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Systemic event prediction by early warning system

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IES Working Paper: 01/2014



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Systemic Event Prediction by Early Warning System

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Abstract:

This work develops an early warning system framework for assessing systemic risks and for predicting systemic events, i.e. periods of extreme financial instability with potential real costs, over the short horizon of six quarters and the long horizon of twelve quarters on the panel of 14 countries, both advanced and developing. First, we build Financial Stress Index to identify starting dates of systemic financial crises for each country in the panel. Second, early warning indicators for assessment and prediction of systemic risks are selected in a two-step approach; relevant prediction horizons for each indicator are found by the univariate logit model followed by the

application of Bayesian model averaging method to identify the most useful indicators. Next, we validate early warning model, containing only useful indicators, for both horizons on the panel. Finally, the in-sample performance of the constructed EWS over both horizons is assessed for the Czech Republic. We find that the model over the 3 years' horizon slightly outperforms the EWS with the horizon of 1.5 years on the Czech data. The long model attains the maximum utility in crises detection as well as it maximizes area under Receiver Operating Characteristics curve which measures the quality of the forecast.

Keywords: Systemic risk, Financial stress, Financial crisis, Early warning indicators, Bayesian model averaging, Early warning system

JEL: C33, E44, F47, G01

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Introduction

In the wake of the recent global crisis, research in the area of financial stability including Early Warning Systems (EWS) has attracted renewed attention. EWS can be characterized as functional, data-driven approaches that draw attention to variables associated with past crises with the main objective of alerting policy-makers of the potential for future crises (Gramlich, Miller et al., 2010). Essentially EWSs are based on the existence of causality between crises and crisis-driving factors and the possibility of crisis-driving factors identification *ex ante*. In the financial context, EWSs can be used for risk prediction of both a single financial institution risk from microeconomic point of view as well as the risk of an entire financial system, i.e. macroeconomic risk. Of the aforementioned risks the latter is the point of interest of this study.

Before the concepts and development of EWSs are presented over the years, it is prudent to provide the general definition of systemic risk as “the possibility that an event will trigger a negative feedback loop that significantly affects financial markets’ ability to allocate capital and serve intermediary functions, which, in turn, will create spillover effects on the real economy that have no clear self-healing mechanism” (Hendricks, Kambhu, and Mosser (2007, p. 65)). As such the functioning of the financial system is impaired to the extent that economic growth and welfare suffer materially (Peltonen and Lo Duca, 2011).

The earliest literature on macroeconomic risk focuses on currency crises. Krugman (1979) concludes that under a fixed-rate exchange system, credit expansion exceeding money demand growth diminishes foreign reserves and eventually leads to a speculative attack on the currency. An influential contribution to this branch of literature are a series of papers by Eichengreen, Rose and Wyplosz (1994, 1995, 1996), which centre on countries that peg their exchange rates (fixed-rate exchange system) and come to the conclusion that the behaviour of key macroeconomic variables for the European Exchange rate Mechanism (ERM) countries vary across periods, but that these differences do not appear in countries outside of the ERM. These results lead them to conclude that there are no clear early warning signals of speculative attacks as opposed to conclusions of many of the subsequent papers in the literature. One such paper by Frankel and Rose (1996) shifts the focus of this literature towards modelling currency crashes for developing countries using probit analysis. They use solely large exchange rate movements for their currency crisis definition unlike Eichengreen et al. (1994, 1995, 1996). The ultimate finding of Frankel and Rose (1996) is that an early warning of a currency crisis can be provided by their model as low levels of foreign direct investment and international reserves, high domestic credit growth, high foreign interest rates, and the overvaluation of the real exchange rate increase the probability of a currency crash.

In the wake of the Mexican crisis, Kaminsky and Reinhart (1999) developed EWS model to consider currency and banking crises and analyse the links between the two. In a series of subsequent papers, Kaminsky, Lizondo and Reinhart (1998) and Goldstein, Kaminsky and Reinhart (2000) build upon this research, using the signal extraction method, which allows for assessing the behaviour of macroeconomic and financial variables around the time of the crisis. They find that the majority of crises have numerous weak economic fundamentals at their core, which leads them to the conclusion that banking and currency crises in emerging markets do arrive with certain early warnings. However, the model’s predictive power is greater for currency crises than for banking crises. Based on this body of research, including some recent papers, e.g.

Reinhart and Rogoff (2009), a common conclusion can be derived that banking crises occur when rapid credit expansion fuels sustained asset-price growth that substantially deviates from trend (Borio and Lowe, 2002).

In general, financial stress can apply to various institutions or segments of the economy, such as financial companies, securities, the banking system or market segments, such as foreign exchange markets. In light of this fact, there have been some attempts at categorizing financial crises into types and measuring them individually. Ishihara (2005), for example, defines six types of financial crises (banking liquidity, banking solvency, balance of payments, currency, external debt, growth rate, and financial crisis) as well as proposes their measures. As an excessively narrow crisis definition may lead to inconsistent policies, as well as crises being progressively multidimensional, a broader concept for financial crises assessment should be beneficial. In this regard, De Bandt and Hartmann (2000) offer a systemic crisis definition as an “event that affects a considerable number of financial institutions or markets in a strong sense”. More recent research characterizes systemic crises by means of transition structures where “systemic risk is the movement from one stable (positive) equilibrium to another stable (negative) equilibrium” (Hendricks, Kambhu, and Mosser (2007)). Following this line of reasoning, there has been a shift from classical bank-based crises to more recent market-based ones.

This paper contributes to the early warning literature by developing EWS framework for two horizons, the short of six quarters and the long of twelve quarters, preceding a materialization of a systemic event, on the panel of 14 countries (both advanced and developing economies). The constructed EWS for both horizon lengths is then applied to the Czech Republic where its suitability is assessed via its in-sample performance. The paper is organized as follows. Section 1 explains methodology, develops Financial Stress Index (FSI) and identifies systemic event episodes from calculated FSI. Section 2 deals with the identification of leading indicators for systemic events detection. Section 3 evaluates performance of systemic events probability framework on the panel of countries over the short and the long horizon. Section 4 applies and evaluates performance of the developed EWS for both horizons to the Czech Republic. The last section concludes.

1. Financial Stress Indicators

Despite the fact that root causes of financial crises throughout history are often diverse along with their propagating channels and market segments, which are as a consequence affected, it is still interesting to compare these events in terms of systemic stress levels reached. For this reason, a general objective of constructing a financial stress index (FSI) is to measure, in an analytical way, the level of instability (frictions, stresses) within a financial system and to present the findings in a single statistic.

Formerly, the literature on financial crises has substantially depended on historical narratives of crisis episodes, that is mostly for banking crises connected with bank capital erosion and disruption of lending; cases which typically demanded public intervention (Caprio and Klingebiel, 2006). Other such documented episodes further banking crisis episodes with those of currency crises that exhibit reserves depletion and/or major changes in exchange rate mechanism (e.g. Kaminsky and Reinhart, 1999). Despite the fact that these historical crises narratives provide a wide database of crisis episodes, there has been an outbreak of a more analytically based

research that aspires to quantify financial stress within the economy by means of a single comprehensive statistic, FSI. The underlying reason for this branch of research is the existence of several drawbacks linked to the above-mentioned historical approaches to crises identification. First, these crisis episodes are known *ex post* to have large output effects and often require large public intervention while high stress episodes of little macroeconomic impact are often disregarded. Second, episodes identified by historical approaches usually spread over considerable time periods and thus incorporate stresses of varying magnitudes, making it challenging to identify stress peak dates. Third, as databases tend to focus on banking and currency crises, security market stress or liquidity squeezes are easily overlooked, e.g. Long-Term Capital Management collapse of 1998. To avoid these problems, extreme values of a composite indicator, FSI, are used for financial stress identification.

