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MAGYAR NEMZETI BANK

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

(FSI: faktor alapú pénzügyi stressz index)

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Contents

Abstract

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. This new index is calculated with a dynamic Bayesian factor model methodology, which compresses the available high frequency and high dimensional dataset into stochastic trends. Aggregating the extracted 4 factors into a single index is possible in a multitude of ways but averaging yields satisfactory results. The contribution of the paper is the usage of the dynamic Bayesian framework to measure financial stress, as well as producing the measure in a timely manner without the need for deep option markets. Applied to Hungarian data the FISS is planned to be a key element of the macroprudential toolkit.

JEL codes: G01, G10, G20, E44
Keywords: Systemic stress, Financial Stress Index, Dynamic Bayesian Factor Model, Financial System, Macroprudential Toolkit

Összefoglaló

A pénzügyi stressz aktuális szintjének nyomon követése fontos pillére a makroprudenciális politikának. Tanulmányunk egy új módszert mutat be ennek mérésére: a faktor alapú pénzügyi stressz indexet (FSI). Az index célja, hogy a pénzügyi rendszert leíró adatok közös komponenseit megragadja. Az új indexet egy dinamikus Bayesi faktor modell segítségével számoljuk, amely a rendelkezésre álló magas frekvenciájú és magas dimenziójú adathalmazt közös sztochasztikus trendekbe tömöríti. Az előállított 4 faktor egy indexbe történő aggregálása több módszerrel is lehetséges, de az egyszerű számtani átlag kielégítőnek bizonyult. A tanulmány lényeges újítása, hogy az említett dinamikus Bayesi keretrendszert a pénzügyi rendszer stressz szintjének mérésére alkalmazza, továbbá mély opciós piacok nélkül ad naprakész információt a szabályozónak. Magyar adatokra alkalmazva az FSI fontos szerepet fog betölteni a makroprudenciális eszköztárban.

1 Introduction

Tracking and monitoring financial stress is a key component of financial stability. There are many policy instruments (e.g. release of the countercyclical capital buffers) that rely on knowing the level of financial stress in the financial system. Using these policy instruments when the stress is not adequately high enough carries the cost of not being able to implement the same policy in the near future if the need arises. The aim of the Factor based index of Systemic Stress (hereinafter FISS) is to capture the current level of systemic stress prevalent in the Hungarian financial system.

The literature in recent years has introduced several econometric methods for developing financial stress indices (hereinafter FSI) and financial conditions indices (hereinafter FCI). Both types of indices compress a wide range of financial variables into a single series but FCI's and FSI's are inversely related during financial instability: increasing financial stress means worsening of financial conditions. An FSI narrowly focuses on measuring financial stress (e.g. Hakkio and Keeton, 2009), while an FCI focuses on broad measures of financial conditions (e.g. Koop and Korobilis, 2014). Due to this wider range an FCI frequently includes macroeconomic variables as well as financial variables. The FISS falls in the category of an FSI as it wants to measure the level of financial stress.

There are multiple ways to estimate an FSI which range from simple weighted averaging to more complex econometric methods. This diversity in methodologies is driven by the need to include more financial variables which has been steadily increasing the past decade. Coupled with advances in computing power, more complex econometric models have become commonplace in the literature. The FISS utilises a dynamic Bayesian factor model framework to compress information from 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 non-stationary paths. As such the factors are the common stochastic trends of the data. This was done because differencing the daily data would lead to potential loss of information.

To aggregate the 4 factors the usual weighing scheme used in principal component analysis could not be applied, as the factors are non-orthogonal after imposing a dynamic structure on them. On account of this several methodologies were tested: simple average, quantile regression (hereinafter QR), information value (hereinafter IV) as well as a simulation procedure. The final results did not yield significant differences from the simple average and as such it was used for aggregation.

The paper contributes to the literature in two aspects. First, it creates a non-stationary factor model to capture financial instabilities. Such an approach has not been done in the literature of FSI to the knowledge of the authors. Furthermore, the paper uses Hungarian data, signifying that the methodology of the FISS can be utilised for emerging economies. This later contribution is particularly important because it highlights how accurate FSI's can be constructed in the absence of data from deep option markets, something which emerging markets lack.

Section 2 of the paper discusses the concept of financial stress and systemic stress, and gives a brief literature review of other FSIs available. The aim of this section is to give an economic intuition of what a FSI aims to capture. Section 3 gives an overview of the variables selected in the model categorised by the financial market the variable aims to capture. This section also discusses how the data were transformed, motivating each transformation. Section 4 discusses the dynamic Bayesian factor model framework and briefly discusses the aggregation methods considered. Section 5 shows the results of the FISS. Finally, section 6 concludes.

2 Financial stress

Financial stress can be interpreted as the amount of risk which has materialised. This definition implies that financial stress can be measured by a continuous variable with its extreme values representing crisis events. The most common indication of these events is the acute shift in investors' intention to hold less risky assets, called *flight to quality*, and liquid assets, called *flight to liquidity* (Caballero & Krishnamurthy, 2008; Hakkio & Keeton, 2009). This shift in intention is primarily driven by increased *uncertainty* on the market, increased *information asymmetry* between market participants and *changing risk preferences*. It is important that a FSI does not just include variables that capture flight to quality and flight to liquidity but also indicators that measure increased uncertainty and information asymmetry, to better measure the continuous range of financial stress.

Increased uncertainty on the financial market can stem from two sources: asset valuation and the behaviour of the other market participants. Asset valuation involves a lot of ambiguity and some unexpected development – often referred to as a Minsky moment[1] – can trigger market participants to re-evaluate their previous estimates. This in turn increases the disagreement about the underlying assets' value because the actors' asset valuation differs. This is embodied by increasing volatility on the market.

Perhaps the more pertinent source of uncertainty after a Minsky moment is the behaviour of other market participants. The price of an asset is not just influenced by the underlying dividend stream but also by the selling pressure of other actors. The increased uncertainty about the behaviour of others might induce the trader to liquidate her position early. Fire sales can develop when such a decision is taken by multiple actors in the face of increased uncertainty.

Information asymmetry in the financial markets occurs when one party has more information about the product than the other. There are a variety of cases when information asymmetry can occur in financial markets (e.g.: borrowers have more information than lenders, sellers on secondary markets have more information about the asset than buyers, participants of a swap deal have more information about themselves than about the respective counterparty, etc.). Information gaps can worsen during financial stress due to market participants becoming doubtful about the accuracy of their information about the other parties. This is further exacerbated by the fact that during periods of high financial stress the value of potential collaterals, which aims to tackle information asymmetry on financial markets, is expected to decline (Gorton, 2009). This manifests itself in a higher cost of borrowing and lower lending activity. The lending activity declining is further worsened by firms not knowing for certain their banks solvency situation and, on account of this, not knowing if they can count on their credit line. On secondary markets the increased information gap lowers the average price of the asset.

Risk preferences are non-constant in time. It is well documented that market participants have a tendency to underestimate risks during bull markets and overestimate risks during episodes of high financial stress (Kindleberger & Aliber, 2011; Freixas, Laeven & Peydró, 2015). This changing risk preference further reduces market activity for riskier assets during stressful periods.

Shifting exposures to more liquid and less risky assets is rational at an individual level as it can limit the risk of potential losses that could arise due to the aforementioned effects. On account of flight to quality the spread between the risky and less risky assets widens as market participants flock to safe assets (Caballero & Kurlat, 2008).

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[1] Minsky moment is a name derived from Minsky's financial instability hypothesis (see: Kindleberger and Aliber, 2011)

Flight to liquidity is a result of market participants concern of not being able to sell an illiquid asset close to its fundamental value when the market participant needs cash quickly.[2] The effect of flight to liquidity is an increase in the liquidity risk premia demanded for illiquid assets and a widening of the spread between liquid and less liquid assets' returns.

Systemic stress is a subcategory of financial stress and can be defined as the situation where financial stress becomes so widespread that it impairs several financial institutions and markets of an economy (De Bandt & Hartmann, 2000). This contagion-like spread of financial stress is not limited to the borders of a country. Due to the tight cross-border financial interlinkages, financial stress in a financial market of one country can spread across the region. Accounting for these elements is important when trying to measure the financial stress of a small, open economy.

Systemic stress on the financial markets can be damaging to the real economy as well because it impedes financial intermediation. During periods of high systemic stress financial market participants have limited possibilities to hedge on the market, which may force them to limit their activity to only the most liquid and least risky markets. This raises the cost of doing business for all firms on the market and the net effect is a decrease in investment. As such quantifying and monitoring systemic stress is of key importance.

The financial markets of each economy are different in their level of development and depth. As a result of this, there exist several financial stress indices in the literature. What follows is a non-exhaustive survey of some of the FSIs that have been created so far.

Illing and Liu (2006) is an influential contribution to the literature on financial indices. The authors test several aggregation methods to create a daily FSI that best represents the Canadian financial markets. The authors identified episodes of high financial stress on the basis of a survey they conducted among the Bank of Canada policy makers. Their best performing FSI used 11 financial variables and was aggregated using a weighted average methodology where the weights were determined by the relative size of the financial market the indicator in question was associated with.

Nelson and Perli (2007) created a weekly FSI for the US economy using 12 variables. The authors employed a two-step approach to create their desired measure of financial stress. In the first step they created 3 summary indicators: level factor, rate of change factor and correlation factor. The level factor was constructed by calculating the variance equal weighted average of the indicators. The rate of change factor is the rolling 8 week percentage change in the level factor. The correlation factor is the first principal component of the 11 variables on a rolling 26 week window. The three constructed factors are aggregated into one index with the help of a probit regression on a pre-defined binary crisis indicator.

