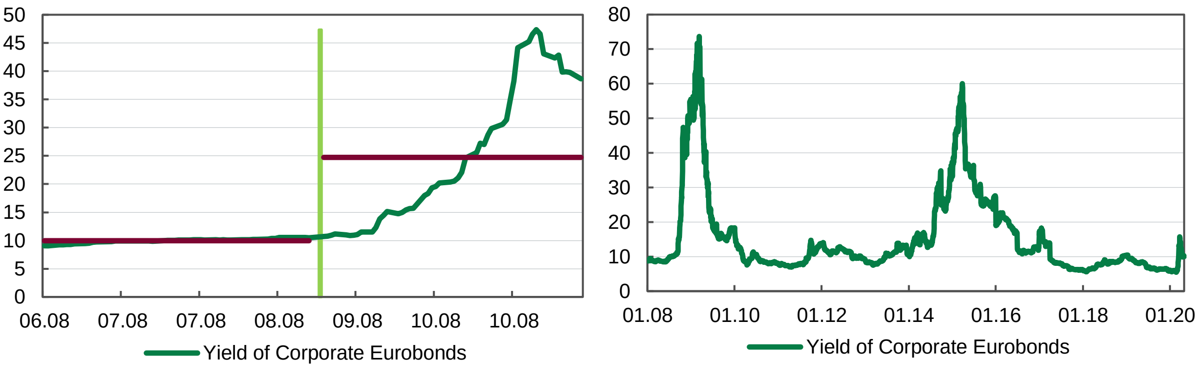
The average values of the AUROC are close to each other. The overall average value of the AUROC is 0.8, and we use this as a reference when making further decisions.

4) <u>Comparing indicators' standard deviation and mean for 2 months before the start of the crisis and the first 2 months during the crisis.</u>
   We use data for the three crises: 2008-2009, 2014-2015, and 2020. For each indicator, we calculate its standard deviation and mean for 2 months before the start of each crisis and the first 2 months during the crisis.

We assume that during the crisis, the standard deviation increases significantly. The mean value must increase if the indicator is positively correlated with the crisis and vice versa. The indicator passes this test if the difference between the means and standard deviations in peaceful and crisis periods is higher than the standard deviation for the whole observed period. This should be true for all three crises.

5) Graphical analysis of indicators.
Graphical analysis was conducted for the whole observation period, as well as for each crisis. Indicators that were marked as "Good" have low volatility before the crisis and react immediately to the crisis[2]. For instance, see the performance of the YTM of Corporate Eurobonds in Graph 5.

Graph 5. YTM of Corporate Eurobonds in 2008 and in all periods



After all selection steps are completed, we finalize the list of indicators. The indicator is selected for the final list if it passes all stages: it is significant in the logit regression with the GDP growth dummy; its AUROC is higher than 0.8 for all 3 dummies; the standard deviation and mean before the crisis and during the crisis differ significantly; and finally, it shows intuitive dynamics during the stress periods. We also choose only one indicator from among similar indicators (for instance, the CDS 5-year spread and CDS 2-year spread).

Based on the final list of indicators, we decide to group them into 5 sub-indices: the 4 sub-indices from FSI 1.0 and a new one: the household behaviour sub-index. This new sub-index shows the reaction of households to stress events. In crises, households start to withdraw money from deposits, which increases the financial market's liquidity risk. Moreover, banks increase deposit rates to reduce this outflow, which creates additional interest rate risk.

All indicators grouped by sub-indices are presented in Table 2.

[2] The first month of each crisis is chosen with the use of survey crisis dummy. Within these months, we found the days when FSI 1.0 started to react. These days were marked and the indicators' reactions were tested on these days.