Varying methodologies for FSI calculation and raw measures aggregation into the composite stress measure can be found in the literature. For Canada, Illing and Liu (2006) construct a financial stress index by attempting various aggregation techniques for individual stress measures. Their final FSI, based on its performance in capturing stress events in Canada, is composed of 11 variables whose weights are determined as size of the market into which each variable belongs relative to the total credit measure in the economy. The Cleveland Financial Stress Index (CFSI) constructed by Oet et al. (2011) also uses the credit-weighting technique. Another approach for variables aggregation into FSI is the variance-equal weighting, i.e. the arithmetic average of individual stress measures. Papers by Cardarelli, Elekdag and Lall (2011), Yiu, Ho and Jin (2010), the ECB (2009a) or Peltonen and Lo Duca (2011) are good examples of this aggregation method. The FSI by Cardarelli, Elekdag and Lall (2011) is built for 17 advanced economies and while they group individual stress measures into three subindices, for securities, banking and foreign exchange markets, this was not of importance for FSI calculation as simple average is ultimately used. Yiu, Ho and Jin (2010) compute their FSI for Hong Kong using 6 raw measures. The FSI by the ECB (2009a) called the Global Index of Financial Turbulence (GIFT) is built for 29 countries, employing indicators from equity, fixed-income and exchange rate markets and again using arithmetic average for their aggregation. Peltonen and Lo Duca (2011) create a parsimonious FSI for 28 countries altogether which comprises five raw stress measures. Another method of FSI computation and aggregation is a principal components approach (Hakkio and Keeton, 2009). The underlying reasoning behind this method is that financial stress is the most important factor for observed correlation between individual indicators and that it can be identified by the first principal component of the correlation matrix calculated for standardized indicators. The calculation of weights for each raw measure entering their FSI is based on the respective measure's contribution to the first principal component. Kliesen and Smith (2010) adopt the same approach for calculation of St. Louis Fed's Financial Stress Index (STLFSI). An alternative approach employed by Louzis and Vouldis (2011) aggregates five subindices into the composite measure by estimating their cross correlation by a multivariate GARCH model. The use of portfolio approach to indicators aggregation in financial crisis literature, specifically in composite indicators calculation, is pioneered in the paper by Hollo, Kremer, Lo Duca (2010) and applied also in its subsequent version of 2012.

To ensure robustness of the Early Warning System we aim to construct, a measure of financial stress within the economy, FSI, is developed for the panel of 14 countries. The panel includes mature economies as well as developing economies from different geographical regions.

The FSI is constructed on a quarterly basis and incorporates indicators from main segments of domestic financial market since the impact of a negative shock on the economy is typically observable in several of its segments. This accounts for fundamental characteristics of systemic financial stress widely documented in the literature (e.g. Hakkio and Keeton, 2009, Fostel and Geneakoplos 2008). We aim to use a minimum set of indicators due to restricted availability of data across time and countries. Furthermore, once that indicators for vital parts of the economy are included in the index adding more components does not significantly change the shape of the composite stress measure (Hollo, Kremer and Lo Duca, 2010). Conversely, inclusion of too many indicators “could potentially contaminate the FSI with noisy indicators” (Cardarelli, Elekdag and Lall, 2011).

For the mentioned reasons, the FSI is calculated by aggregating the following 5 components:

1. *Negative quarterly returns of the main equity index*, calculated from equity returns which were multiplied by -1 so that negative returns increase financial stress while positive returns are set to 0.
2. *Realised volatility of the main equity index*, calculated by determining standard deviation of the main equity index values over the last 12 months leading to each observation date.
3. *Realised volatility of the nominal effective exchange rate*, resulting from computing standard deviation of nominal effective exchange rate values over the last 12 months leading to each observation date.
4. *TED spread*, measured as the difference between 3-month interbank rate and 3-month Treasury bill rate. This component represents the credit risk associated with interbank lending. The higher the TED spread the more the default risk on interbank loans is perceived.
5. *Realised volatility of the yield on 3-month Treasury bills*, calculated as standard deviation of 3-month Treasury bill yields over the last 12 months preceding each observation date.

For some countries an alternative set of indicators is developed due to data unavailability. The alternative FSI is also computed for every other country in the sample as a robustness check to verify that FSI captures high stress periods appropriately. These indicators are aggregated into an alternative FSI (see Figure 1 in the appendix) which differs from the originally constructed FSI in 2 components, namely the last 2 components (4 and 5) are substituted by the following indicators:

1. *Inverted interest rate spread*, calculated as the difference between interest rate paid by banks on demand, savings or time deposits minus interest rate charged by banks on loans. In general, the measure is used as a proxy for profitability in a banking sector.
2. *Realised volatility of the yield on long-term government bonds*, calculated as a standard deviation of long-term government bond yields over the last 12 months preceding each observation date.

Such FSI composition accounts for the four fundamental characteristics of the financial stress widely documented in the literature (e.g. Hakkio and Keeton, 2009, Fostel and Geneakoplos 2008):

- *Significant shifts in asset prices* (captured here through main equity index returns)

- *A sudden increase in risk or uncertainty* (captured here through realised volatility of the main equity index, T-bill rate realised volatility, alternatively through realised volatility of yield on government bonds and realised volatility of nominal effective exchange rate)
- *Abrupt changes in liquidity* (expressed here by TED spread)
- *State of the banking system* (its health is approximated here by interest rate spread as a proxy for profitability)

Each of the 5 components of the FSI is transformed before aggregation in order to facilitate measuring and cross-country comparison of financial stress levels by each FSI. Therefore, every observation at every point in time (year's quarter) for each indicator is assigned the value equal to the percentile it represents of the country-specific distribution function for this indicator. The values of thus transformed observations for each component range from 0 to 1 included. The individual stress components are designed in such a way that their higher values representing higher percentiles of their distributions signal increased financial stress levels.

The transformed variables are then aggregated into the FSI according to the following formula:

$$FSI_{i,t} = \sum_{j=1}^5 w_j \cdot Ind_{j,i,t} \quad (1)$$

where j represents each indicator of FSI, i indicates a country within the panel and t stands for the quarter an observation falls into. The FSI is thus a continuous measure at quarterly frequency that is calculated as a weighted average of the 5 transformed indicators for each country i at each quarter t . Market-equal weighting is chosen for indicators aggregation, i.e. placing a weight of 25% on each market represented within FSI. Inclusion of economies at different stages of their development (both advanced and emerging) with different key market segments justifies the use of market-equal weighting scheme. In contrast, had this paper attempted a country-specific case study of financial stress, a market-equal weighting approach would not be accurate due to existence of large differences among countries within the sample and as such different markets might adequately capture financial stress for each country. Hence, the market-equal weighting is preferred due to the cross-country nature of the model. In this spirit, the distribution of weights among individual indicators is as follows:

- 12,5% for negative returns of the main equity index
- 12,5% for the realised volatility of the main equity index
- 25% for the realised volatility of the nominal effective exchange rate
- 25% for TED spread or inverted interest rate spread
- 25% for the realised volatility of 3-month Treasury bill rate or long-term government bond yield volatility

Systemic events identification from financial stress measure, FSI, is crucial to EWS framework as it indicates crisis occurrence/absence that is used as a dependent within the EWS. Due to the fact that FSI was calculated as the simple average of financial stress captured in different markets by selected indicators and expressed as the percentile value of these indicators' country distributions, it represents average attained levels of stress in the economy as a whole in each time period. Hence, it is possible to set a certain value of FSI as a threshold, which once exceeded, would signal the occurrence of a systemic event. In this spirit, the threshold of 0.7 was chosen for systemic event occurrence, which in turn identifies 30% of the highest stress periods

for each country as crises. This calibration allows for correct identification of most systemic events in this study as compared with the crises database compiled by Laeven and Valencia (2008) (see Figure 2 in the appendix).