Hakkio and Keeton (2009) build their indicator using 11 daily financial market variables. They do so in one step using principal component analysis on the standardised variables. The idea is that financial stress is the factor responsible for most of the variance observed in the series. Hatzius et al. (2010) use the idea of factor analysis as well and apply it to 45 distinct data series in an effort to create an FCI. The authors tested how their FCI fared in forecasting GDP. The conclusion of the paper is that while multiple factors were necessary to capture the co-movement of the financial variables, only the first factor was helpful in forecasting real activity. These results are crucial as it highlights how modelling financial systems might only be possible with the help of multiple factors.

The next two indicators presented here are the Composite Index of Systemic Stress (CISS) created by Holló, Kramer, and Lo Duca (2012) and the System Wide Financial Stress Indicator (SWFSI) developed by Holló (2012). The CISS and SWFSI use the same methodology with the only difference being that the CISS was constructed for the euro area and the SWFSI was made to capture the stress levels of the Hungarian economy. This methodology

[2] For more information about the aspects of liquidity that differentiates markets see Páles and Varga (2008).

requires the chosen variables to be transformed using sample CDF, so that all the variables are on the same (0,1] ordinal scale. These variables are then categorised into the financial markets they represent. The sub-indices are the arithmetic average of these categorised transformed variables. To create a single index out of the sub-indices the CISS and SWFSI uses portfolio theory to give more weight to stress events where the indices are correlated. This correlation matrix is time varying. Furthermore, the sub-indices also receive an additional weight according to how much the sub-index influences the real economy measured by industrial production (hereinafter IP).[3]

As mentioned, the CISS is constructed for the EU market and the SWFSI was developed for the Hungarian economy in mind. This difference influences the variable selection and the number of sub-indices created. CISS aggregates 15 variables into 5 sub-indices while the SWFSI uses 27 indicators to create 6 sub-indices.

Apart from the SWFSI there have been other attempts at creating an FSI for emerging markets. One such paper is Cevik, Dibooglu and Kutan (2013), where the authors construct an index for Bulgaria, the Czech Republic, Hungary, Poland, and Russia. In creating the FSIs, this paper uses 6 core components to gauge financial stress: banking sector fragility, security market risk, currency risk, external debt, sovereign risk and trade finance. These 6 variables are aggregated using principal component analysis and the first factors are used as the FSIs of each country.

One important conclusion of the literature review is that there exists no consensus in how to create a FSI: the indices currently available differ in their methodology as well as their variable selection. It is therefore important to have a rigorous data selection procedure that is guided by economic considerations. This also implies that, on account of different market structures across the different countries, the indicator selection will vary. Furthermore, financial markets are elusive and ever-changing, necessitating the frequent and different attempts at measuring financial stress.

[3] This is calculated with the help of Impulse response functions in a VAR. These weights can be time varying as well to account for structural changes in the economy if necessary.

3 Data selection and transformation

The aim of the FISS is to capture financial stress in the financial system of Hungary. Thus, following SWFSI and CISS, different segments of the financial system were defined for data collection. Four segments were identified: government bond market, foreign exchange market, bank segment and interbank market, and capital market. To get a good mix of financial data that is not influenced excessively by market deepening, the starting point was set at January 1, 2005.

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 outlined in section 2. Additionally, as the Hungarian financial markets are open and closely connected to their European counterparts, variables that capture increased uncertainty in the European markets were considered as indicators of potential cross border contagion effects.

Table 1
List of variables included in the FISS

	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

Out of considered variables, 19 were chosen that maximise the explained variance. In doing so all possible combinations of the variables were tested to see which selection yields the 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 final list of variables is shown in Table 1. The following sections detail the final variable selection. For the full list of variables considered see the appendix (Section 8.1).

3.1 GOVERNMENT BOND MARKET

The government bond market is captured by 3 variables: risk premium on the 5 year government bond compared to the German 5 year government bond, reference yield on the 3 month bond and the reference yield on the 10 year bond.

The risk premium measure is chosen as it can capture flight to quality episodes. As such it yields information about traders' expectations about the Hungarian economy compared to Germany. For the calculation of this risk premium German government bond was chosen as it is the closest substitute to a euro area bond. The choice of using Germany as a base is further supported by the fact that the Hungarian economy is intertwined with the German economy. Thus, using German bond yields as a base gives a better measure of idiosyncratic stress of the Hungarian government bond market.

The yield on the 3 month government bond and the 10 year government bond together represent the yield curve. In effect, during elevated levels of financial stress, the short term outlook of an economy becomes uncertain raising the short term yield. This can lead to the yield curve inverting, a situation where short term bond yields exceed long term yields, which captures the increased uncertainty in the market.

These two price based measures capture forward looking aspects of financial stress. This is useful for a FSI as it can measure how materialised risk influences the actors' expectations about future risks. The FSI will still be a measure of materialised risks, but with the inclusion of forward looking measures the full effect of it can be captured, as stress is derived not only from past events but market participants' uncertainty about future outcomes.

3.2 FOREIGN EXCHANGE MARKET

5 variables encapsulate the foreign exchange market in the model: EUR/HUF spot market volatility, USD/HUF spot market volatility, CHF/HUF spot market volatility, GBP/HUF spot market volatility, and bid-ask spread of EUR offers on the spot market.

The volatility measures together aim to capture uncertainty surrounding the Hungarian forint. Multiple currency pairs were included so as to make sure only the volatility related to the Hungarian markets is captured. Out of all the currencies the volatility of the Hungarian forint with respect to the euro is of key importance due to the economic links between the Hungarian economy and the euro zone.

To calculate the volatility of the currency an exponentially weighted standard deviation (hereinafter EWSD) of the daily log change with a delay parameter of 0.95 was chosen. Standard deviation on daily log changes of currencies is commonly used to measure exchange rate volatility (see: Hooper & Kohlhagen, 1978; Akhtar & Hilton, 1984; Gotur, 1985) due to its simplicity in calculation and the fact that it requires no assumptions to be made to fit the model. Because the aim of the FISS is to capture financial stress in a timely manner exponential weighting was imposed on the standard deviation so that older observations have a lower impact on the current level of standard deviation. The EWSD was calculated with the following formula:

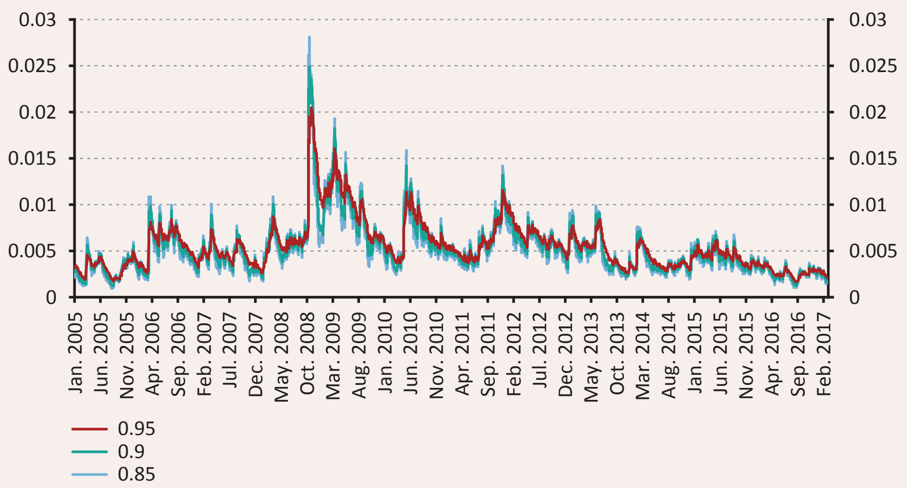
$$\sqrt{\frac{\sum_{i=1}^{N} w_i \left(x_i - \overline{x}^*\right)^2}{\sum_{i=1}^{N} w_i - \frac{\sum_{i=1}^{N} w_i^2}{\sum_{i=1}^{N} w_i}}} \qquad (1)$$

where w_i is the weight and $\overline{x}^*$ is the exponentially weighted moving average using the same weighting setup.

Although a GARCH model or a variance from the long term trend approach might be better at identifying episodes of high exchange rate volatility, there is no guarantee that the same model will hold as newer data is added to the sample. Due to this robustness concern the simpler EWSD approach was favoured.

When deciding on the decay factor the following values were considered: 0.85, 0.9, 0.95. The EWSD of each decay factor is shown in Figure 1. Upon inspecting figure 1 it is visible how the EWSD of the decay factors of 0.9 and 0.85 drop deeper after reaching their maximum value only to rebound instantly during the crisis. Such erratic movement is not desirable and as such the decay factor of 0.95 was chosen. Larger values than 0.95 were not considered because then weights (albeit small ones) are given to observations that occurred over 90 days ago. One major drawback of using this measure of volatility is that it is backward looking and has no information about the expectation of investors.

Figure 1
EUR/HUF exponentially weighted standard deviation with different decay factors



Bid-ask spreads are frequently used to measure liquidity risk of a market (Holló, 2012; Páles & Varga, 2008). In periods of low financial stress the bid ask spread is low which show a low transaction cost associated with doing business. High bid-ask spread is associated with increased liquidity risk during periods of adverse market conditions. This is because during high stress period's market participants are less inclined to enter an illiquid market or only at a price below its fundamental value, leading to lower bid prices being registered. At the same time market participants partaking in flight to liquidity want to sell the asset as close to its fundamental value as possible to not incur needless losses. It should be noted that a spike in bid-ask spread can occur during periods of low financial stress as well due to structural factors (eg: due to new issuance, market concentration, etc.). As such it is important to have the other measures of foreign exchange market stress level to maximise the information content of the bid-ask spread.