Table 2. The final list of indicators

Name of indicator	Description
BANKING sub-index	
Ukrainian OverNight Index Average (UONIA)	Change in the overnight interbank interest rate. Calculated by the National Bank of Ukraine.
Kiev interbank bid and offer rates (KIEIBOR), 1-month	Change in the interbank rate for a 1-month term. Calculated by the Association of Ukrainian Banks.
Price of Ukrainian banks' Eurobonds	Price of Eurobonds issued by Oschadbank, Ukreximbank, First Ukrainian International Bank, and PrivatBank (until the bail-in in December, 2016).
Liquidity coverage ratio (LCR)	An average of banks' LCR, weighted by expected outflows in the LCR denominator.
Support of NBU to banks	Amount of the National Bank of Ukraine's liquidity support transactions for the last 60 days. Only transactions with terms less than 90 days are included.
GOVERNMENT DEBT sub-index	
Ukrainian credit default swaps (CDS), 5-year	Price of 5-year CDS of Ukrainian sovereign bonds.
Sovereign risk of Ukrainian Eurobonds	The spread between the weighted average yield of Ukrainian Eurobonds and the yield on 10-year US Treasury bonds.
Yield of domestic bonds in UAH	A simple average of yield-to-maturity for Ukrainian domestic bonds in UAH.
Bid-ask spread of Ukrainian Eurobonds	A simple mean bid/ask spread of Ukrainian Eurobonds on a given date.
HOUSEHOLD BEHAVIOUR sub-index	
Ukrainian Index of Retail Deposit Rates (UIRD), 3-month	Change in retail 3-month deposit rates in UAH of the 15 largest banks. Calculated by Thomson Reuters.
Change of retail deposits in UAH	The percentage change in the stock of retail deposits in UAH over the last 30 days.
Change of retail deposits in USD	The percentage change in the stock of retail deposits in USD over the last 30 days.
CORPORATE sub-index	
Yield of corporate Eurobonds	Corporate bonds yield-to-maturity for Ukrainian enterprises. Calculated by Cbonds Agency.
Stock index	Deviation of stock index from its maximum over the last year. The PFTS Index is used before 2012 and the Stock Index on the Warsaw Stock Exchange (WIG Ukraine) afterwards.
Volatility of stock index	The standard deviation of the stock index over the last 30 days. The PFTS Index is used prior to 2012 and the Stock Index on the Warsaw Stock Exchange (WIG Ukraine) afterwards.
FOREIGN CURRENCY MARKET sub-index	
USD/UAH exchange rate	Deviation of the USD/UAH exchange rate from the maximum over the last year.
Volatility of USD/UAH exchange rate	The volatility of the USD/UAH exchange rate over the last 30 days.
Expectations for national currency devaluation	The difference between the non-deliverable forward (NDF) of UAH/USD for 3-month and spot UAH/USD exchange rates.
Yield of non-deliverable forward, 3-month	Change in the yield-to-maturity of 3-month UAH/USD NDFs.
Currency intervention of the NBU	The net purchase/sale of foreign currency by the NBU on the interbank FX market.

4. Methodology for the index composition

4.1. Normalization of indicators and their aggregation to the sub-indices.

Each indicator has different units of measurement, which is why we normalize them. Following the literature, we test several approaches. One of them is the cumulative distribution function, an approach that, for Ukrainian data, gives many noisy and false signals. This is due to the high volatility of Ukrainian markets even in normal times. This method may be appropriate for developed economies; nonetheless, it is not applicable for emerging markets such as Ukraine. Another method is Z-score normalization, which Lang et al. (2019) use in the development of domestic systemic risk indicators. This method of normalization gives us stable, expected and logical results. It is not sensitive to outliers and does not create much noise.

The formula for Z-score normalization is:

$$\frac{X_{i,t} - \mu_i}{\sigma_i}, \qquad (3)$$

where μ_i is the mean value of the indicator and σ_i is the standard deviation of the indicator.

Another approach, MINMAX-range normalization, gives similar results. The weakness of this method is a need for retrospective recalculation when a new value appears that is historically the highest or the lowest observed.

The formula for MINMAX-range normalization is:

$$\frac{(X_{i,t} - MIN_i)}{(MAX_i - MIN_i)}. \qquad (4)$$

Comparing these two methods, we have decided to use MINMAX because this method gives a complete and finite range [0:1], while Z-score values may be outside of this range. Second, we use this method in our FSI 1.0; therefore, we have decided to continue its use in the new FSI for Ukraine (FSI 2.0) to ensure the results are comparable.
To compose each sub-index, we use a simple average of the normalized indicators. This is common practice for FSI methodologies, and it decreases the probability of one indicator dominating the index.

4.2. Weights for sub-indices.

Regardless of the aggregation approach, we need to start with a fixed weight for the sub-indices. There are several approaches to estimate the weights.

Tyschenko and Csajbok (2017) describe one approach. They choose weights based on the importance of a sector according to its size relative to GDP. Lang et al. (2019) propose using the regression approach to estimate the weight of each sub-index. The authors estimate regression coefficients and divide each coefficient by the sum of all coefficients. There are other methods, for instance, estimation by pairwise vector autoregressive models (VARs) with GDP; however, this method is not suitable for short samples.

In this research, we replicate the estimations of sector size proposed by Tyschenko and Csajbok (2017). We also use Lang et al.'s (2019) approach. However, a logit model that includes all sub-indices gives us unstable and unintuitive results that could be a sign of multicollinearity. This is why we estimate a single-factor logit for each sub-index. After that, we sum the coefficients of the five logit regressions to find the weight for each sub-index.

For weight robustness checks, we use AUROC to test each sub-index. A sub-index with a higher AUROC should receive a higher weight. For instance, even if the ratio to GDP approach and the logit-regression approach assign low weights, we can increase the weight if the AUROC is high. Hence, a robustness check with AUROC gives us more information for the final weight calibration.

