FISS – A Factor Based Index of Systemic Stress in the Financial System[1]

Tracking and monitoring stress within the financial system is a key component of macroprudential policy. This paper introduces a new measure of contemporaneous stress: the Factor based Index of Systemic Stress (FISS). The aim of the index is to capture the common components of data describing the financial system. The FISS is a Financial Stress index (FSI) and as such focuses narrowly on detecting the outbreaks of financially turbulent times.

Table 1: Variable selection

	Raw variable	Aspect of financial stress captured
Govt. Bond Market	Risk premium on 5 year bond	Flight to quality
	Yield on 3 month bond	Increased uncertainty
	Yield on 10 year bond	
Foreign Exchange Market	EUR/HUF volatility (α=0.95)	Increased uncertainty
	USD/HUF volatility (α=0.95)	
	CHF/HUF volatility (α=0.95)	
	GBP/HUF volatility (α=0.95)	
	Bid-Ask spread (EUR)	Flight to liquidity
Capital Market	CMAX of BUX (60 day window)	Increased uncertainty, Flight to quality
	CMAX of BUMIX (60 day window)	
	CMAX of CETOP20 (60 day window)	Increased uncertainty, Contagion
	CMAX of DAX (60 day window)	Increased uncertainty, Contagion
	VDAX	Increased uncertainty, Contagion
Bank Segment and Interbank Market	Harmonic Distance	Increased information asymmetry, Liquidity drought
	Domestic Banks PD	Increased uncertainty
	Foreign Banks PD	Increased uncertainty, Contagion
	3 month BUBOR	Increased uncertainty, Increased information asymmetry, Flight to liquidity
	Overnight rate of HUFONIA	
	Turnover of HUFONIA	Increased information asymmetry, Liquidity drought

The selection of potential variables was constrained by further data requirements. First of all, the aim of the FISS is to quantify financial stress in a timely manner, thus only daily data were considered. Second, movements in the indicator should capture developments that are market-wide. Finally, the variables in the model should capture some feature of financial stress. Out of considered variables, 19 were chosen (shown in table 1) that maximise the explained variance. In doing so all possible combinations of the variables were tested to see which selection yields the

[1] The full paper can be reached through the following link: https://www.mnb.hu/letoltes/mnb-wp-2017-9-final.pdf

best explanatory power while not including variables that offer limited information. Although factor analysis is capable of handling the inclusion of all the variables, Boivin and Ng (2005) found that including less but pre-screened variables in the factor model yielded as good if not better results than using all the available series.

The FISS utilises a dynamic Bayesian factor model framework to compress information from the 19 financial variables into 4 factors. The choice of four factors was supported on both intuitive grounds (data from 4 financial markets was used), and empirical grounds (4 factors yielded an explanatory power of around 85%). Furthermore, the factors were allowed to follow nonstationary paths. As such the factors are the common stochastic trends of the data.

In a dynamic factor model the common behaviour of a high dimensional vector of time series variables is described by a few latent dynamic factors together with a vector of zero mean idiosyncratic disturbances. The idiosyncratic noise term arises from measurement error and from specific features of the individual data series. The latent factors usually follow a VAR structure of lag order p. This is shown in equation (1) and (2) below:

$$y_{it} = \lambda_{i0} + \lambda_i f_t + \varepsilon_{it} \qquad \varepsilon_{it} \sim N(0, {\sigma_i}^2) \tag{1}$$

$$f_t = \sum_{i=1}^{p} \phi_i f_{t-i} + \varepsilon_t^f \qquad \varepsilon_t^f \sim N\left(0, \Sigma^f\right) \tag{2}$$

Equation 1 is the observation equation signifying that the vector y_{it} can be described by i independent regressions. The disturbance term of this equation, ε_{it}, is assumed to i.i.d. The FISS uses a simplified version of the dynamic factor model since, the possible AR structure of these disturbance terms are ignored (Koop and Korobilis 2010).

Equation 2 plays the role of the state equation, describing the structure of the latent factors. In the FISS the vector of latent factors follows a VAR structure. The disturbance term of the state equation, ε_t^f, is assumed to be i.i.d. In most cases Σ^f is a diagonal, for the model presented in this paper this condition is fulfilled. One last assumption is that the two disturbance terms, ε_t^f and ε_{it}, are independent of each other.

The prior for the coefficients in the observation equations are a normal-inverse gamma, and the elements of Σ are inverse gamma. Since the observation equations are independent, the posterior parameters: ${\sigma_i}^2$, λ_{i0}, and λ_i can be simulated separately in the ith dimension (Geweke and Zhou 1996). The matrix of factor loadings is normally distributed with restrictions on the block structure of matrix and with positive, truncated normally distributed elements in the diagonal.

The prior for the state equation is normal-inverse Whishart. The state equation is in VAR form, so we can apply the Gibbs sampler only, no Metropolis-Hastings steps are required (Kadiyala and Karlsson 1997).

The prior selection is supported by Uhlig (1991) where it is stated that in the presence of a unit root the choice of a Normal-Wishart prior centred at the unit root yields the best results.

The FISS builds upon the recent developments of non-stationary factors (Engle and Watson 1981). The decision to do so was primarily driven by the fact that the aim is to get an index that captures the level of financial stress rather than the change in financial stress. By differentiating the data, information content of the indicators changes, which is undesirable (e.g.: Harmonic distance gives

information about the prevalence among banks to focus on repayment of current loans while the first difference of this variable captures the change of this effect which, while informative, is different). Furthermore, differencing the data yields a more erratic FSI, which would make policy implementation less feasible.

Although not all of the chosen variables portray non-stationary tendencies this is not a problem as the factors that are gained all have unit-root tendencies and as such can be explained well with a random walk structure. Furthermore the algorithm is capable of handling scenarios where some factors are stationary while the others are not (Eickmeier 2005).

When weighing the factors into one comprehensive index it was found that more complex quantile regression and information value methods do not change the final index considerably, when using the simple unweighted average as a benchmark. As such the factors aggregated into one index using the arithmetic average at time i.

The final FISS is shown in table 2 for the period of 2005 to 2018. All the movements of the index can be described by events that occurred either in the Hungarian financial market or on the European financial markets. Furthermore, the index is robust as cutting the sample into subsamples does not change the movement of the index considerably.

Table 2: The development of the FISS

The FISS is capable of capturing the core dynamics of financial instability on the Hungarian financial markets and will be a useful FSI for future policy use. As such the FISS will be part of the broader macroprudential toolkit of the Hungarian Central Bank. As opposed to the widely used early warning indicators, the FISS will provide information about the current level of tension in the financial system of Hungary acting as a thermometer of stress. Furthermore, as the FISS is a continuous variable it can be used as a threshold variable in nonlinear macro models, to study the behaviour of banks in different regimes.

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