3.3 CAPITAL MARKET

Several stock market indices were included to capture the movement of the capital market of Hungary. These are the BUX, BUMIX, and the CETOP20. The BUX is the primary capital market index of Hungary which includes the 14 major Hungarian companies trading on the Budapest Stock Exchange (hereinafter: BSE). In its aggregation method it is equivalent to the American Dow Jones Industrial Average and the German DAX. The BUMIX is the stock market index of 25 small and medium sized companies listed on the BSE. The calculation is the same as for the BUX with the exception that only companies below a market value of 125 billion Forints are applicable. The BUMIX and the BUX together can capture flight to quality aspects as it is expected that BUMIX will react to financial stress faster than the BUX which includes larger firms in its composition.

The CETOP20 follows the performance of 20 companies with the biggest market value in the Central European region. There is a condition applied during the construction of the index and that is that only 7 companies from one stock exchange may be included in the index. It serves as a benchmark for the region. It was included in the variable selection to capture aspects of region specific stress.

The CMAX methodology was imposed on these stock market indices, which is common practice in the literature (Illing & Liu, 2006; Holló, Kramer & Lo Duca, 2012; Holló, 2012). It uses the following formula to construct a series to capture cumulative losses on the stock market:

$$CMAX_t = 1 - \frac{x_t}{\max\left[x \in \left(x_{t-j} \middle| j = 0, 1, \ldots, T\right)\right]} \tag{2}$$

where x_t is the stock market index at time t and the moving average window is T. The idea behind the CMAX is that it compares the current value of the stock market to its maximum value over the rolling window. This value is then subtracted from 1 to get an index that increases when the cumulative losses increase. The CMAX's strength is that it is a hybrid loss-volatility measure as high values do not just mean cumulated losses but also increased uncertainty on the market. Following the SWFSI the rolling window size was chosen to be smaller (60 days) than is common in the literature, which is 1-2 years. This was done on account of the FISS aiming to capture financial stress as opposed to trying to identify stock market crashes. The smaller window means that the values from the CMAX will represent only the most recent market developments.

The VDAXNEW (hereinafter VDAX) was also included as a variable to measure stress of the capital markets. The VDAX measures the level of volatility to be expected in the next 30 days on the DAX. The calculation methodology is equivalent to that of the VIX index which measures implied volatility of the S&P500. The strength of the VDAX is that it is a completely forward-looking index and can capture market participants' expectations about the near future. The inclusion of the VDAX and CMAX of the DAX in the model is motivated by the desire to capture contagion effects. As mentioned previously the two economies are intertwined and difficulties in the German capital markets can influence companies with Hungarian subsidiaries which in turn can have a knock-on effect on the Hungarian capital markets.

3.4 BANK SEGMENT AND INTERBANK MARKET

The bank segment is the largest market in the model composed by 6 variables: Harmonic distance measure of bank network, Domestic Banks' Probability of Default (hereinafter PD), Foreign Banks' PD, The average daily rate of a 3 month unsecured interbank loans as indicated on the BUBOR, the average daily overnight rate of unsecured interbank loans as measured by the Hungarian Forint Overnight Index Average (hereinafter: HUFONIA), and total turnover per day of the HUFONIA. This was done intentionally: to get an accurate representation of the Hungarian financial market stress level, an accurate measure of bank segment and interbank stress is necessary on account of the financing of the Hungarian economy being bank based.

The aim of using a network measure was to capture tensions present in the banking system as a whole. Such measures indicate when the banks' lending behaviour reverses on the interbank market: banks stop lending to each other and instead focus on paying back their loans. This is a clear indication of increased information asymmetry. Four measures of this type were tested: harmonic distance, betweenness, closeness, and the sum of the degrees. Fukker (2017) shows that for the Hungarian banking system betweenness performs worse than the other three measures using a factor model as a way to evaluate the different measures. We follow Fukker (2017) in choosing harmonic distance out of the aforementioned variables as this measure increases the variance while exercising an effect on more factors. The idea of including a network variable in a FSI is not novel and has been suggested in Hałaj and Kok (2013).

It has to be noted that the network measures perform well partly due to their close link to global turnover. On account of this network indicators are also good indicators of liquidity droughts which occur when market liquidity abruptly decreases during episodes of high financial stress.

HUFONIA turnover was also included alongside the harmonic distance variable to give an explicit measure of market liquidity decreasing. The HUFONIA is an unsecured market and elevated financial stress can be captured well on this market. This variable is also a measure of information asymmetry but measures overall lending activity of the interbank market instead of measuring banks shift in behaviour which the harmonic distance captures.

Bank PD measures the vulnerability of a bank and the uncertainty associated with the bank in question. The banks were grouped according to whether their ownership is domestic or foreign. This was done for two reasons: for banks which are foreign subsidiaries, CDS was available for their parent banks, and foreign banks' lending activity may be influenced by their parent companies' market's level of financial stress. Due to the latter reason it is deemed necessary to separate foreign and domestic banks as this way the model could capture cross-border contagion effects on the interbank market. For the domestic banks' the PD was calculated using the Merton (1974) model.[4] The individual banks were weighted according to their asset size to get a single PD for domestic and foreign banks.

The final two measures in this category are the daily rates on the unsecured interbank market. These are similar to the turnover measure in that, due to its unsecured nature financial stress appears in these indicators early. Including both an overnight and a 3 month rate helps the model gauge market participants expectation about the near future. Furthermore, these price variables together with the PD indicators carry information about the prevalence of information asymmetry in the market.

[4] More information on the Merton model is provided in the appendix (Section 8.3).

4 Methodology

4.1 DYNAMIC FACTOR MODEL

The literature of factor models in macroeconomics is extensive: Bernanke and Boivin (2003) introduced factor methods among macroeconomists, while Geweke and Zhou (1996), Otrok and Whiteman (1998) and Kose, Otrok and Whiteman (2003) among others, implemented Bayesian estimation within a factor model framework. Later on Bernanke, Boivin and Eliasz (2005) and Stock and Watson (2005) have enhanced the factor approach with VAR methods. Dynamic factor models were originally introduced by Geweke (1977) who extended factor models to time series data. The explanatory power of dynamic factor models is best portrayed in Sargent and Sims (1977) whose model explains a large fraction of the variance of the most important macroeconomic variables of the United States. This paper presents a model built on the methodological foundation of these works. As such it will represent the index in the form of dynamic, Bayesian factor model.

The FISS utilises standardised time series data which are often autocorrelated and persistent, thus dynamic effects must be considered. This is underpinned by the unit root tests (see: Appendix, section 8.2) showing the importance of dynamics in the data set. 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 (see: Eickmeier, 2005). Furthermore, Sims (1988) and Uhlig (1991) argue that Bayesian procedures are simpler and often more reasonable in the presence of unit roots as it avoids the drawbacks that arise due to classical distribution theory. This underpins the choice of using a Bayesian dynamic factor model.

The persistent nature of the data can be tackled in two ways: differentiate them until they become stationary; or let the factors portray non-stationary tendencies. The latter solution was first introduced by Engle and Watson (1981) and later extended by Bai (2004) with the so-called common stochastic trend approach. The FISS builds upon the recent developments of non-stationary factors. 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 applying dynamics to a factor model is enticing, it is not costless: orthogonality of factors, information on explained variance and factor interpretability is given up. These caveats have to be kept in mind when creating a dynamic factor model as each aspect carries different consequences. The lack of orthogonality of factors means that special care has to be taken when multiple factors are obtained. If the factors are too correlated there is a possibility that the added factors do not yield additional information. If the factors are non-stationary then cointegration can exist between the factors which would require a different modelling framework. Giving up information about explained variance is costly because it makes aggregating multiple factors into one comprehensive index a non-trivial task. Sacrificing factor interpretability means that it is hard to determine what each factor captures.

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 (3) and (4) below:

$$y_{it} = \lambda_{i0} + \lambda_i f_t + \varepsilon_{it} \qquad \varepsilon_{it} \sim N\left(0, \sigma_i^2\right) \tag{3}$$

$$f_t = \sum_{i=1}^{p} \phi_i f_{t-i} + \varepsilon_t^f \qquad \varepsilon_t^f \sim N\left(0, \Sigma^f\right) \tag{4}$$

regressions. The disturbance term of this equation, ε_{it}, is assumed to be independent identically distributed (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 (see: Koop and Korobilis, 2010).

Equation (4) 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.

This system of equations turns out to be a regular form of a state space model. This is an important observation because it allows the application of the Carter-Kohn algorithm (see: Carter and Kohn, 1994) to draw factors. Furthermore, all methods for posterior simulation for state space models are available due to the model following the structure described above.

4.2 THE CHOICE OF THE FACTORS AND THE ESTIMATION OF THE COMMON STOCHASTIC TREND

The first problem to be addressed is the choice of the number of factors. There are two main guidelines on how to choose the optimal factor structure: the first is to find the statistically optimal factor set (see: Bai and Ng, 2002; Lopes and West, 2004), the other is to predefine the number of factors based on intuition or empirical aspects (see: Engle and Watson, 1981). When choosing the number of factors the authors tried to merge the two ideas and four factors were chosen. As described in section 2 the indicators were categorised by the financial market they represent. On account of this the intuitive number of factors would be the number of categories constructed. The ultimate goal of the FISS is to capture as much information from the different sources of financial stress as possible and four factors satisfies this goal with an explained variance of around 85%.[5] Furthermore, these factors are not too correlated which highlights how they capture different aspects of financial stress.

Section 2 showed that it is very common for a factor methodology based FSI to use only the first factor. This was unfeasible for the FISS as using only one factor captured a mere 55% of the total variance in the data. This low explanatory power would have violated the first guideline mentioned above.