We use such metrics to compare sector size to GDP (ratio to GDP) for each market and sub-index:

1) Banking sub-index—the total volume of loans to residents (non-financial corporations and households);
2) Household behaviour sub-index—the volume of household deposits;
3) Corporate sub-index—the sum of stock market capitalization and the volume of the corporate bond market. This value was taken from Tyschenko and Csajbok (2017), which was estimated for FSI 1.0;
4) Government debt sub-index—the volume of outstanding local-currency sovereign bonds and sovereign Eurobonds;
5) Foreign currency market sub-index—the share of financial assets and liabilities in foreign currency (loans and deposits dollarization).

Table 3 summarizes the results of the estimation based on several approaches.

Table 3. Estimation of weights for sub-indices

Sub-indices	Banking	Household behaviour	Government debt	Corporate	Foreign currency market
Logit-regression coefficient adjusted	19.5%	13.5%	20.8%	22.0%	24.2%
Ratio to GDP	20%	12%	26%	10%	32%
FSI 1.0	30%		25%	10%	35%
AUROC for survey crisis dummy	0.83	0.77	0.92	0.91	0.90
AUROC for survey crisis peaks dummy	0.87	0.84	0.87	0.94	0.92
RESULTS	**20%**	**15%**	**20%**	**20%**	**25%**

The final weights are based on all values mentioned above. There is no doubt about the weights for the banking and household behaviour sub-indices, as all values show similar results[3]. The weight for the foreign currency market sub-index varies in the range from 24.2% to 32%. Based on the AUROC results, we decided to choose 25%. Moreover, FX risks have decreased in recent years in Ukraine. The final reallocation of weight is between the government debt and corporate sub-indices. The AUROC for the corporate sub-index is the highest, which is why we take the value from the high end of the 10-22% range. Correspondingly, we choose the minimum value for the government debt sub-index.

4.3. Aggregation of sub-indices

[3] In FSI 1.0, banking sub-index consists of indicators for the banking and household behaviour sub-indices in the new FSI. The total weight of these sub-indices now is 35% compared to 30% in FSI 1.0.

The next step is to aggregate the sub-indices. A review of other index methodologies shows us different approaches that can be generalized into several groups. The first group of authors uses a simple or weighted average to aggregate the sub-indices. Easy interpretability and understandability are the main advantages of this method. However, a significant disadvantage is the sensitivity of the index to changes in one sub-index and underestimation of the synergistic relationships between variables. The second group of authors experiment with different models, such as factor augmented VARs and principal component analysis. These approaches have the best performance in particular countries and are able to account for some features of those countries. However, they are very often not useful for other countries. The last group of authors use an approach that is based on portfolio theory. We decide to estimate the FSI using a weighted-average method and the portfolio theory method.

4.3.1. The weighted-average approach to aggregation

The weighted-average aggregation approach is currently used in FSI 1.0.

$$FSI_t = \sum_1^i s_{i,t} \times w_i, \tag{5}$$

where $s_{i,t}$ is the value of sub-index *i* in period *t* and w_i is the weight of sub-index *i.*

In this case, the weights of the sub-indices are stable. However, in reality, the impact and size of each market may change over time. For example, government debt-to-GDP in 2008 and in 2016 are completely different. This means that after structural changes in the economy, we should re-estimate these weights to obtain precise estimates.

4.3.2. Portfolio theory approach to aggregation

The main innovative feature in the design of the CISS is the use of portfolio theory for sub-index aggregation. After the introduction of the CISS, many other institutions have considered portfolio theory for their domestic indices. Today, the Swedish FSI, UK FSI, European CISS, European FSI by Duprey et al. (2017), and Canadian FSI use this methodology:

$$FSI_t = (s_t \times w)\, C_t\, (s_t \times w)^T, \tag{6}$$

where s_t is the vector of the values of the sub-indices in period *t*, w is the vector of weights for the sub-indices and C_t is the dynamic correlation matrix for the sub-indices in period t, given by:

$$C_t = \begin{bmatrix} 1 & & & & \\ \rho_{12,t} & 1 & & & \\ \rho_{13,t} & \rho_{23,t} & 1 & & \\ \rho_{14,t} & \rho_{24,t} & \rho_{34,t} & 1 & \\ \rho_{15,t} & \rho_{25,t} & \rho_{35,t} & \rho_{45,t} & 1 \end{bmatrix}, \tag{7}$$

Where $\rho_{ji,t}$ is the correlation between sub-index *j* and sub-index *i* in year *t*.

We can obtain this correlation matrix in different ways. As already mentioned, the exponentially weighted moving average (EWMA) and multivariable dynamic conditional correlation GARCH (DCC-GARCH) are among them.