In order to ensure that FSI behaves as an appropriate early warning indicator by signalling upcoming systemic events, it needs to equal 1 in periods leading to the outbreak of these events. The horizon for signalling upcoming systemic events of 2 different lengths, short and long, is of interest in our work. For this purpose, the two models (short and long) are built to account for the appropriate signalling of upcoming crises over each of these horizons.

Therefore, in the short model FSI is set to 1 in 6 quarters leading to an event as this time length should be sufficient for policy makers to prepare adequate policy response (Peltonen and Lo Duca, 2011). Furthermore, in line with Peltonen, Lo Duca (2011) and Bussiere, Frantzscher (2006) the so-called periods of economic recovery, i.e. transitions from systemic events to tranquil periods, are excluded from the sample since during these periods “economic variables go through an adjustment process before reaching again the path they have during tranquil periods”, that could consequently lead to a „post crisis bias“ (Bussiere and Frantzscher, 2006). In practice this means that FSI is set to 0 after a crisis outbreak, i.e. in periods during which it originally remained above the set threshold. Additionally, FSI is assigned 0 in all tranquil periods shorter than 6 quarters as any subsequent high stress periods could still be continuations of previous systemic events (Peltonen and Lo Duca, 2011). As for the long model with the horizon of 12 quarters, the binary FSI transformation applies the same reasoning that was implemented for the transformation over the short horizon. In this case, however, FSI is set to 1 in 12 quarters preceding a systemic event outbreak and to 0 in all other periods.

2. Leading Indicators for Systemic Events Detection

In regards to constructing a framework for assessment and probabilistic prediction of systemic events, it is essential to include among potential leading indicators variables with the capacity to capture presence of imbalances within both the domestic and the global economy that may lead to an outbreak of a systemic event. The initial set of variables in this study is based on indicators that tend to appear in early warning system mechanisms, such as Peltonen and Lo Duca (2011), Babecký et al. (2011), Jakubik and Slacik (2013). This set contains not only domestic and global variables but also interactions between selected domestic variables, between global variables and between domestic and global variables.

In this spirit, for each country in the panel, the growth in domestic asset prices is approximated by real annual growth of the local MSCI index while asset price valuations are expressed by the ratio of equity market capitalization to GDP. As for leverage, it is measured by the ratio of private credit to GDP while growth in a country’s bank credit is approximated by private credit annual growth. Moreover, interaction between domestic asset price growth and asset price valuations as well as interaction between domestic credit growth and leverage level is expressed as the product of the two variables that should capture the dynamics. The same set of variables and their interactions as for domestic economy is prepared also for the global economy. In an attempt to capture additional fragilities that emerge when the overheating of the domestic economy coincides with the vulnerabilities in the global conditions, interactions between domestic and global variables were included as products of relevant variables. Global variables

were approximated by GDP-weighted averages of four large economies within the sample, i.e. Euro area, Japan, United Kingdom and United States (Peltonen and Lo Duca, 2011).

Apart from these variables the set of potential leading indicators includes proxies for macroeconomic conditions on the domestic level as well as on the global level. The short and long trends are derived from Hodrick-Prescott filter with values of the smoothing parameter of 1600 and 400 000, respectively. All indicators are in quarterly frequency. However, the variables from table 1 that are indicated as obtained from the World Bank (WB) were initially in annual frequency, thus to ensure their quarterly frequency for the purposes of this analysis a decomposition by cubic-match method is applied (Babecky et al., 2011). Real variables within the dataset are calculated by deflating a nominal variable by the consumer price index (CPI). Ultimately, the set of amassed variables covers the period between 1990Q1 and 2013Q1 for 14 countries altogether.

Table 1: Set of potential leading indicators

Indicator	Description	Source	Indicator	Description	Source
Real GDP	year-on-year change	OECD, NCB	Real private credit annual growth	interaction between global and domestic variables	BIS
Real M2	year-on-year change	IMF, NCB	Private credit/GDP	interaction between global and domestic variables	BIS
Real money	year-on-year change	IMF, NCB	Real MSCI annual growth x Global market capitalization/GDP	interaction between global and domestic variables	WB, www.msci.com
M2	share of GDP	IMF, NCB	Private credit growth x Global Private credit/GDP	interaction between global and domestic variables	BIS
Money	share of GDP	IMF, NCB	CPI	year-on-year change	IMF, OECD, NCB
Real domestic credit	year-on-year change	IMF	Real effective exchange rate	period-on-period change	BIS
Government deficit	share of GDP	IMF, NCB, Reuters	Global real private credit	year-on-year change	BIS
Government debt	share of GDP	OECD, NCB, Reuters	Global market capitalization	share of global GDP	WB
Private credit	share of GDP	BIS	Global private credit	share of global GDP	BIS
Real MSCI index	deviation from HP trend (short)	www.msci.com	Global private credit growth x Global private credit/GDP	interaction between global variables	BIS

Indicator	Description	Source	Indicator	Description	Source
Reserves	period-on - period change	IMF, OECD	Global real GDP	year-on-year change	OECD, NCB
Trade balance	period-on - period change	IMF, OECD	Global CPI	year-on-year change	IMF, OECD, NCB
Current account/GDP	share of GDP	OECD, NCB	Real private credit	year-on-year change	BIS
Unemployment rate	share of labour force	IMF, NCB	Real MSCI index	deviation from HP trend (long)	www.msci.com
Gross fixed capital formation	period-on-period change	IMF	Real MSCI index	year-on-year change	www.msci.com
Industrial production	period-on-period change	IMF, OECD, NCB	Property price index	year-on-year change	BIS, NCB
Market capitalization	share of GDP	WB	Real MSCI annual growth x Market capitalization/GDP	interaction between domestic variables	author based on WB, www.msci.com
Private credit growth x Private credit/GDP	interaction between domestic variables	author based on BIS	Real MSCI annual growth	interaction between global and domestic variables	author based on www.msci.com
Market capitalization/GDP	interaction between global and domestic variable	author based on WB	Global real MSCI index	year-on-year change	author based on www.msci.com
Non-performing loans	share of total loans	WB	Global real MSCI annual growth x Global market capitalization/GDP	interaction between global variables	author based on WB, www.msci.com

The set of potential leading indicators is prepared in a way to ensure their stationarity, i.e. expressing indicators by mostly growth rates. Nevertheless, stationarity check is performed for each variable in the panel using Augmented Dickey-Fuller (ADF) test in order to investigate the presence of a unit root process. Moreover, as ADF test checks for stationarity in each cross-sectional unit separately, it is prudent to also check stationarity of a variable across all units in the panel, which is performed via Im, Pesaran, Shin (2003) statistics and Choi (2001) tests. The Im, Pesaran, Shin's test is based on the average of (augmented) Dickey-Fuller statistics computed for each group in the panel while Choi's approach combines p-values from a unit root test applied to each group in the panel. The stationarity is rejected for the following variables: M2/GDP, Money/GDP, Government deficit/GDP, Government debt/GDP, domestic private credit/GDP, Current account/GDP, interaction of domestic private credit growth with domestic private credit/GDP, interaction between domestic and global private credit/GDP and real private credit annual growth. For nonstationary variables, their stationarity is ensured by first differencing.

Furthermore, as leading indicators are explanatory variables and FSI a dependent in latter analysis, avoidance of potential correlations between indicators of systemic events and the

variables from the FSI composition needs to be kept in mind when building the set of indicators. Therefore, correlations were checked for critical indicators. Those variables for which null of no correlation is rejected, are ultimately excluded from the analysis. The list of excluded indicators for which correlations are statistically significant can be found on the right-hand side of table 1 from the bottom and is the following: deviation of real MSCI index from long Hodrick-Prescott trend (smoothing parameter of 400 000), annual growth of real MSCI index, property price index annual growth, interaction between domestic real MSCI index annual growth and domestic market capitalization/GDP, interaction between domestic and global real MSCI index annual growth, annual growth of global real MSCI index and finally interaction between global real MSCI index annual growth and global market capitalization/GDP.