The second problem that had to be tackled is the persistence of the dataset. The factors in the model are estimated, following Bai (2004), as so-called stochastic trends: non-stationary dynamics are allowed in the state equation. In this way the model can fully capture the information contained in the financial data. Nevertheless, it is imperative to check the relations between the factors to avert any spurious regressions in the model.

[5] Explained variance for the model was obtained from principal component analysis before applying dynamics to the system.

Table 2
Coefficient matrix of the state equation

	F1	F2	F3	F4
$F1_{t-1}$	0.997	–0.001	0.006	0.000
$F2_{t-1}$	0.002	0.987	0.009	0.003
$F3_{t-1}$	0.002	–0.021	1.001	0.016
$F4_{t-1}$	0.003	–0.004	0.009	0.994

Table 2 shows the coefficients of the state equation matrix. This matrix is close to a unit matrix which highlights how the factors of the model behave like independent random walks. This simple structure makes it unnecessary to deal with the possible linkages between the factors such as cointegration (see: Banerjee et al., 2014). On the other hand, it has to be noted that the predictive power of a model described by such dynamics is very limited. Thus, the expansion of this modelling framework in the direction of a forecasting approach is not straightforward.

4.3 BAYESIAN MODEL SPECIFICATION

As mentioned before, due to the regular state-space form of the FISS, the standard algorithms can be used to draw factors. The measurement equations conditional on the factors are just normal linear regression models, which are independent from each other. Thus simulating the equations one by one is possible.

An identification issue arises when applying the PCA type factor model as a starting point: the matrix of factor loadings and factors are unique only in case rotations are ruled out. One way of surmounting this issue is imposing restrictions on the loadings (see: Lopes and West, 2004). As such the matrix of the loading was transformed in a block lower triangular form with strictly positive elements in the main diagonal. After performing this transformation the simulation procedure can commence without any problems. The Carter and Kohn algorithm was used to draw factors, which uses Gibbs sampler to simulate the parameters: ${\sigma_i}^2$, Σ^f, λ_{i0}, λ_i, ϕ_j.

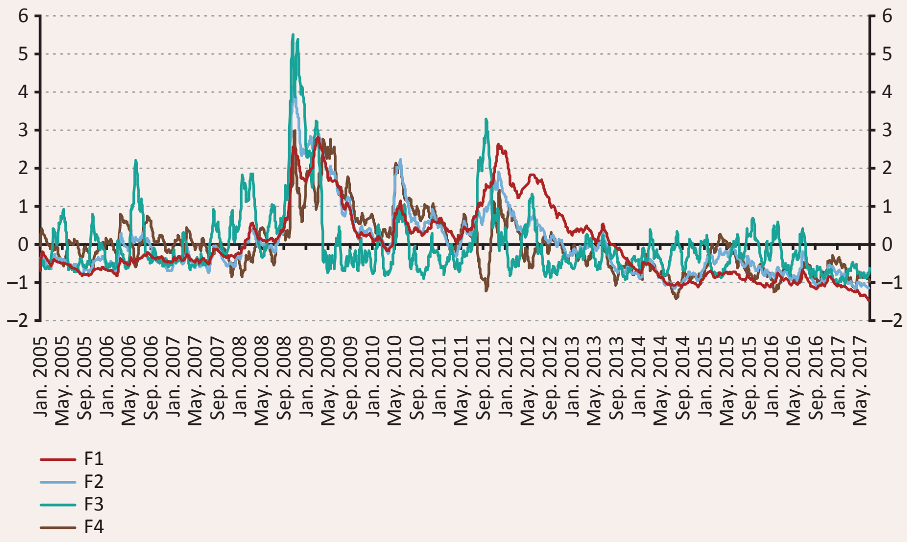
The prior for the coefficients in the observation equations are a normal-inverse gamma, and the elements of Σ are inverse gamma. Since the observation equations are independent, the posterior parameters: ${\sigma_i}^2$, λ_{i0} and λ_i can be simulated separately in the i^{th} dimension (see: Geweke and 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 the Gibbs sampler with no Metropolis-Hastings steps can be applied (see: 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 number of simulations run was set at 10000 with a burn in of 2000 and a thin value of 7. This was done to get the most accurate estimates for the factors. Detailed evaluation of the convergence of the used algorithm is discussed in Appendix 8.6. The factors obtained with these specifications are shown in Figure 2.

Figure 2
Factors of the FISS



Several things can be observed in Figure 2. First of all, the factors can take on a negative value and the factor level values range from -2 to +5.5. Although not necessary, it is useful to convert the final FISS to a range between 0 and 1. This was achieved by shifting each factor up by 2. After the factors were aggregated (more on this in section 4.4) the index values were divided by the historical maximum giving the final FISS. It has to be emphasised that these transformations are not necessary, the factors are informative without them, and were only done so the final index is on a scale between 0 and 1. Another important feature of the factors is that they seem to be correlated during certain periods. This is important because we expect multiple financial markets to show signs of instability during periods of high systemic stress.

4.4 AGGREGATION OF THE FACTORS

Aggregating the factors into a single index is not trivial. As mentioned before the factors in question are not orthogonal, and due to this using the common practice in principal component analysis, namely the usage of the square root of the eigenvalues as weights, is not possible. On account of this, a handful of aggregation methods were tested: unweighted average, weighted average where the weights are obtained using IV methodology, weighted average where the weights are obtained from QR and weighted average where the weights are simulated with no prior information imposed.

Unweighted average

While the simplicity of the unweighted average is appealing it is not its only strength. The primary reason it is considered is that no ex-ante assumption about when the index should peak or about what variables it should interact with are required. Nevertheless, there is a drawback associated with aggregation using unweighted averages: it implicitly assumes that all factors are equally informative. This assumptions validity depends on whether the alternative weighting schemes produce different dynamics in the FISS. These considerations make the unweighted average a good benchmark to compare the alternative weighting systems.

Weighted average using quantile regression

The reasoning behind using QR to get weights is motivated by the fact that certain factors may be more informative about financial stress than others. This can be measured by the factors effects on IP. Following the intuition of De Bandt and Hartmann (2000) the information content about the factors, in relation to the real economy is contained in its extreme values. As such a quantile regression measures the interaction between the tail events of the factors and the IP. Nevertheless there are drawbacks to utilising a QR. First of all the IP is recorded only monthly while the FISS is recorded daily. Conversion of the FISS is not an issue but there is an undeniable loss of information in doing so. Furthermore, IP is a non-stationary process by definition. As such it has to be differenced along with the factors to utilise QR which further depresses the information content of the obtained factors.[6] In addition, the aim of the FISS is to be a thermometer of stress and tying its weighing too closely to the tail events of IP can also lead to loss of information. For more information on the methodology see the Appendix (Section 8.4).

Weighted average using information value

The last methodology considered is the IV, which is widely used to measure the separation power of a variable in creating PD and LGD models (Siddiqi, 2012). The approach relies on a variable indicating problem in the right time, so in the case of a FSI whether the indicator gives high values in *bad* times and low values in *good* times. Using the IV methodology has the benefit of no conversions being required like in the previous scenario. Furthermore, the IV doesn't restrict itself to the IP and as such no information is lost about financial markets that did not have much effect on the real economy. However, this comes at the cost of having to define a crisis and an evaluation periods ex-ante to measure the ratio of good and bad signals. A further drawback is that bins need to be manually defined after checking the ratio of good and bad observations in each decile. These introduce ad-hoc elements to the weighting structure which can bias the final FISS to represent preconceptions about financial stress episodes in the market. For more information on the methodology see the Appendix (Section 8.5).

Simulated weights

Finally weights were also simulated without imposing any prior information about the distribution of the draws. As such a simplex method was created to get an estimate for all possible weight combinations. In total 18500 potential weight pairings were calculated. The aim of this exercise was to check how sensitive the final index is in regards to the weighting. Furthermore, it has information about how much information the other weighting methods add compared to this uninformed simulation. Only the middle 80% of combinations is presented so as to maintain reasonable bands around the benchmark estimate.

Comparison of results

Table 3 shows the weights gained from the different estimations. It has to be noted that because the QR method utilises differenced data and yields slope estimates close to zero, it is only shown for completeness (for more information see appendix section 8.4 and footnote 7). One striking feature is that the weights are very close to the unweighted benchmark case with the IV method portraying the biggest deviation from it for the fourth factor.

[6] Only the weights from the 99th quintile estimates are used as the slope coefficient are most likely to be different than 0 for this quintile only. It has to be noted that the sign of the coefficients is the opposite of the expected sign; as such the QR is only presented for illustrative purposes. For further details on the methodology see the Appendix.

Table 3
Weights gained by the different estimation procedures

	F1	F2	F3	F4
Unweighted	25.00%	25.00%	25.00%	25.00%
QR	37.80%	20.00%	16.02%	26.18%
IV	34.06%	37.92%	21.71%	6.30%

The FISS with weights of Table 3 are shown on Figure 3. All indices were transformed onto a [0,1] scale as described in section 4.3. From this figure it can be seen that the different weights do not change the index too much. The figure reinforces the findings of Table 3 that the different weight estimations do not result in significantly different indices. There is no real way to determine which version represents reality the best with such small difference. On account of this the unweighted average will be used for the remainder of the paper.

Furthermore, the bands around the average estimate show that the possible weight combinations don't diverge from the average estimate too much during periods when the index increases suddenly and dramatically. The fact that the "confidence" band around the average is existent is further proof of the factors capturing different aspects of financial stress while the observation that the bands become extremely narrow during sudden increases highlights how the aggregation of the factors yields a good measure of systemic stress. Additionally, this gives further justification for the usage of the simple average as an aggregation method.