<u>EWMA</u>

Exponentially weighted moving average is a moving average model. It allows for larger reactions to recent changes. The β-s parameter corresponds to the memory of the process. The higher this parameter is, the more resistant the correlation matrix is to recent data.

$$\rho_{ji,t} = \sigma_{ji,t}/\sigma_{i,t}\sigma_{j,t} \tag{8}$$
$$\sigma_{ji,t} = \beta\sigma_{ji,t-1} + (1-\beta)z_{i,t}z_{j,t} \tag{9}$$
$$\sigma_{i,t}^2 = \beta\sigma_{i,t-1}^2 + (1-\beta)z_{i,t}^2 \tag{10}$$

In line with Hollo et al. (2012), we test different values for β-s. The range of β-s is from 0.89 to 0.98. The authors of the UK FSI and Swedish FSI also use a β-s value from this range. Graph 6 shows the results of aggregation for β=0.89, β=0.93, and β=0.97.

Graph 6. EWMA aggregation with different values of β

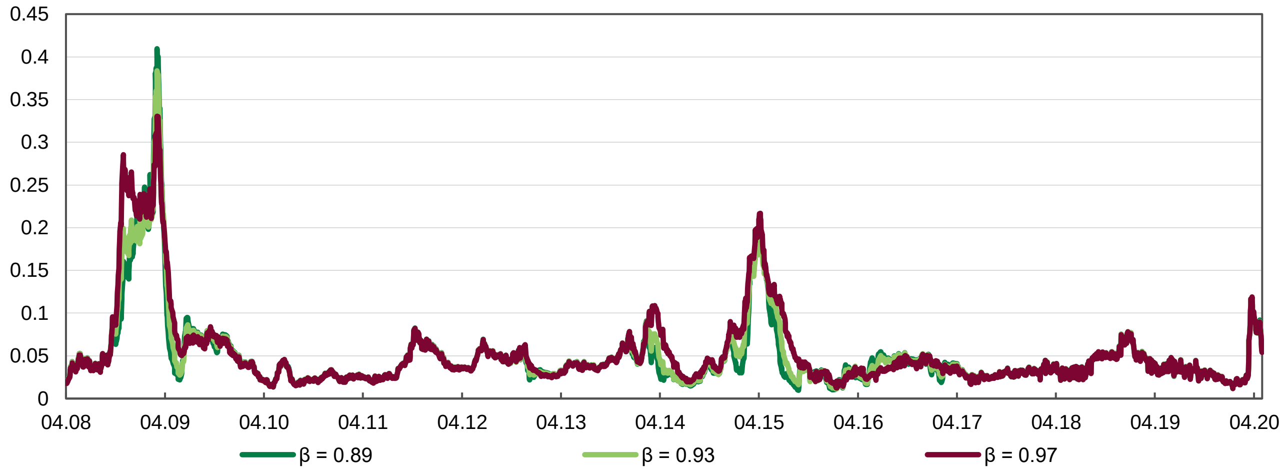


Table 4 reports the AUROC results applied to these alternative indices. We observe that β=0.97 is the value that gives the highest AUROC value. Moreover, the index calculated using this parameter best explains the crisis in 2014-2015. Other parameters show that stress in 2008-2009 is 2 times larger than in 2014-2015; however, real data show that in 2014-2015, at least the same level of stress was observed as in 2008-2009. Setting the value of β to 0.97 allows us to reproduce this empirical observation.

Table 4. AUROC testing of EWMA results with different parameters

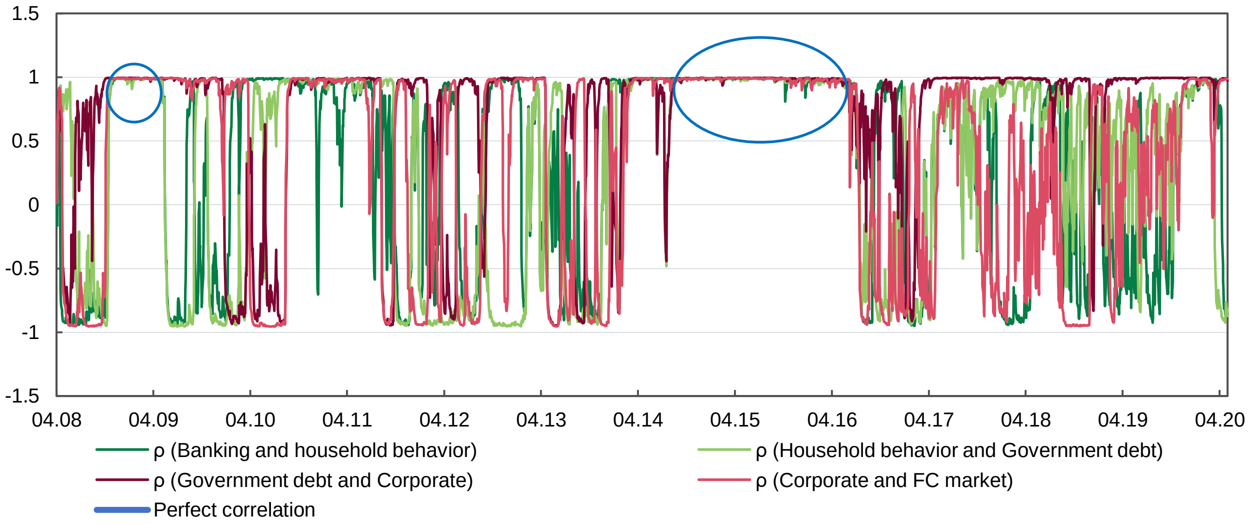
	Survey Crisis	Survey Crisis Peaks
β=0.89	0.771	0.808
β=0.91	0.794	0.833
β=0.93	0.816	0.863
β=0.95	0.84	0.898
β=0.97	**0.874**	**0.946**