The crisis-detecting ability of indicators and hence their usefulness within the EWS can be assessed in a framework that takes into account missing systemic events, false signal emissions as well as policy-maker's preferences. This analysis follows the approach by Alessi and Detken (2011), which allows finding the optimal early warning thresholds for indicators and thus rank them with respect to their crisis detecting usefulness. The objective of this analysis is to find a threshold for each indicator that maximizes the utility function². In order to find a country-specific optimal threshold for every potential indicator within the dataset, all the observations of each indicator are transformed into percentile values of an indicator's country-specific distribution function. Every such percentile value is then set as a threshold for which the value of utility function is computed. The threshold which maximizes the utility function, apart from minimum and maximum value of the country distribution, is consequently chosen as optimal.

Table 2 presents the results of signalling analysis for potential indicators in the dataset. The set of indicators for which it is possible to calculate their utility functions is, however, reduced compared to the original dataset in table 1 as some time series are too short to cover both tranquil and crisis periods within a country's history. The crisis dating needed for these calculations is provided from the crises database by Laeven and Valencia (2008, 2012) while for the Euro area and the global economy the crisis dating includes only one systemic event, i.e. the global current crisis, within the observed period of 1990Q1-2013Q1.

Table 2: Average maximum utility of indicators across the panel, source: author's own calculations

Average maximum utility of indicators across the panel:			
Private credit/GDP	0.3233	Market capitalization/GDP	0.1113
Global CPI annual growth	0.2727	Government deficit/GDP	0.1101
M2/GDP	0.2655	Real M2 annual growth	0.1098
Government debt/GDP	0.2217	Global real annual GDP growth	0.1063

² $U = \min[\mu, 1 - \mu] - \left(\mu * \left(\frac{C}{A+C} \right) + (1 - \mu) * \left(\frac{B}{B+D} \right) \right)$, where $\left(\frac{C}{A+C} \right)$ is the proportion of missing signals, $\left(\frac{B}{B+D} \right)$ the proportion of false signals, μ is set to 0.5 and expresses policy-maker's neutrality towards either error type.

Average maximum utility of indicators across the panel:			
Money/GDP	0.2142	Trade balance change	0.1027
Unemployment rate	0.1821	Real money annual growth	0.0958
CPI annual growth	0.1678	Interaction Market capitalization/GDP	0.0715
Global real annual growth of private credit	0.1599	Real effective exchange rate growth	0.0698
Global private credit growth x Global private credit/GDP	0.1599	Gross fixed capital formation growth	0.0655
Reserves growth	0.1333		
Real domestic credit annual growth	0.1328	Private credit growth x Private credit/GDP	0.0653
Real MSCI index HP short trend	0.1278	Industrial production change	0.0551
Current account/GDP	0.1278	Global private credit/GDP	0.0400
Global market capitalization/GDP	0.1250	Real GDP annual growth	0.0185

The maximum average utility of an indicator across the panel of countries is calculated by averaging the maximum utilities of the indicator across the panel. The country-specific threshold for utility maximisation is employed for the calculations (Peltonen and Lo Duca, 2011). The best performing indicator from the signalling analysis is the ratio of private credit over GDP which coincides with common findings in the literature (e.g. Alessi and Detken, 2011). There are two indicators for monetary aggregates among the top 5 indicators in our analysis which, though quite useful in general, are not considered as well-performing as credit indicators according to the literature (Alessi and Detken 2011; Borio and Lowe 2004). Surprisingly, in contrast to Peltonen and Lo Duca (2011), global indicators and interactions between global and domestic indicators do not perform better than the top 5 indicators, all of which are domestic. The best performing non-domestic indicators, ranked 8th and 9th, are both global as well as they are credit indicators. In addition, both of these global indicators have the same maximum utility, i.e. global real annual growth of private credit and interaction between global private credit annual growth and global private credit over GDP are equally successful in crises signalling.

Since the set of indicators for which it is possible to calculate maximum utility is quite constricted compared to the set of all amassed indicators in table 1, the signalling analysis can only be viewed as an alternative or complementary technique to selecting indicators into the EWS model. We perform the final selection of appropriate indicators in a more comprehensive way later in this section.

Optimal lags selection for the indicators to be included in EWS poses a challenging question as different indicators might be able to discern the probability of a systemic event occurrence with a varying lead time length. In this view, various indicators are capable of issuing either a late warning for a 1-3Q horizon ahead or an early warning for 4-8Q ahead of a systemic event materialization as specified in Babecký et al. (2012). Generally, the indicator lags selection is

conditional upon researchers' expert opinion (Kaminsky and Reinhart, 1999) or to allow for publication lags of selected indicators (Peltonen and Lo Duca, 2011).

In this paper a quantitative approach towards lag selection is performed, inspired by Babecký et al. (2012), who choose panel vector autoregression model to account for differing dynamics of indicators in regards to systemic event occurrences. In contrast to that paper, we obtain important lags for each indicator from a univariate logit model with FSI as a dependent (transformed into binary) and an indicator along with its lags from 1 to 8 (in quarters) as independent variables. This setting investigates the dynamics of each indicator and FSI separately with the aim to extract lags that are relevant for explanation of systemic events occurrences as defined by binary FSI. Moreover, logit model is chosen for this purpose to maintain consistency throughout the entire analysis. Lags of each indicator that emerged significant from these univariate logit models are included in further analysis. The method for relevant lag selection is performed twice with the same set of initial indicators from table 1, once for FSI in the short form, i.e. flashing 1 in six quarters preceding the identified outbreak of a systemic event, and once for FSI in the long form, i.e. flashing 1 in twelve quarters preceding the identified outbreak of a systemic event. Finally, after the inclusion of the relevant lags the set of potential indicators expands from 33 as presented in table 1 to 78 for the short model, i.e. with FSI in the short form, and to 74 for the long model with FSI in the long form. From these two broad sets of potential indicators only the indicators with the highest usefulness for the construction of EWS framework need to be extracted for each model.

In presence of many potential variables the issue of discerning and selecting only the meaningful ones arises. When attempting to deal with the problem some hindrances materialize (Koop, 2003). First, including a large number of potential variables in one regression might lead to large standard errors, a consequence of the presence of irrelevant variables. Another hindrance in testing for inclusion of only relevant variables is inadvertent omission of an important variable during the sequential testing.

Therefore, the Bayesian model averaging technique is applied to the datasets containing selected lagged variables.³ This approach addresses model uncertainty in the area of financial stability research also by Babecký et al. (2012).

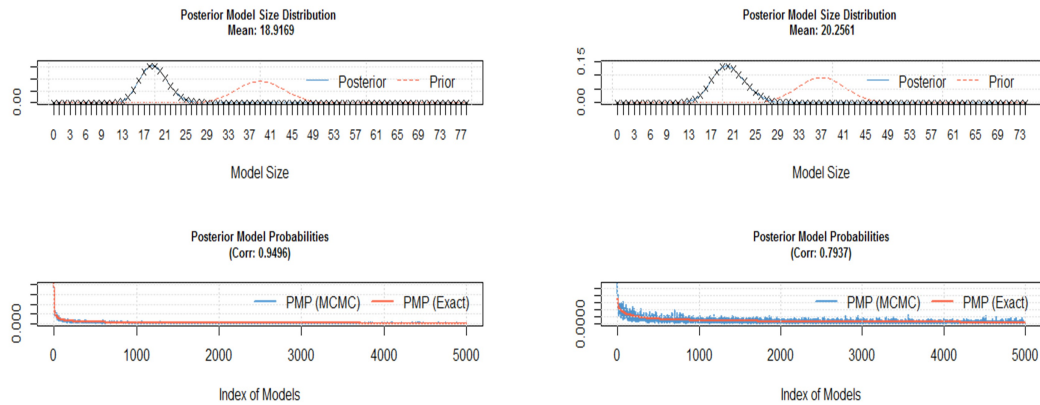
Due to a large number of potential variables (and their lags) to be input into the Bayesian model averaging, enumeration of all potential combinations of variables becomes not only time consuming but with increasing number of variables even infeasible (Feldkircher and Zeugner, 2009). Therefore, Markov Chain Monte Carlo (MCMC) samplers developed by Madigan and York (1995) are used to obtain results on the most important part of the posterior model distribution and thus deliver as precise estimates as possible. The quality of the MCMC approximation to the actual posterior distribution, i.e. the correlation of MCMC approximation results and the analytical ones, is linked to the number of draws the sampler is set to go through during the estimation process (iterations). However, as the MCMC sampler might start sampling from models that might not yield the best results and only after some time converge to models with high posterior model probabilities, it is advisable to discard these initial iterations (burn-ins).