Figure 3
Weighted and unweighted averages of the FISS

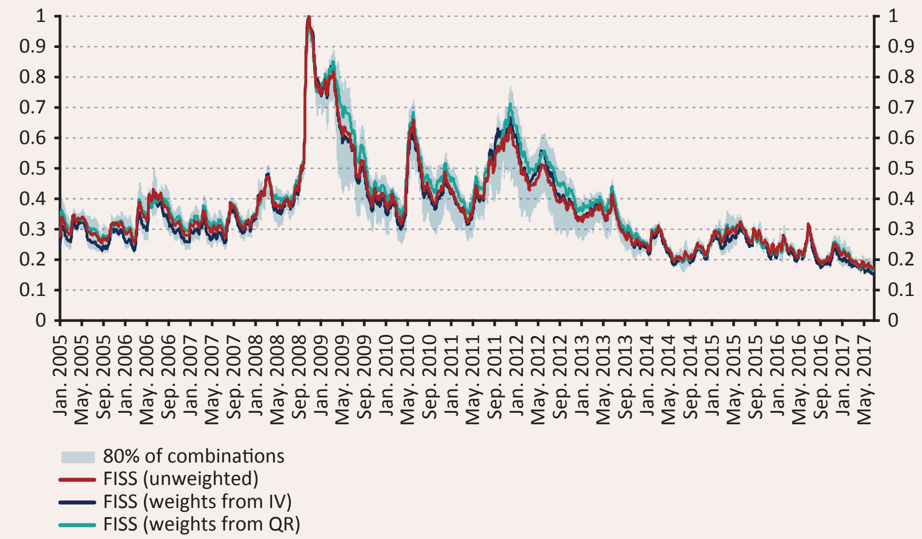


Figure 3 also portrays how due to the dynamic nature and the Bayesian methodology the index can reach high levels quickly while it takes longer time for it to decrease. From a policy maker perspective this property is important as it decreases the probability of the index breaching levels that signal crisis levels of stress only for this level to disappear the following week. One interesting observation from the figure is that the volatility of the index seems to portray heteroskedastic tendencies. Accounting for this could be a further improvement to the FISS.

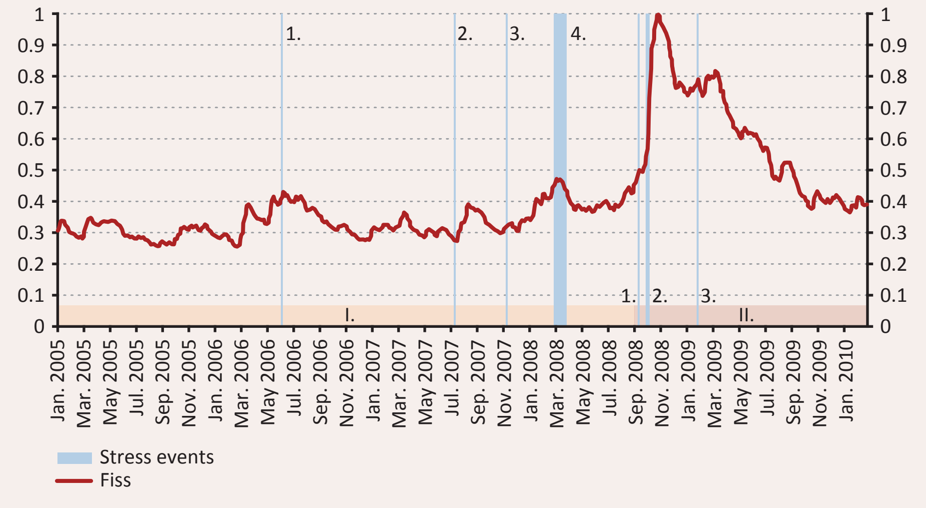
5 Results

5.1 PERFORMANCE OF THE INDEX

Having an objective, empirical way to determine the performance of the FISS is difficult. Measuring financial stress means that the FISS has to reflect all material disturbances of the financial sector irrespective of whether the connected risks materialize in the real economy. Thus, the only objective, numeric measures of FISS would be the very indicators it aggregates.

Following Holló (2012), Hakkio and Keeton (2009) and Holló, Kramer and Lo Duca (2012), the performance of the constructed index is verified by whether its' peaks match up with events of importance for the financial markets. Due to the large size of the dataset (T=3126 after adjustments, January 3, 2005 – June 30, 2017) the index is broken down into two subsamples for this section: one from 2005 until 2010 shown in Figure 4; and the other from 2010 until 2017 shown in Figure 5. Furthermore, the two figures were broken down into 2 periods. Figure 4's two periods are the events before the Global Financial Crisis (hereinafter GFC; January 2005-September 2008) and the GFC (September 2008-March 2010). Figure 5's two periods are the European sovereign bond crisis (March 2010-September 2013) and the period encompassing the post crisis events (September 2013-February 2017).

Figure 4
Values of FISS until February 28, 2010



I./1.: Introduction of the fiscal austerity package in Hungary on June 12, 2006. The FISS starts to increase a month before the program was announced, due to markets expecting that some austerity measures will be introduced, but the type and severity of the measures was unclear. This increased uncertainty on the markets lead to the FISS increasing sharply during May and June.

I./2.: Bear Sterns announces two of its subprime hedge funds lost all of its value on July 16, 2007. This announcement can be viewed as the start of the subprime debacle that eventually lead up to the collapse of Lehmann Brothers. This announcement increased both information asymmetry and uncertainty on the financial markets. Following this date the FISS's value increases as capital markets and foreign exchange markets reacted to the news. The third event on Figure 4 (I./3.) was also about Bear Sterns: On November 15, 2007 Standard & Poor downgraded the investment bank amid concerns of their solvency.

I./4.: Turbulence on the Hungarian government bond market during March 2008. Although Hungarian banks did not have large exposures to Mortgage Backed Securities (hereinafter MBS), the decreased risk appetite of international traders narrowed Hungary's opportunities to access funding, raising the price of funds. This effect was amplified as the government bond market came under selling pressure as there were concerns about their financing due to deteriorating macroeconomic fundamentals. These events are captured in the FISS as its level rose sharply during the month. Although the index value drops off after the month, the aftermath is higher levels of stress, as the underlying fundamentals did not improve. The fact that the model is able to capture this persistence in uncertainty is partly due to the dynamic structure and it yields a more intuitive picture of how market participants internalise such events.

II./1.: Bankruptcy of Lehmann Brothers on September 15, 2008. The following day Moody's and Standard & Poor downgraded the ratings of AIG due to concerns about the compounding losses of MBS, which triggered fears that the company may be insolvent. These events generated widespread uncertainty on the financial markets. The aftermath was the deepening of the GFC which lead to a sudden spike in the FISS. Concerns in regards to the solvency of holders of unhedged foreign currency denominated debt, as well as concerns about the stability of the overall banking system lead to further fears about the financing of the economy. This was further worsened by the fact that October 6-10 (sixth event on Figure 4; II./2.) was the worst week of the stock market in the United States in 75 years (Dow Jones dropped 22.1% while the S&P500 dropped 18.2%). The aftermath of these events lead to the FISS recording its highest level, as uncertainty increased leading to traders shifting their preferences around the globe, flocking to safer investment options (flight to quality). The value of the FISS eventually dropped off as a result of the credit-line agreement with the IMF in late October. Nevertheless, the level of stress didn't reach pre-Lehmann levels.

II./3.: Turbulence on the Hungarian foreign exchange spot market during January 2009. During this turbulence the EUR/HUF exchange rate breached the 300 level eventually reaching a value of 316 on March 6^{th} of the same year. This was coupled with increased volatility on the spot market which lead to the FISS to spike in values momentarily. This increased volatility also affected the Hungarian banking system due to their large exposure to foreign currency denominated debt holders, whose solvency came under heavy scrutiny.

III./1.: Downgrade of Greece to junk bond category by Standard & Poor's on April 27, 2010. Portugal was also downgraded on the same day but it still kept its investment grade status. This event is the first on Figure 5 and can be viewed as the start of the euro area sovereign debt crisis. Furthermore, there was uncertainty surrounding the newly formed Hungarian government. There were statements comparing the situation of Hungary to Greece which unsettled markets (see article published on portfolio.hu: "Kósa: "szűk esélyünk van arra, hogy elkerüljük Görögország helyzetét"", 2010). The value of the FISS elevates as it captures this increased uncertainty through the increased volatility on the exchange rate market and the government bond market.

III./2.: Turbulence on the Hungarian foreign exchange swap market during December 2010. This turbulence was mainly driven by the foreign currency denominated debt problem not being adequately addressed yet. Furthermore, the government introduced several new policies to stabilise government debt. The market reacted to these events through the government debt market. Coupled with the increased uncertainty of the euro area, causing exchange rate volatilities to rise, these issues caused the FISS to increase.

III./3.: Standard & Poor's raises the possibility of downgrading Italy on May 21, 2011. This had a profound impact on the FISS as some Italian banks have subsidiaries in the Hungarian market that are systematically important. As the PD of these banks increased the FISS started to climb gradually, signifying the increased uncertainty on the interbank market.

III./4.: Euro area sovereign debt problem worsens in mid-July of 2011. During this time Greece was downgraded further by Standard & Poor's to speculative grade on July 27, 2011. Furthermore, Standard & Poor's announced that it will closely monitor the sovereign debt process of the United States on July 25, 2011, eventually downgrading the United States on August 5, 2011. This caused investors to scramble to perceived safe haven assets such as the Swiss bonds (flight to quality). This had the effect of increasing the CHF/HUF exchange rate to a level of 230. Apart from the increased volatility on the exchange rate market, this further impaired Swiss franc denominated debt holders position. This increased concerns about the solvency and liquidity of Hungarian banks. The increase in the FISS is attributed to turbulence in the foreign exchange market and the government bond market.