DCC-GARCH

The dynamic conditional correlation (DCC-) GARCH was introduced by Engle and Sheppard in 2001. Following Chatterjee et al. (2017), we use GARCH (1,1). The model includes 2 parameters (α,β), and we estimate them using the full sample. Details of the methodology are described in Appendix A. The results of the model estimation are presented in Appendix B.

With the use of this approach, we obtain a dynamic correlation matrix. In Graph 7, we can see periods of almost perfect correlation among the sub-indices where the correlation in the sub-indices reinforces the direct effect of sub-indices. Periods of perfect correlation are observed during the crises. During normal times, correlations between sub-indices usually decrease.

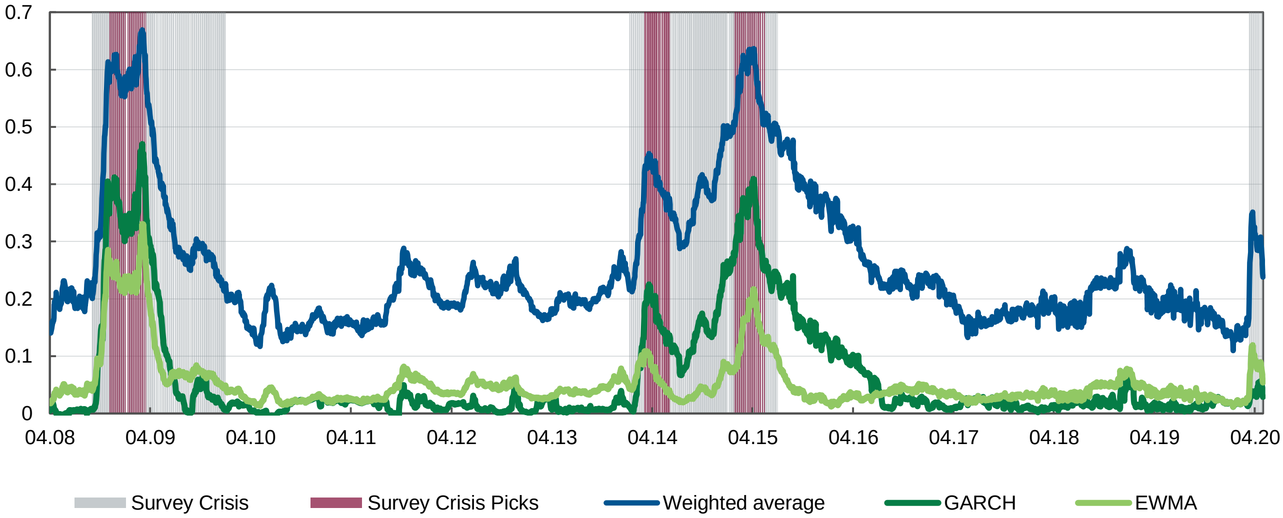
Graph 7. Correlation of sub-indices



5. Results

Graph 8 reports the values of the three indices calculated using different approaches to the sub-index aggregation. However, first impressions may be misleading. In the graph, the weighted-average approach shows the highest level of stress during the crises; however, we should consider the specifics of each method. The weighted-average approach assumes perfect correlation between all sub-indices in all periods. Moreover, it is calculated using simple averaging, while two other methods require multiplication. This is why the EWMA and GARCH approaches by default have lower values than the weighted average approach, including during crisis periods.

Graph 8. Comparison of indices



As the direct graphical comparison is inaccurate in this situation, we use other approaches to investigate the pros and cons of each index.

We consider several aspects:

1) values during the crisis of 2008-2009 ("+" if the index produces high values);

2) values during the crisis of 2014-2015 ("+" if the index produces high values);

3) values during the crisis of 2020 ("+" if the index produces medium values, as currently the impact of the crisis on the financial sector in Ukraine is moderate);

4) volatility during normal times ("+" if the index has low volatility during normal times);

5) peaks in crisis ("+" if the index identifies the peaks);

6) AUROC robustness checks.

In Table 5, we can observe the comparison of the indices.