For both models, i.e. both sets of potential indicators, the number of iterations is set to 45 000 000 after the initial 2 000 000 are discarded as burn-ins. The correlations obtained between the MCMC and analytical results for the short and the long model are 0.9496 and 0.7937,

³ The computation is performed in R using „BMS“ package by Feldkircher and Zeugner (2009).

respectively, which could be considered a sufficient convergence. Figure 1 below details these results as well as it shows prior and posterior model size distributions for both models:

Figure 1: Convergence and model size distributions for the short and the long model



As is discernible from figure 1, uniform model prior was employed in the computations so that expected prior model parameter size equals half the number of potential indicators entered into the Bayesian model averaging. However, after having updated the model prior with data it yields a smaller expected posterior model parameter size as parsimonious models are preferred.

BMA technique ultimately identifies the following 12 indicators as useful in crisis signalling over the short horizon of 6 quarters (short model): real money growth and its 4th lag, the 5th and 8th lags of real MSCI deviation from short Hodrick-Prescott trend, the 2nd lag of unemployment rate, the 7th lag of global private credit annual growth, the 7th lag of interaction between global private credit annual growth and global private credit/GDP, the 4th and 5th lag of interaction between private credit annual growth and global private credit/GDP, the 1st lag of global real GDP annual growth, the 1st lag of real GDP annual growth and global CPI annual growth. As for other selected variables, domestic GDP annual growth, unemployment rate, real money growth and global CPI growth are also considered informative and will be therefore included in the final short model.

For the EWS over the long horizon of 12 quarters the following 13 variables are selected as the most informative: the 1st lag of real domestic credit annual growth, the 4th lag interaction between domestic private credit annual growth and global private credit/GDP, the 5th lag of unemployment rate, the 1st and 8th lag of domestic CPI annual growth, the 4th lag of interaction between domestic and global real private credit annual growth, real domestic GDP annual growth, global market capitalization/GDP and its 3rd lag, the 8th lag of MSCI deviation from short Hodrick-Prescott trend, the 1st lag of global private credit annual growth, the 1st lag of interaction between global private credit annual growth and global private credit/GDP and M2/GDP ratio.

In line with common findings in the literature (e.g. Alessi and Detken (2011), Peltonen and Lo Duca (2011)), credit and private credit indicators both domestic and global as well as their interactions are found useful for the models over both horizon lengths. Overall 5 credit indicators are to be included into EWS over the long horizon and 4 over the short horizon. Moreover, the ratio of global market capitalization/GDP is selected even twice over the long horizon, which

coincides with the finding by Peltonen, Lo Duca (2011) that this is the most useful global indicator, i.e. the most useful indicator overall, in their study. As for asset prices, they are an important indicator in both models, though only their 8th lag appears in the long model.

Same as for the short model indicators, domestic GDP, CPI growth and unemployment rate are selected into the long model. When it comes to money aggregates the ratio of M2/GDP is selected for the long model as opposed to real money growth that appears in the short model.

3. Systemic Events Probability Framework

Having selected appropriate indicator lags and indicators themselves, we focus now on estimating the joint impact of useful indicators on the probability of a systemic event. As FSI in a binary form is the dependent variable, a logistic regression is applied to the data to ascertain the relation between useful indicators of vulnerabilities and crisis probability (advocated e.g. by Demirguc-Kunt and Detragiache (2005, pp. 5-9)). To estimate logit model, the maximum likelihood estimation technique is used which yields coefficient estimates that are consistent and asymptotically efficient as well as asymptotic standard errors of the coefficient estimates (Cramer, 2003).⁴

Short Model Estimation and Performance

The short logit model contains binary FSI, with values of 1 in 6 quarters preceding the pre-defined outbreak of a systemic event and 0 in all other periods, on the left-hand side, i.e. the dependent variable. On the right-hand side there are 12 useful indicators, the outcome of BMA technique. However, this model initially displays high collinearity between 2 of the indicators, the seventh lag of global annual private credit growth (Globpcrdgl7) and the seventh lag of the interaction between global annual private credit growth and global private credit over GDP (GlobpcgxglobpcGDPl7). Therefore, to achieve noncollinearity among independent variables, the seventh lag of the interaction between global annual private credit growth and global private credit over GDP (GlobpcgxglobpcGDPl7) is omitted from the model based on the Wald test statistic, which is higher than the respective p-value for the seventh lag of global annual private credit growth (Globpcrdgl7). All in all, the final short model composition includes 11 indicators. The model is then fitted to all available data, then to data until 2011 and to data only until 2006. For each model in-sample predictions are computed the same as out-of-sample predictions for the period of 2011Q1- 2013Q1 and for pre-crisis period of the Global crisis, i.e. 2006Q1-2008Q1.

Due to the nature of logit model, the coefficient estimates for independent variables are log-odds ratios. Thus logit regression estimates express how the log-odds of a systemic event occurrence change with a unit change in an independent variable. The sign of log-odds ratios indicates either a positive or a negative relationship between an explanatory variable and the likelihood of a systemic event occurrence. However, in order to estimate more precisely the extent of the change in likelihood given a change in an independent variable, an exponential of the log-odds ratio indicates actual odds of materialization of an event. For a negative relationship between the

⁴ All calculations are performed in R using package “verification” that follows the process outlined in Mason and Graham (2002).

explanatory and the dependent variable odds lie between 0 and 1, in case of a positive relationship they exceed 1.

Table 3: Short model estimation on all available data

	<i>Coefficient</i>	<i>Std. Error</i>	<i>z</i>	<i>p-value</i>	
Const	-2.26005	0.452736	-4.9920	5.98e-07	***
realmoneygl4	-12.5276	2.26024	-5.5426	2.98e-08	***
MSCIhpshortl5	5.34506	1.51967	3.5172	0.00044	***
Uratel2	22.1122	6.88392	3.2122	0.00132	***
Globpcredgl7	40.2897	10.0369	4.0142	5.97e-05	***
MSCIhpshortl8	1.85216	0.928	1.9959	0.04595	**
realmoneyg	-7.32671	2.27894	-3.2150	0.00130	***
Int_pcgxglopcGDPI4	11.6145	9.21088	1.2610	0.20732	
Int_pcgxglopcGDPI5	23.2149	9.92291	2.3395	0.01931	**
GlobGDPgl1	14.747	9.168	1.6085	0.10772	
realGDPgl1	20.7753	6.63864	3.1294	0.00175	***
GlobCPIg	31.2841	19.104	1.6376	0.10151	
Mean dependent var	0.192453	S.D. dependent var		0.394599	
McFadden R-squared	0.452249	Adjusted R-squared		0.406020	
Log-likelihood	-142.1812	Akaike criterion		308.3624	
Schwarz criterion	359.6369	Hannan-Quinn		328.4320	

Likelihood ratio test: Chi-square(11) = 234.783 [0.0000]

Note: The number following each indicator states an indicator's lag (in quarters), * represents significance on 10%, ** on 5% and *** on 1% significance level.