Figure 5
Values of FISS from March 1, 2010

III./5.: Government announces plans related to early repayment of foreign currency denominated loans at a fixed exchange rate on September 9, 2011. This was done to tackle the concerns about the solvency of these debtholders. This announcement increased the FISS as it forced the Hungarian banking system to absorb the losses that arose from the early repayment of the loans at a non-market exchange rate. The final payment possibility was open until February 2012. The program cost the Hungarian banking system over HUF 250 billion (see article published on portfolio.hu: Vége a végtörlesztésnek, 2012). This increased the PD of all banks and lead to an uptick in the FISS.

III./6.: Papademos resigns on April 11, 2012. After reaching a post-Lehmann peak in January 2012 the index starts to gradually decrease as the financial markets of Europe seemed to stabilise. This tendency was halted when concerns about the solvency of Greece re-emerged. The resignation of Papademos further intensified these concerns making the FISS rise as uncertainty on the financial markets increased. The increased uncertainty occurred on the government bond market and the foreign exchange market.

III./7.: Cypriot financial crisis during March 2013. There was a slight uptick in the FISS during this time, but the Cypriot financial crisis was dealt with swiftly. Furthermore, the Hungarian financial system did not have exposures to Cyprus and the uptick in FISS is mostly due to the increased exchange rate volatility.

IV./1.: Hungarian government bonds came under selling pressure during January 2014. This selling pressure came from Templeton drastically decreasing its holdings of Hungarian government bonds. This selling pressure affected the risk premium charged on Hungarian government bonds leading to a slight uptick in the FISS.

The next two events are the economic sanctions imposed on Russia by the EU on July 29-31, 2014 (IV./2.) and September 9, 2014 (IV./3.). These sanctions were met with Russian embargos on imports from the EU. Since Hungary had export exposure to Russia in agricultural goods, these countermeasures hurt the general economy of Hungary raising the FISS moderately as the foreign exchange market, capital markets and the government bond market reacted to the news.

IV./4.: The start of the Quaestor debacle on March 10, 2015. The core of the breakdown was the revelation that Quaestor operated with fictitious bonds: of the HUF 210 billion bond stock HUF 150 billion were issued without permission. This event increased the information asymmetry on the Hungarian financial system (especially on the interbank market), which increased the FISS gradually until the summer of 2015.

IV./5.: Greek debt repayment debacle on June, 2015. Tsipras announces a referendum on the bailout agreement, which the Greek parliament approved on June 28, 2015. Furthermore, capital controls were imposed and the Greek banks were forced to close on account of lacking liquidty and remained closed until July 20, 2015. These events increased the volatility of the euro which resulted in a local maximum in the FISS.

The final two events on Figure 5 are the Brexit vote on July 23, 2016 (IV./6.), and the US presidential election results on November 23, 2016 (IV./7.). These last two events are minor in terms of its effects on the Hungarian financial markets and the upticks are due to the increased volatility on the exchange rate of the euro and British pound on the first of these events, and the US dollar on the latter.

In order to evaluate the effectiveness of FISS, a summary table was created (see: Table 4) highlighting the events causing a material change in the index. Here the effects are categorized by it having an anticipation period, in other words wether the event came as a surprise or not, and the geographical source of the disturbance. The first striking feature is that there appears to be no difference in the movement of the index with respect to the source of the disturbance. This is reassuring as the aim of the model is to capture financial stress regardless of the source of the event.

It has to be noted that market anticipation only matters because the events shown are imperfect proxies of stress events. The Hungarian government's austerity program announcement (I./1) did not happen in a vacuum for example: the market participants already started to react to the worsening financials of the Hungarian government. As such the true start of the stress period is not the announcement but when the financial markets start to react to the worsening economic fundamentals in Hungary. However, this start of the event is impossible to determine ex-ante. In Table 4 the start of the anticipation was determined as the minimum point in the FISS around the marked event.

Table 4
Ranking the effects of the events on the FISS

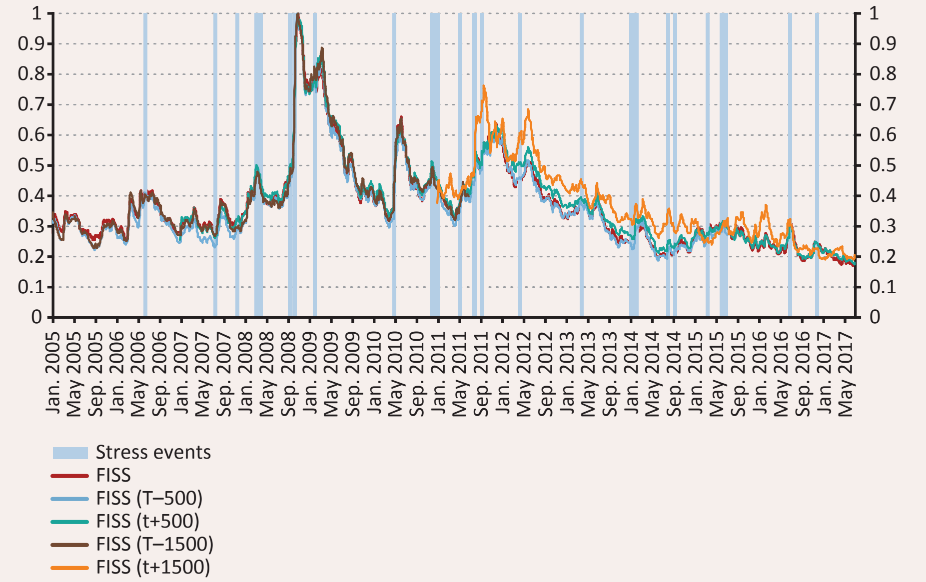
Event			Minimum		Maximum		Change		Rank	
Number	Source	Anticipation	Date	Value	Date	Value	in %	raw	By % change	By raw change
I./1	HU	Yes	09-May-06	0,33	15-Jun-06	0,43	31,57%	0,103	8	10
I./2	US	No	16-Jul-07	0,28	17-Aug-07	0,39	40,07%	0,112	4	6
I./3	US	Yes	31-Oct-07	0,30	27-Nov-07	0,33	10,49%	0,031	18	18
I./4	HU	No	18-Feb-08	0,41	10-Mar-08	0,47	14,41%	0,059	16	14
II./1	US	Yes	18-Jul-08	0,37	17-Sep-08	0,50	34,68%	0,130	7	4
II./2	US	Yes	26-Sep-08	0,50	31-Oct-08	1,00	100,83%	0,502	1	1
II./3	HU	No	09-Jan-09	0,75	12-Mar-09	0,81	8,16%	0,061	21	13
III./1	HU/EU	Yes	13-Apr-10	0,35	09-Jun-10	0,66	89,49%	0,310	2	2
III./2	HU	Yes	05-Oct-10	0,38	01-Dec-10	0,49	27,33%	0,105	11	9
III./3	EU	No	11-Apr-11	0,32	25-May-11	0,44	37,64%	0,121	5	5
III./4	EU/US	No	11-Jul-11	0,43	10-Aug-11	0,53	24,65%	0,106	12	8
III./5	HU	No	01-Sep-11	0,49	01-Dec-11	0,64	30,87%	0,150	9	3
III./6	EU	Yes	20-Mar-12	0,43	01-Jun-12	0,51	18,87%	0,081	14	12
III./7	EU	No	13-Feb-13	0,34	26-Mar-13	0,37	8,89%	0,030	20	19
IV./1	HU	No	17-Jan-14	0,23	13-Mar-14	0,31	36,31%	0,083	6	11
IV./2	EU/RU	No	29-Jul-14	0,20	12-Aug-14	0,22	10,20%	0,020	19	21
IV./3	EU/RU	No	09-Sep-14	0,21	20-Oct-14	0,25	16,99%	0,036	15	17
IV./4	HU	No	10-Mar-15	0,27	08-Jun-15	0,32	20,41%	0,054	13	16
IV./5	EU	Yes	22-Apr-15	0,29	16-Jun-15	0,32	10,51%	0,030	17	20
IV./6	EU	Yes	19-Apr-16	0,21	27-Jun-16	0,32	53,35%	0,111	3	7
IV./7	US	Yes	26-Oct-16	0,19	25-Nov-16	0,25	28,15%	0,055	10	15

An interesting question is whether the FISS should be interpreted in a log scale. As noted before looking at the FISS the value seems to be more volatile the higher the level of the index is. This could be due to functional misspecification. Table 4 tries to tackle this concern by looking at the change in the index at the events portrayed in the previous section and ranking them by raw as well as percent change. From the table it can be seen that the percent change ranking puts too much weight on the changes occurring at the end of the sample as opposed to the events that occurred during high stress periods. As such it can be concluded that there is no functional form misspecification and that the FISS is informative in raw levels. This is further supported by the fact that the included variables were kept in raw form and were not converted to log form.

5.2 ROBUSTNESS

The FISS is not run recursively, thus it is important to make sure that the model does not change drastically as more data is added to the sample. To test this the model is rerun on several sample sizes to verify that the peaks of the model capture the important stress events of the Hungarian financial markets in levels, while capturing the minor events in dynamics. Figure 6 shows the results of this robustness test. The following sample sizes were tested: the FISS with the last 500 observations not taken into account, the last 1500 observations not taken into account, the FISS with the first 500 observations not taken into account and the FISS with the first 1500 observations not taken into account.

Figure 6
FISS on different sample sizes



Note: To scale the (t+1500) series the maximum of the full length estimation was used.