Table 5. Comparison of aggregation methodologies

	Crisis 2008-2009	Crisis 2014-2015	Crisis 2020	Volatilities during normal times	Peaks in crises	AUROC Survey Crisis	AUROC Survey Crisis Peaks
Weighted average	+	+	+	–	+–	0.939	0.978
EWMA	+	–	+	+ –	+ –	0.874	0.946
GARCH	+	+	+ –	+	+	0.886	0.978

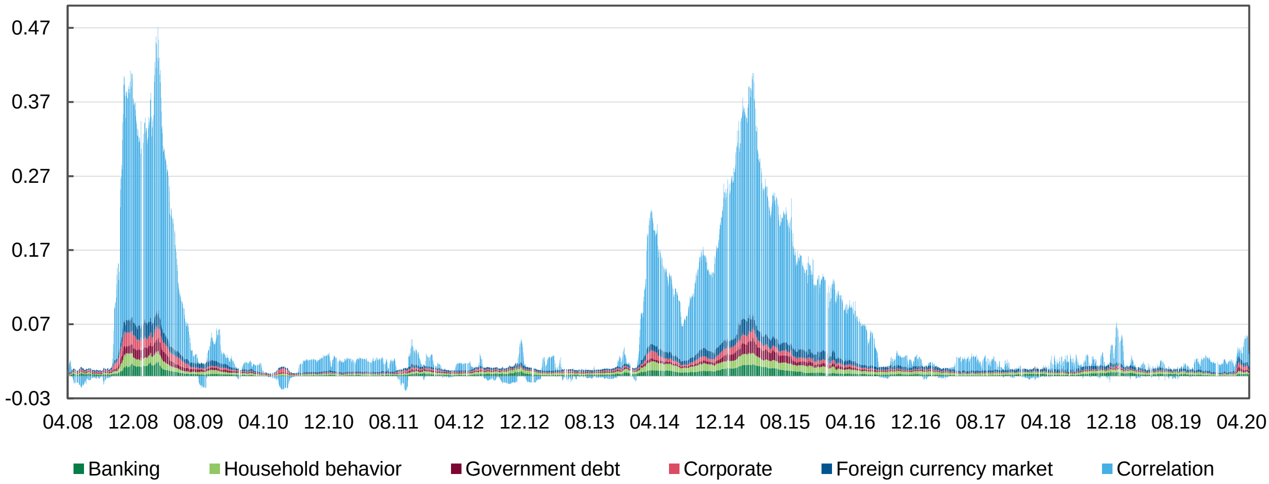
Based on these metrics, we decided to use the GARCH approach for aggregation. The main reason is that it generates fewer false signals during normal times and higher values during crises. The purpose of the index is to show the magnitude of the stress in the whole financial sector, not for one specific sector. To make the selected index more visually attractive, we normalize it with the use of the MINMAX methodology. This is done to (i) eliminate the negative values in the FSI, (ii) make the index more attractive: a range from 0 to 1 is much easier to interpret than a range from -0.1 to 0.5, and (iii) simplify the transition from FSI 1.0 to FSI 2.0.

Graph 9 shows the final version of FSI 2.0, noting the main economic and political events. We can observe that after the Lehman Brothers bankruptcy, the index spikes drastically. We can also see a useful insight for policymakers: the peak of the crisis in 2014-2015 is just before the talks on Ukrainian external debt reprofiling were launched. However, FSI 2.0 has not reacted significantly to the COVID-19 quarantine, while the FSIs of other European countries have experienced a significant leap. The reason could be that the effect of the COVID-19 crisis is currently much lower for the Ukrainian financial sector than that of previous crises.

Graph 9. The final version of the FSI 2.0

The decomposition of the index shows us a variety of insights. It depicts the impact of the estimated time-varying correlation on the index value compared to the zero-correlation assumption. Graph 10 shows that correlation matters the most when using the GARCH approach; it accounts for approximately 80% of index values in crisis times. However, in times of macroeconomic stability, the correlation is low or even negative, which is intuitively expected.

Graph 10. Decomposition of FSI 2.0



6. Conclusions and policy recommendations

In this paper, we build a new FSI for Ukraine, called FSI 2.0, with the objective of improving the performance of this tool that has become popular among Ukrainian and international institutions, experts, and analysts. The new FSI consists of 20 indicators grouped into 5 sub-indices (banking, household behaviour, government debt, corporate, and foreign currency market) and gives the opportunity to interpret their respective effects. The aggregation of the sub-indices is based on a dynamic conditional correlation (DCC) multivariate generalized autoregressive conditionally heteroscedastic (MGARCH) model. This methodology implies that the FSI shows significant growth only if several sub-indices demonstrate growth. In other words, it is not sensitive to one-factor movements.

This new FSI allows policymakers to more accurately assess the level of stress in real-time. In particular, it can be useful for determining anti-crisis policies of the central bank when timely reactions are very important. Currently, the NBU uses the FSI to monitor the ongoing situation due to the COVID-19 restrictive measures and to measure the level of systemic risk in the financial sector, particularly for decision making on FX control measures. From a macroprudential point of view, the FSI may trigger the release of the countercyclical capital buffer.