Only one variable, real money growth (realmoneyg) and its fourth lag (realmoneygl4), have a negative relationship with the likelihood of an event occurrence. A unit change in all other independent variables increases the odds of a crisis by more than 1.

Table 4: In-sample performance of short logit models

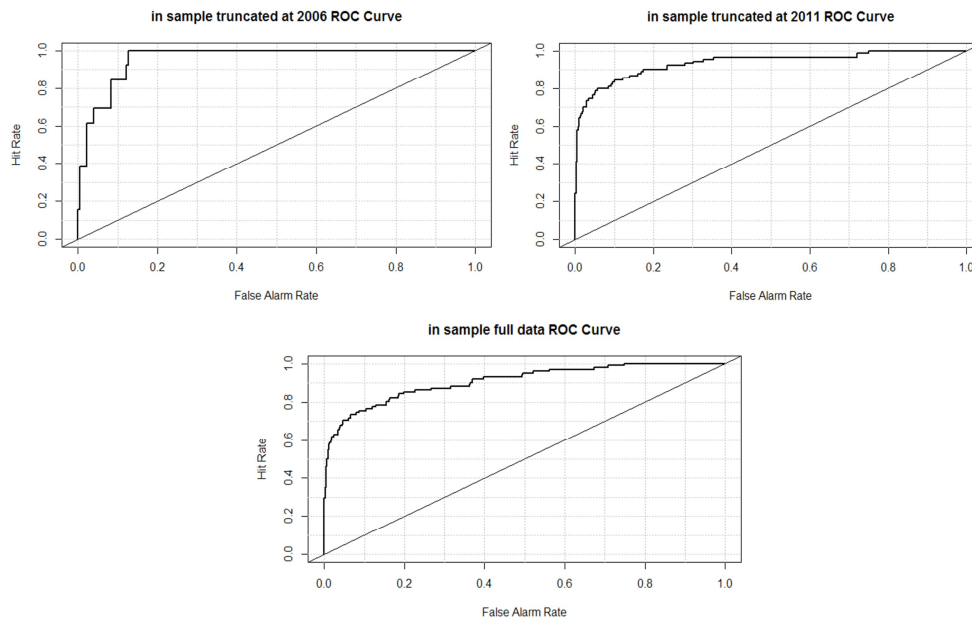
In-sample performance of short logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Short truncated till 2006	0.436	0.812	87.56	100	0.133	0.959	1.75E-08
Short truncated till 2011	0.372	0.756	88.70	84.44	0.122	0.937	2.66E-38
Short on full data	0.335	0.805	89.43	73.53	0.092	0.908	6.38E-38

As shown in table 4 the short model performance is measured by several indicators: maximum utility measure (U), threshold for which the model's utility is maximized, percentage correctly predicted (PCP)⁵, percentage of crises predicted⁶, Noise to Signal ratio (NtS ratio)⁷, ROC area⁸ and p-value⁹.

According to these calculations the best-performing in-sample short model is the one estimated on truncated data until 2006. It has the highest U measure, the percentage of crises predicted and area under ROC curve which is also highly significant with p-value of 1.75E-08. On the other hand, the model's NtS ratio is the largest out of the compared in-sample short models while the percentage correctly predicted is the lowest. On the whole, the in-sample performance of the short model appears to be more than satisfactory, verifiable by low p-values and signifying strong rejection of the null of no forecast skill for all three fittings of the short model.

Areas under ROC curves presented in table 4 are obtained from ROC curve plots in figure 2. The further the ROC curve for a model is from the diagonal, the larger the discrimination (analogy with Gini coefficient as a measure of inequality), i.e. the higher the forecast's skill to anticipate correctly the occurrence or non-occurrence of pre-defined events.

Figure 2: ROC curve plots for in-sample performance of short logit model estimated on data until 2006, until 2011 and on all available data



⁵ The utility-maximizing threshold is used as a cut-off

⁶ It is calculated as the number of periods when signal was correctly issued over the number of periods in which the signal should have been issued (sum of “correct signal” periods and “missing signal” periods).

⁷ A useful indicator is supposed to have a NtS of less than 1, a value of 1 would result if an indicator provides purely random signals (Kaminsky et al., 1998).

⁸ A value of 1 indicates a perfect model while a random forecast would have the ROC area equal to 0.5. The ROC area calculation follows Mason and Graham (2002).

⁹ p-value helps estimate the adequacy of a model forecast via ROC area and is related to Mann-Whitney U statistics. The statistics tests the null of the area under the ROC curve equal to 0.5 or the forecast has no skill.

Once in-sample performance of the short logit model is validated, its performance out-of-sample is verified. This check is performed to estimate a model's forecasting ability. The results of forecasts for the model on truncated data till 2011 over the period of 2011Q1-2013Q1 and those of the model on truncated data until 2006 over pre-crisis period of 2006Q1-2008Q1 are summarized in table 5 below.

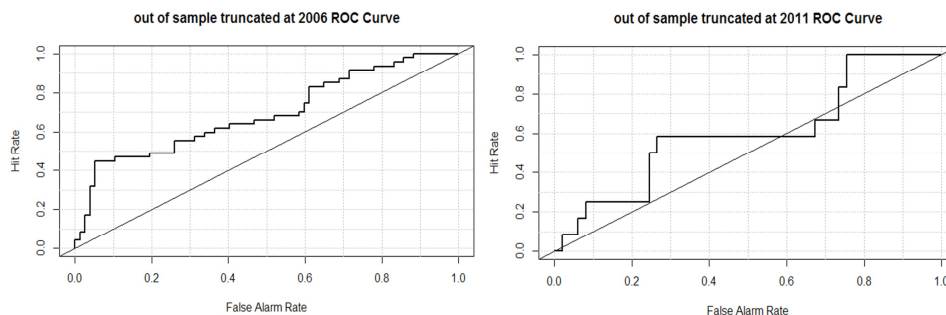
Table 5: Out-of-sample performance of short logit models, source

Out-of-sample performance of short logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Short truncated till 2006	0.197	0.796	75	44.68	0.145	0.691	0.00019
Short truncated till 2011	0.159	0.666	68.85	58.33	0.490	0.599	0.150506

As expected the out-of-sample performance of the model is lower compared to its in-sample results. The maximum utility is about half of that for in-sample performance as well as all other performance measures decrease (apart from NtS ratio which increases) indicating weaker performance in general. The better out-of-sample performance is for the model on truncated data till 2006 due to having higher utility measure, PCP, lower NtS ratio and a larger area under ROC curve, which is significant on 0.02% significance level. However, its percentage of crises predicted is lower than that for the model on data truncated till 2011. The worse out-of-sample performing short model, on data truncated until 2011, does not differ dramatically in terms of performance measures from the better one apart from NtS ratio that is almost 0.5 and the area under ROC curve of 0.599 which is significant only on 16% significance level even if the model itself is not a random forecast (area of 0.599 is still larger than 0.5).

Overall, the short model on truncated data until 2006 is ranked as the best performing by its U measure both in-sample and out-of-sample. However, out-of-sample the model experiences almost 55% fall in its utility, 14.5% decline in its PCP, the fall of 55.3% in its percentage of crises predicted, 9% rise in its NtS ratio while the area under ROC curve shrinks by 28%. In comparison, the out-of-sample performance of the worse model, estimated on data up till 2011, declined from its in-sample performance by 57% for U, 22.4% for PCP, 31% for percentage of crises predicted and by 36% for ROC area while its NtS ratio shot up by 302% to the level of almost 0.5. In addition, the best ranked model, estimated on truncated data till 2006, appears to be more stable when estimated out-of-sample than the second best ranked short model (see Figure 3).