Inspection of Figure 6 reveals that the estimates are extremely robust when observations are taken off the end of the sample. The dynamics match up almost identically and the difference in the levels is minimal. This level of robustness is maintained also when the first 500 observations are taken off the estimation sample. The only subsample where the model yields somewhat different results is when the first 1500 observations are ignored. This is due to the reason that the biggest shock in the data, the 2008 crisis, is not accounted for in this set up and as such the factor identification for financial stress is hindered. However, even with this caveat the model performs admirably in the given subsample.

This level of robustness is partly attributed to the Bayesian structure of the model: Even when almost half of the sample is not taken into account the model reaches its historic maximum in the same week. It is possible to create a recursive variant of the FISS, but Figure 6 shows that it is not necessary as the model correctly identifies the underlying factors of financial stress.

6 Conclusion

The paper presented the FISS as a measure of financial stress in the Hungarian financial system. This FSI aims to capture the financial instabilities in the 4 core segments of the financial system: foreign exchange market, interbank and bank segment, government bond market and capital market. In total 19 variables were used across the four segments, and compressed into four common stochastic trends.

To aggregate the four factors different weight estimation procedures were tested, namely a quantile regression, information value as well as a simulation method. It was found that the simple average yields satisfactory results and the more complex methods do not increase the information content of the FISS.

The time varying methodology of the factors allows the underlying common stochastic trend compositions to change as the financial markets further develop. Nevertheless, as the financial market of Hungary deepens the indicators of the FISS should be revisited to make sure the data selection reflects the underlying structure of the financial system.

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.

One further improvement of the FISS stems from the data and the factors portraying significantly higher volatility during times of financial stress, or more precisely, heteroscedastic features. From this fact it follows that the model can be extended and improved by accounting for these innovations. Del Negro and Otrok (2008) outline such an approach: using time varying parameters and stochastic volatility in both the factors and the loadings, the heteroscedastic features of the factors can be tamed.

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8 Appendix

8.1 COMPLETE LIST OF VARIABLES TESTED

Government Bond Market	Foreign Exchange Market	Capital Market	Bank Segment and Interbank Market
Risk premium on 5 year bond	EUR/HUF volatility (α=0.95)	CMAX of BUX (60 day window)	Harmonic Distance
CDS risk premia on 5 year bond	USD/HUF volatility (α=0.95)	CMAX of BUMIX (60 day window)	Betweenness
Yield on 3 month bond	CHF/HUF volatility (α=0.95)	CMAX of CETOP20 (60 day window)	Closeness
Yield on 6 month bond	GBP/HUF volatility (α=0.95)	CMAX of DAX (60 day window)	Sum of the Degrees
Yield on 1 year bond	EUR/HUF spot rate	VDAX	Domestic Banks PD
Yield on 3 year bond	USD/HUF spot rate	VIX	Foreign Banks PD
Yield on 5 year bond	CHF/HUF spot rate	VNIKKEI	Overnight rate of HUFONIA
Yield on 10 year bond	GBP/HUF spot rate	Correlation of German gov rate and BUX	Turnover of HUFONIA
Yield on 15 year bond	Bid-Ask spread (EUR)		Overnight BUBOR
	Price effect of tomnext rate change		1 week BUBOR
	Implied yield (3 month)		2 week BUBOR
	EUR/HUF volatility (60 day window)		1 month BUBOR
	USD/HUF volatility (60 day window)		2 month BUBOR
	CHF/HUF volatility (60 day window)		3 month BUBOR
	GBP/HUF volatility (60 day window)		6 month BUBOR
			9 month BUBOR
			12 month BUBOR

8.2 UNIT ROOT TEST OF THE VARIABLES INCLUDED IN THE FISS

	ADF			KPSS	
	Model type	Number of lags	t-stat	Model type	t-stat
Risk premium on 5 year bond	Autoregressive	1	2.348**	No Trend	1.249***
	Autoregressive with drift	1	2.347	Trend	1.019***
	Trend stationary	1	2.444		
Yield on 3 month bond	Autoregressive	5	0.400	No Trend	5.263***
	Autoregressive with drift	5	0.395	Trend	1.056***
	Trend stationary	5	1.503		
Yield on 10 year bond	Autoregressive	1	1.521	No Trend	3.862***
	Autoregressive with drift	1	1.520	Trend	1.281***
	Trend stationary	1	2.483		
EUR/HUF volatility (α=0.95)	Autoregressive	3	1.714*	No Trend	1.658***
	Autoregressive with drift	3	3.698***	Trend	0.754***
	Trend stationary	3	3.960**		
USD/HUF volatility (α=0.95)	Autoregressive	0	1.228	No Trend	1.220***
	Autoregressive with drift	0	2.879**	Trend	0.829***
	Trend stationary	0	3.039		
CHF/HUF volatility (α=0.95)	Autoregressive	0	2.350**	No Trend	0.721**
	Autoregressive with drift	0	4.378***	Trend	0.597***
	Trend stationary	0	4.439***		
GBP/HUF volatility (α=0.95)	Autoregressive	1	1.255	No Trend	0.796***
	Autoregressive with drift	1	3.325**	Trend	0.732***
	Trend stationary	1	3.358**		
Bid-Ask spread (EUR)	Autoregressive	9	3.734***	No Trend	0.669**
	Autoregressive with drift	9	3.733***	Trend	0.649***
	Trend stationary	9	3.749**		
CMAX of BUX (60 day window)	Autoregressive	0	3.873***	No Trend	0.689**
	Autoregressive with drift	0	5.257***	Trend	0.229***
	Trend stationary	0	5.421***		
CMAX of BUMIX (60 day window)	Autoregressive	0	3.111***	No Trend	0.733**
	Autoregressive with drift	0	4.093***	Trend	0.399***
	Trend stationary	0	4.233***		
CMAX of CETOP20 (60 day window)	Autoregressive	1	3.771***	No Trend	0.280
	Autoregressive with drift	1	4.997***	Trend	0.182**
	Trend stationary	1	5.039***		
CMAX of DAX (60 day window)	Autoregressive	0	4.427***	No Trend	0.199
	Autoregressive with drift	0	5.637***	Trend	0.203**
	Trend stationary	0	5.634***		
VDAX	Autoregressive	3	4.341***	No Trend	0.486*
	Autoregressive with drift	3	4.340***	Trend	0.497***
	Trend stationary	3	4.331***		

	ADF			KPSS	
	Model type	Number of lags	t-stat	Model type	t-stat
Harmonic Distance	Autoregressive	20	3.584***	No Trend	1.237***
	Autoregressive with drift	20	3.583***	Trend	0.717***
	Trend stationary	20	3.755**		
Domestic Banks PD	Autoregressive	93	4.420***	No Trend	0.381*
	Autoregressive with drift	93	4.419***	Trend	0.243***
	Trend stationary	93	4.483**		
Foreign Banks PD	Autoregressive	1	2.025**	No Trend	2.211***
	Autoregressive with drift	1	2.025	Trend	1.099***
	Trend stationary	1	1.913		
Average rate of 3 month BUBOR	Autoregressive	0	0.138	No Trend	5.251***
	Autoregressive with drift	0	0.136	Trend	1.025***
	Trend stationary	0	1.861		
Overnight rate of HUFONIA	Autoregressive	10	1.120	No Trend	5.408***
	Autoregressive with drift	10	1.119	Trend	0.853***
	Trend stationary	10	2.363		
Turnover of HUFONIA	Autoregressive	15	5.417***	No Trend	2.795***
	Autoregressive with drift	15	5.416***	Trend	1.056***
	Trend stationary	9	8.796		

*Note: The ADF and the KPSS have a different null hypotheses. The ADF null hypothesis is that the series has a unit root while the null hypothesis of the KPSS test is that the series in question is stationary. SBC was used to determine lag length of ADF. The asterisk' represents the level of significance: * 10% level, ** 5% level, *** 1% level.*

8.3 CALCULATING THE BANK PD USING THE KMV MODEL

The default risk measure of listed Hungarian banks is based on the structural valuation model of Merton (1974). Merton applied the idea that corporate securities are contingent claims on the asset value of the issuing firm.

The so-called KMV (Kealhofer, McQuown and Vasicek) structural model is based on the work of Black and Scholes (1973) and Merton (1974) and further extended Merton's idea. It is based on a fundamental accounting identity: the asset value of the firm (V) is equal to the sum of its total equity (S) and its liabilities (D), and the firm value is following a geometrical Brownian motion under the physical measure:

$$dV_t = \mu V_t dt + \sigma V_t dW_t, \;\; V_t > 0$$

where μ is the mean rate of return on the assets and σ is the asset volatility. Further assumptions need to be made: the liquidation value equals the firm value, and debt and equity are frictionless tradeable assets.

Large and medium cap listed firms are funded by shares ("equity") and bonds ("debt"). The Merton model assumes that debt consists of a single outstanding bond with face value D and maturity T. At maturity, if the total value of the assets is greater than the debt, the debt is paid back and the remainder is distributed among shareholders. However, if $V_t < D$ then default occurs: the bondholders exercise a debt covenant giving them the right to liquidate the firm and receive the liquidation value (which is equal to the total firm value). Shareholders receive nothing in this case, but because of the principle of limited liability, they are not required to pay any additional funds for the debt. From these observations follows that shareholders receive a cash flow at T equal to

$$S = \max(0, V\text{-}D)$$

so equity can be viewed as a European call option on the firm's assets with a strike price equal to the book value of the firm's liabilities D. On the other hand, bondholders receive $min(V_t, D)$.

If the market price of equity is available, the market value and volatility of assets can be determined directly using an option pricing based approach. The Black-Scholes-Merton option pricing formula for European options is applied, where the value of the liabilities is equated with the sum of the short term liabilities and the half of the long term liabilities (Chan-Lau and Sy, 2006; Merton, 1974).

$$D = D_{short} + {}^{1}/_{2} {}^{*}D_{long}$$

The measure of Distance-to-Default (DD) after T periods is calculated by:

$$DD_T = \frac{ln\frac{V}{D} + \left(\mu\text{-}\frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}},$$

where μ is the drift and σ is the volatility of asset value of the firm.