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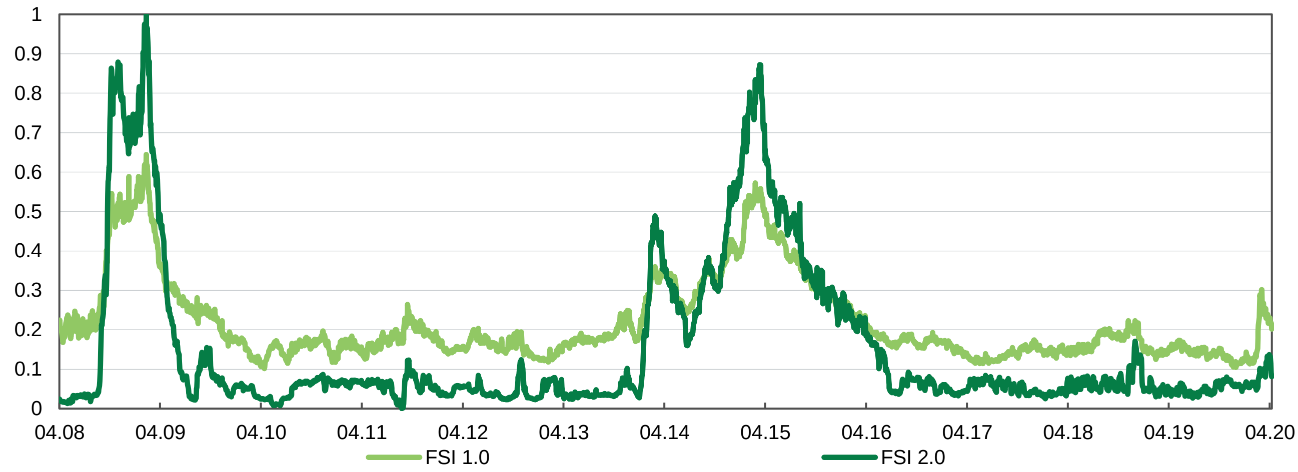
Appendix A

Graph A.1. Comparison of FSI 1.0 and FSI 2.0



FSI 1.0 and FSI 2.0 both increase during crisis periods. Moreover, their reactions generally coincide.

However, there are significant differences between the two indices. We can observe that FSI 1.0 stays at a level of approximately 0.2 in normal times, while the FSI 2.0 normal level is only 0.05. There is also a significant difference in magnitudes during crises. The value of FSI 1.0 in crises is 3 times higher than in normal times, while FSI 2.0 demonstrates up to a 10-fold jump during crises.

This means that by using the FSI 2.0, policy-makers will receive fewer false signals of crisis in normal times, and it should see an undoubtedly higher level of stress during a crisis.

Appendix B

According to the Stata Manual:

DCC-MGARCH estimates the parameters of dynamic conditional correlation (DCC) multivariate generalized autoregressive conditionally heteroscedastic (MGARCH) models in which the conditional variances are modelled with the use of univariate generalized autoregressive conditionally heteroscedastic (GARCH) models and the conditional covariances are modelled as nonlinear functions of the conditional variances. The conditional quasi-correlation parameters that weight the nonlinear combinations of the conditional variances follow the GARCH-like process specified in Engle (2002).

According to Elisabeth Orskaug (2009):

The dynamic conditional correlation GARCH model is defined as:

$$r_t = \mu_t + a_t \quad (1)$$

$$a_t = H_t^{1/2} z_t \quad (2)$$

$$H_t = D_t R_t D_t \quad (3)$$

Notation:

r_t: n × 1 vector of log returns for n assets at time t.

a_t: n × 1 vector of mean-corrected returns for n assets at time t; i.e., $E[a_t]$ = 0 and $Cov[a_t]$ = H_t.

μ_t: n × 1 vector of the expected value of the conditional r_t.

H_t: n × n matrix of conditional variances of a_t at time t.

$H_t^{1/2}$: Any n × n matrix at time t such that H_t is the conditional variance matrix of a_t. $H_t^{1/2}$may be obtained by a Cholesky factorization of H_t.

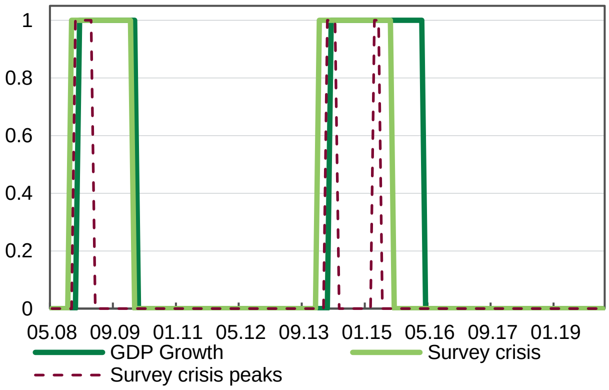
D_t: n × n, diagonal matrix of conditional standard deviations of a_t at time t.