Figure 3: ROC curve plots for out-of-sample performance of short logit model estimated on data up till 2006 and till 2011



Long Model Estimation and Performance

In the long model, the dependent is the binary FSI, with values of 1 in 12 quarters preceding the pre-defined occurrence of a systemic event and 0 in all other periods, on the left-hand side while there are 13 indicators, selected from BMA technique, on the right-hand side. Similarly to the short model, the long model also displays high collinearity between 2 of the indicators, i.e. the first lag of global annual private credit growth (Globpcrdgl1) and the first lag of the interaction between global annual private credit growth and global private credit over GDP (GlobpcgxglobpcGDPI1). Thus to ensure noncollinearity among explanatory variables, the first lag of the interaction between global annual private credit growth and global private credit over GDP (GlobpcgxglobpcGDPI1) is omitted in the spirit of the short model analysis. The decision is justified by the Wald test statistic for this variable with p-value of 0.154462, which is again higher than the respective p-value for the first lag of global annual private credit growth (Globpcrdgl1) that equals 0.152273.

After this adjustment the final long model containing 12 indicators is fitted, as in the case of the short model, to all available data, to data truncated till 2011 and truncated till 2005. For each model in-sample predictions are calculated as well as out-of-sample predictions for the period of 2011Q1- 2013Q1 and for pre-crisis period of the Global crisis, i.e. 2005Q1-2008Q2.

Next, the analysis resumes the structure of that for the short model. As such, indicator coefficients are estimated for each of the subperiods followed by in-sample and out-of-sample performances of long logit models.

Table 6: Long model estimation on all available data

	<i>Coefficient</i>	<i>Std. Error</i>	<i>z</i>	<i>p-value</i>	
const	-10.9152	1.23256	-8.8557	8.31e-019	***
rdomcredl1	-1.07904	2.10306	-0.5131	0.60790	
Int_pcgxglopcGDPI4	50.8465	13.926	3.6512	0.00026	***
Uratel5	8.77642	5.82841	1.5058	0.13212	
CPIgl8	4.54716	4.36299	1.0422	0.29731	
Int_realpcrdgl4	-309.252	109.757	-2.8176	0.00484	***
CPIgl1	-54.7731	8.75562	-6.2558	3.96e-010	***
realGDPg	-14.7407	5.81822	-2.5335	0.01129	**
GlobmcapGDP	5.26878	1.47088	3.5821	0.00034	***
MSCIhpshortl8	1.59052	0.949851	1.6745	0.09403	*
Globpcrdgl1	2.48314	10.0189	0.2478	0.80425	
GlobmcapGDPI3	7.26515	1.38609	5.2415	1.59e-07	***
M2GDP	2.06582	0.844418	2.4464	0.01443	**
Mean dependent var	0.275362	S.D. dependent var		0.447102	
McFadden R-squared	0.459095	Adjusted R-squared		0.419078	
Log-likelihood	-175.7201	Akaike criterion		377.4402	

Schwarz criterion

433.5163

Hannan-Quinn

399.3503

Likelihood ratio test: Chi-square(12) = 298.286 [0.0000]

Note: the number following each indicator states an indicator's lag (in quarters), * represents significance on 10%, ** on 5% and *** on 1% significance level.

From long model estimation on the full data sample, it is observable that 4 independent variables, the 1st lag of real domestic credit growth, the 4th lag of interaction between domestic and global real private credit growth, the 1st lag of CPI annual growth and annual growth of real GDP, have a negative relationship with the dependent, a likelihood of a systemic event occurrence. A unit change in all other explanatory variables increases the odds of a crisis occurrence by more than 1. The model validation is performed the same way as for the short model by comparing model on full data, model estimated on truncated data till 2011 and model on truncated data till 2005.

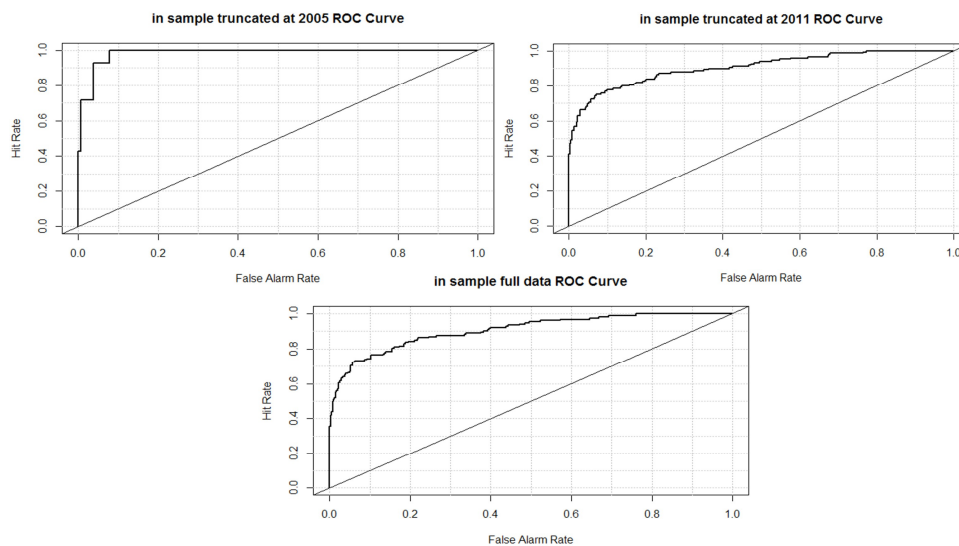
Table 7: In-sample performance of long logit models

In-sample performance of long logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Long truncated till 2005	0.461	0.845	92.31	100	0.084	0.984	1.04E-09
Long truncated till 2011	0.339	0.726	87.37	75	0.099	0.905	1.18E-46
Long on full data	0.334	0.753	87.86	73.03	0.089	0.905	2.44E-49

In the spirit of the short model analysis, the best in-sample performing long model is the one estimated on data up till 2005. This model boasts the highest PCP, percentage of crises predicted as well as area under ROC curve while it has the lowest NtS ratio of only 0.084.

All in all, the differences in performance measures between the best performing long model in-sample and the second best are not very substantial with the largest difference of 36% for U measure.

Figure 4: ROC curve plots for in-sample performance of long logit model estimated on data up till 2005, till 2011 and on all available data



Now, it is of interest to analyse the model's performance out-of-sample and to detect the differences.

Table 8: Out-of-sample performance of long logit models

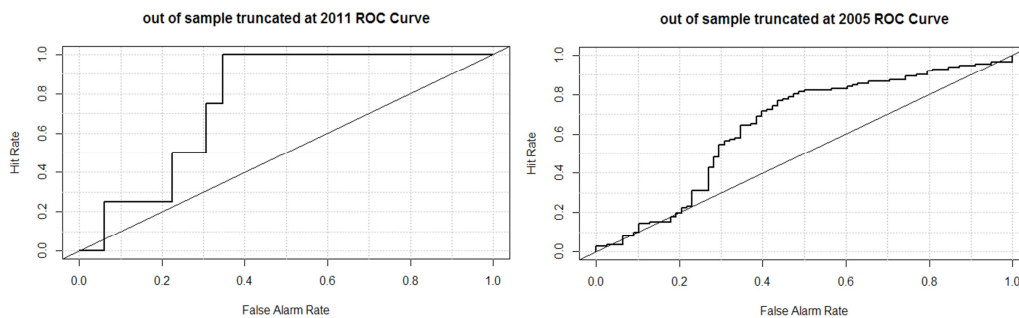
Out-of-sample performance of long logit models							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Long truncated till 2011	0.327	0.596	66.04	100	0.367	0.765	0.041465
Long truncated till 2005	0.166	0.365	67.89	76.79	0.584	0.639	0.000579

The first look reveals that the better performing long model is not the one estimated on data up till 2005 as is the case for short models but the one estimated on data till 2011 and projected over the last couple of years till present. The U measure of the better performing model is double of that for worse performing one. The percentage of crises predicted for this model is 23% higher than that of its counterpart while NtS ration is 37% lower and area under ROC curve is almost 20% larger. However, despite the larger ROC area the better out-of-sample model is significant only on 5% level while the worse model's ROC area is significant on 0.06%.