Financial institutions operate with larger proportion of liabilities compared to total assets than non-financial firms, so larger liabilities can cause default. Hence the measure DD for financial institutions is corrected in the following way: it is accepted to use the measure Distance-to-Capital (DC) instead of DD, which can be calculated with a minor modification to DD:

$$DC_T = \frac{ln\frac{V}{\lambda D} + \left(\mu\text{-}\frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}.$$

If we simplify it further ($\mu = \frac{1}{2}\sigma^2$):

$$DC_T^* = \frac{ln\frac{V}{\lambda D}}{\sigma\sqrt{T}}$$

Where in case of the measure of DD: $\lambda = 1$, otherwise (for DC): $\lambda = \frac{1}{1-PCAR}$. The most often used value of PCAR is the minimal capital adequacy ratio.

The measure Probability-of-Default (PD) applied in our model is derived from the measure Distance-to-Capital (DC), and can be calculated by:

$$PD_T = N(\text{-}DC).$$

Where $N(\text{-}DC)$ is the standard normal distribution function given the argument –DC.

The measure Distance-Risk (DR) is also generally used; in fact it is a z-score:

$$DR_t = \frac{\left(\frac{V_t\text{-}\lambda D}{V_t}\right)}{\sigma\sqrt{T}}$$

Where V_t is the actual value of the firm at time t. This quantity has an advantage compared to DC: it does not contain the value of parameter μ, the calculation of which can often be a concern.

The calibration of μ and σ

The difficulty in estimating these parameters comes from the fact that the firm value (V_t) is not observable, so one has to approximate it. The parameters μ and σ are the trend and volatility of this process, so after approximating V_t they have to be estimated or calibrated.

The FISS uses the "Market Value Proxy" technique, which was developed first by Moody's, see Crosbie and Bohn (2003). The "Market Value Proxy" method is used primarily because of its simplicity.[7] In this approach the asset value of the firm (V_t) is approximated with the sum of the market capitalization of the firm (the total value of its equity) and the amount of the liabilities of the firm. In the next step the log-return of the asset value (V_t), and then its mean and standard deviation, namely μ and σ, is calculated. This solution clearly has a drawback: it has an upward bias in the asset value, so a downward bias in the PD because of the time-lag in the estimation.

8.4 QUANTILE REGRESSION

Quantile regression as introduced by Basset and Koenker (1978) is the estimation of the conditional quantile function that is expressing the quantiles of the conditional distribution of the response variable in terms of the observed covariates. As the sample mean can be defined as the solution to the problem of minimizing the sum of the squared residuals, the median can be defined as a solution to the problem of minimizing the sum of the absolute residuals. Minimizing the sum of asymmetrically weighted absolute residuals yields the other quantiles τ:

$$\min_{\gamma} \sum \rho_\tau(y_i\text{-}\gamma) \tag{5}$$

where $\rho_\tau(.)$ is the tilted absolute value function. Now turning to the conditional quantiles: this can be calculated with the help of the minimization exercise:

$$\min_{\beta} \sum \rho_\tau\big(y_i\text{-}\gamma(x_i, \beta)\big) \tag{6}$$

where $\gamma(x, \beta)$ can be formulated as the linear function of the parameters. It can be solved efficiently by linear programming (for more information consult: Koenker, 2005)

The main idea was to test if the quantiles of the differenced series of IP[8] can be regressed with the help of quantile regressions on the differenced factors to see the possible co-movement of the higher quantiles of the IP with the factors. For the purposes of this paper the 90%, 95% and 99% quantile was tested.

The results of the quantile regression are shown in Table 5. From the table it can be seen that the choice of the quantiles yield different slope estimates. Furthermore, the sign of the coefficients is not consistent across the quantile choices of 90, 95 and 99. This suggests that the slopes are not necessarily different from 0 when looking at the difference of the factors and the difference of the IP. The only quantile where the coefficients of the slope seem to have practical significance is the 99. However, the slope coefficients are expected to be positive due to the IP being multiplied by -1 and all the coefficients have a negative sign in this specification. The only specification where the majority of the coefficients have a positive sign is for the 90th quantile. It has to be noted that the estimates closeness to zero highlights how the differenced factors do not yield much information. This finding reinforces the idea to create FSI's that try to measure the level of financial stress.

[7] In further extensions of the model this simple approach can be replaced by the "transformed data MLE" method (see: Duan et al., 2004; Duan and Wang, 2012)

[8] It has to be noted that IP was transformed by multiplying it with -1. This was done as high values of the index should induce low performance of the IP.

Table 5 Quantile regression estimates and weights					
		F1	F2	F3	F4
90	Intercept	0.031	0.031	0.031	0.030
	Slope	0.009	–0.003	–0.003	0.005
95	Intercept	0.039	0.041	0.042	0.041
	Slope	–0.001	–0.008	0.001	–0.006
99	Intercept	0.095	0.092	0.098	0.083
	Slope	–0.062	–0.033	–0.026	–0.043
Weights					
90		43.82%	14.23%	14.46%	27.49%
95		7.78%	50.61%	4.37%	37.24%
99		37.80%	20.00%	16.02%	26.18%

To get weights from the estimated coefficients the absolute values are taken for calculation. It has to be noted that this liberty is taken because the coefficients are unlikely to be significantly different from 0, and the results from the QR will only serve illustrative purposes.

8.5 INFORMATION VALUE

The start date of the crisis period was set as October 13, 2008 because the Hungarian Central bank intervened in the foreign exchange swap market on this day, thus it can be viewed as the beginning of the 2008-2009 financial crisis in Hungary. Tying the start of a crisis period to intervention is a common practice in the literature (see: Laeven & Valencia, 2008; Kaminsky & Reinhart, 1999). The end of the stress period was defined as May 15, 2009 as this yields a big enough window for evaluation. The evaluation period was also constrained to be around the crisis. This was done because between 2009 and 2016 there were several smaller but important financial events but it is unclear *ex-ante* how large the financial stress index should be in these periods.

Before calculating the IV the factors were broken down into deciles of equal size to ensure that higher deciles have enough observations in them. The deciles were further distributed into 2 bins: A good observation bin, and a bad observation bin. The IV is then calculated for each factor with the following equation:

$$IV = \sum_{i=1}^{b}\left((G_i\text{-}B_i)\times \ln\left(\frac{G_i}{B_i}\right)\right) \tag{7}$$

where b is the number of bins, G_i is the correct signal rate and B_i is the incorrect signal rate for the given bin.

Table 6 shows the 2 bins and the weights for each factor. The bad observation bin includes deciles with good observations below 65% and the good observation bin includes deciles with a good observation rate of above 65%.

Table 6
IV bins and weights

	F1	F2	F3	F4
10	0.00%	0.00%	18.42%	0.00%
20	0.00%	0.00%	18.92%	0.00%
30	0.00%	0.00%	15.79%	0.00%
40	0.00%	0.00%	16.22%	32.43%
50	0.00%	0.00%	5.26%	47.37%
60	21.62%	16.22%	2.70%	35.14%
70	67.57%	72.97%	27.03%	54.05%
80	100.00%	100.00%	92.11%	78.95%
90	100.00%	100.00%	91.89%	78.38%
100	100.00%	100.00%	100.00%	63.16%
		Weights		
	34,06%	37,92%	21,71%	6,30%

Upon inspecting Table 6 it could be argued that the 4^{th} factor yields not much information about financial stress according to this method. Nevertheless, running the model on only 3 factors resulted in an explained variance below 80%. Furthermore, in a 3 factor setup of the same model, factor 1 and 2 become virtually identical reducing the systemic risk information carried in a 3 factor version of the model.

8.6 CONVERGENCE RESULTS

The Carter-Kohn algorithm is known for its simplicity: it applyies Gibbs sampling without a Metropolis-Hastings step within the Gibbs-algorithm. Its convergence is not very fast, so the convergence properties were tested based on four evaluation criteria:

1. Size of the simulations draws

2. Length of the time series

3. Proportion of the noise in the state space model

4. Value of the VAR coefficients: stationary and unit root case

A dynamic factor model was built using 9 variables and 3 factors and normally distributed noise based on the assumed structure of our model. The simulation was performed using a fixed random seed. The results are summarised in the table below, which shows the RMSE for each simulation:

Table 9
Summary of convergence results

		Stationary process	Unit root process
T=200		**Draw=1000**	
	Loadings	0,124	0,196
	VAR coefficient	0,035	0,039
		Draw=3000	
	Loadings	0,125	0,197
	VAR coefficient	0,035	0,039
T=2000		**Draw=1000**	
	Loadings	0,080	0,068
	VAR coefficient	0,034	0,007
		Draw=3000	
	Loadings	0,080	0,068
	VAR coefficient	0,020	0,004
T=3000		**Draw=12000**	
	Loadings		0,069
	VAR coefficient		0,002

The main implications of the tests are the following:

- The most important criterion in terms of the convergence is the length of the time series: T=2000-3000 gives much better estimates of the loading and the VAR coefficient matrix than T=200.
- Increasing the number of the simulation draws over 1000 improves the quality of the estimates only in the case of unit root VAR process. This is in line with the findings of Sims, (1988) and Uhlig (1994).
- The proportion of the simulated noise basically does not affect the quality of the estimates.
- The simulation setup we are applying: T≈3000, n=1200 and persistent variables in the model guarantees very good quality estimate of the VAR coefficient matrix, good to fair quality estimates of the loading matrix.

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