R_t: n × n conditional correlation matrix of a_t at time t.

z_t: n × 1 vector of iid errors such that $E[z_t]$ = 0 and $E[z_t z_t^T] = I$.

Appendix C

Graph C.1. Dummies for crises



Graph C.1 shows the values of 3 dummies. The GDP growth dummy is a proxy for real economic development. We estimate GDP growth on a monthly basis. Values significantly less than 0 are considered a crisis. The survey crisis and survey crisis peaks dummies are proxies for financial sentiments. We calculated these values using a survey of eight Ukrainian financial experts. The GDP growth and survey crisis dummies are similar during the 2008-2009 crisis. However, in 2014-2015, the survey crisis dummy indicates an earlier beginning and end to the crisis. We can conclude that the GDP growth dummy is somewhat lagged relative to the survey crisis dummy. This is reasonable because financial markets react to shocks rapidly, while the real economy reacts with inertia.

The financial stress index shows stress in the financial system, which is why we used the survey crisis and survey crisis peaks dummies to guide final decisions on the construction of the index.

Appendix D

This appendix reports the estimates of the dynamic conditional correlation MGARCH model.

Sample: 4/1/2008 - 4/30/2020, but with gaps	Number of obs	=	2,988
Distribution: Gaussian	Wald chi2(.)	=	.
Log likelihood = 28769.66	Prob > chi2	=	.

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Bank						
_cons	.1963962	.0010779	182.20	0.000	.1942835	.1985088
ARCH_Bank						
arch L1.	1.052678	.0230972	45.58	0.000	1.007409	1.097948
garch L1.	.0078573	.0019864	3.96	0.000	.003964	.0117506
_cons	.0001587	.0000145	10.92	0.000	.0001302	.0001872
House						
_cons	.4152186	.0033426	124.22	0.000	.4086672	.42177
ARCH_House						
arch L1.	1.026288	.0245627	41.78	0.000	.9781464	1.07443
garch L1.	.0223549	.0064762	3.45	0.001	.0096618	.0350481
_cons	.0005937	.0000561	10.58	0.000	.0004837	.0007036
Gov						
_cons	.1255739	.0014005	89.66	0.000	.122829	.1283188
ARCH_Gov						
arch L1.	1.092741	.0243771	44.83	0.000	1.044963	1.14052
garch L1.	.0022359	.0013509	1.66	0.098	-.0004119	.0048837
_cons	.0001512	.0000133	11.40	0.000	.0001252	.0001772
Corp						
_cons	.1258361	.0015623	80.54	0.000	.122774	.1288982
ARCH_Corp						
arch L1.	1.065097	.0233514	45.61	0.000	1.019329	1.110865
garch L1.	-.0007316	.0010762	-0.68	0.497	-.0028409	.0013776

```
           _cons |   .0001448    .000014    10.35   0.000     .0001174    .0001722
-----------------+----------------------------------------------------------------
FC               |
           _cons |   .2479268   .0013201   187.81   0.000     .2453394    .2505142
-----------------+----------------------------------------------------------------
ARCH_FC          |
            arch |
             L1. |   1.003051   .0233487    42.96   0.000      .957288    1.048813
                 |
           garch |
             L1. |   .0074366   .0052299     1.42   0.155    -.0028139     .017687
                 |
           _cons |   .0006876   .0000381    18.05   0.000     .0006129    .0007622
-----------------+----------------------------------------------------------------
 corr(Bank,House)|  -.0352305   .0461985    -0.76   0.446    -.1257778    .0553168
   corr(Bank,Gov)|   .2312903   .0435409     5.31   0.000     .1459516     .316629
  corr(Bank,Corp)|   .3036198   .0406918     7.46   0.000     .2238654    .3833742
    corr(Bank,FC)|   .1375141   .0433231     3.17   0.002     .0526023    .2224259
  corr(House,Gov)|  -.2618662   .0516691    -5.07   0.000    -.3631358   -.1605965
 corr(House,Corp)|  -.1233393   .0471128    -2.62   0.009    -.2156787   -.0309999
   corr(House,FC)|   .0636928   .0466911     1.36   0.173      -.02782    .1552056
   corr(Gov,Corp)|   .4522382   .0329725    13.72   0.000     .3876133     .516863
     corr(Gov,FC)|   .1106468   .0496914     2.23   0.026     .0132535    .2080402
    corr(Corp,FC)|   .1053424   .0457757     2.30   0.021     .0156238    .1950611
-----------------+----------------------------------------------------------------
Adjustment       |
         lambda1 |   .3017777   .0065506    46.07   0.000     .2889388    .3146166
         lambda2 |   .6908224   .0067923   101.71   0.000     .6775098     .704135
```