In comparison to the in-sample performance of the model estimated on data up till 2011, its out-of-sample performance measures declines by 3.7% for U, 24.4% for PCP and 15.5% for area under ROC curve. Other measures increase out-of-sample, namely percentage crises predicted by 25% and NtS ratio by 270%.

As for the worse out-of-sample performing model but the best one in-sample, estimated on data up till 2005, its U measure falls by 64%, PCP by 26.5%, percentage of crises predicted by 24.2%, its area under ROC curve by 35% while its NtS ratio rockets by 595% to almost 0.6, all out-of-sample.

Figure 5: ROC curve plots for out-of-sample performance of long logit model estimated on data up until 2011 and till 2005



To conclude, comparatively it appears that out-of-sample performance of the model estimated on data until 2011 deteriorates less than that of the model estimated on truncated data till 2005 making the better model more stable when estimated both in-sample and out of it.

4. Model Application to the Czech Republic

In addition to the problem of collinearity, which is also often the case in linear regression, discrete data regressions can also become unstable from separation. Separation or perfect prediction arises when some linear combination of the predictors is perfectly predictive of the outcome (Albert and Anderson, 1984 and Lesaffre and Albert, 1989). In order to solve separation, independent variables are gradually removed until the final model is identifiable. However, according to Zorn (2005) this approach may result in removing the strongest predictors from the model. Therefore the technique to employ in case of perfect prediction is Bayesian inference. The Bayesian estimation of logistic regression is used for both, the short and the long model, on the Czech data as the traditional maximum likelihood estimation suffers from perfect prediction. This demonstrates by producing abnormally large coefficient as well as standard error estimates while p-value equals 1 for all coefficient estimates.¹⁰

Gelman, Jakulin, Pittau and Su (2008) adapt the classical maximum likelihood algorithm within logit model in a way to obtain approximate posterior inference for the coefficients β . The standard logistic regression algorithm, upon which this technique expands, proceeds by approximately linearizing the derivative of the log-likelihood, solving by means of weighted least squares, and then iterating this process, each step evaluating the derivatives at the latest estimate $\hat{\beta}$ (McCullagh and Nelder, 1989). We do not introduce any additional information about prior distribution in the logit model estimation for the Czech Republic.

Estimation and Performance of the Short Model for the Czech Republic

The short model with 11 independent variables and an intercept is estimated by Bayesian inference on the full Czech data from 1990Q1 till 2013Q1 as well as only on truncated data up until 2011 with the objective of evaluating its fit, i.e. the quality of its in-sample forecasting performance. In addition, coefficient estimates resulting from fitting the short model on data of different length are also commented on for the purpose of observing their stability.

Table 9: Short model estimation on all available Czech data

	coef estimate	coef st. error
(Intercept)	-0.59	5.3
realmoneygl4	19.45	18.2
MSCIhpshortl5	4.67	4.77
Uratel2	-44.6	61.1
Globpcrdgl7	45.47	34.02
MSCIhpshortl8	-0.52	3.26
realmoneyg	3.6	15.3
Int_pcgxglopcGDPI4	37.16	42.07
Int_pcgxglopcGDPI5	-22.76	42.79

¹⁰ To yield stable coefficient estimates for logit models via Bayesian inference the “arm” package in R, built to accompany the paper by Gelman, Jakulin, Pittau and Su (2008), was used for the calculations.

	coef estimate	coef st. error
GlobGDPgl1	5.67	31.88
realGDPgl1	55.7	30.7
GlobCPIg	9.22	99.61

n=38, k=12

residual deviance=9.3

null deviance=36.3

(difference=27)

Note: the number following each indicator states an indicator's lag (in quarters)

From table 9 it is apparent that the Bayesian estimation of the logit model provides only coefficient estimates and their standard errors while excluding information about their significance. A negative relationship is detected only between three independent variables. Thus a unit change in either of these three variables increases the odds of a crisis materialization between 0 and 1. Moreover, the fitted model appears to explain the data quite well compared to a model with intercept only as the reduction in deviance (difference between the null and the residual deviance) is quite large.

The short model estimated on data till 2011 preserves the signs of the estimated coefficients and estimates themselves differ only slightly. This supports the model stability. However, the model might be a slightly worse fit to truncated data than to the full sample given that the difference in deviance is lower for the truncated model.

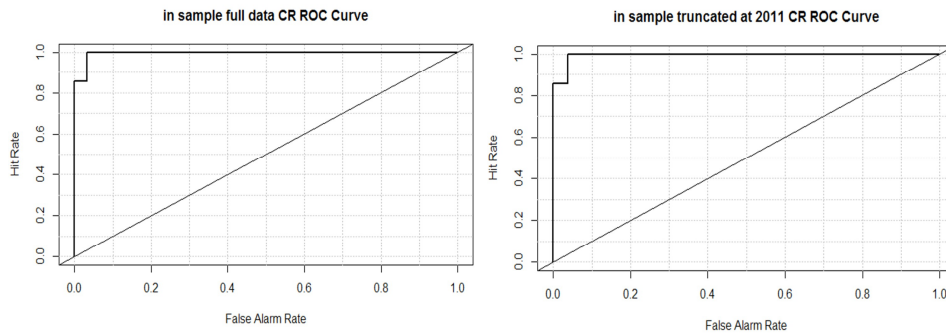
Now the same measures that were employed to assess the model's performance on panel data are also applied here.

Table 10: In-sample performance of the short model for the Czech Republic

In-sample performance of the short model for the Czech Republic							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Short full data	0.484	0.783	94.74	100	0.065	0.9954	1.58E-07
Short truncated till 2011	0.481	0.75	93.94	100	0.077	0.9945	4.68E-07

As evidenced from table 10 the short model estimated on all available data for the Czech Republic performs better in all performance statistics than the model on truncated data. The model successfully predicts 94.74% of observations as well as 100% of systemic events. The worse of the two regressions, on truncated data, predicts observations only 0.8% less successfully while it also predicts 100% of systemic events. The quality of in-sample forecast is captured by the area under ROC curve and no discrimination line (the diagonal), that attains for both almost maximum (1) while its p-value is quite low. This indicates almost perfect forecasting skill of the short model on both data samples.

Figure 6: ROC curves for in-sample performance of the short logit model on full data and truncated data for the Czech Republic



Estimation and Performance of the Long Model for the Czech Republic

Bayesian inference is also used for the Long model estimation on the Czech data. In similar fashion, the long model with 12 most useful indicators from BMA technique is applied to all available Czech data as well as to truncated data up till 2011. The objective is the same as for the short model estimation on the Czech data, to assess model's fit to the data, i.e. its in-sample predictive ability. For this purpose, a set of performance measures is applied to evaluate model's prediction of the binary dependent while model's stability is discussed by comparing results from full data regression with those from truncated sample.

Table 11: Long model estimation on all available Czech data

	coef estimate	coef st. error
(Intercept)	-27.62	13.63
rdomcred11	-3.05	12.39
Int_pcgxglopcGDPI4	3.73	79.4
Uratel5	1.5	67.82
CPIgl8	-17.12	46.81
Int_realpredgl4	24.82	348.26
CPIgl1	-17.67	45.42
realGDPg	9.39	30.16
GlobmcapGDP	31.47	14.58
MSCIhpshortl8	0.02	3.62
Globpredgl1	13.25	58.6
GlobmcapGDPI3	0.87	5.66
M2GDP	-1.22	13.25
n=37, k=13		
residual deviance=2.6		

null deviance=48

(difference=45.4)

Note: the number following each indicator states an indicator's lag (in quarters)

As shown in table 11 there is a negative relationship between 4 indicators and the likelihood of a crisis occurrence. A unit change in all other 8 indicators increases odds of a crisis occurrence by more than 1. As for the usefulness of the fitted model overall, its deviance decreases by 45.2, a large change from an intercept-only model.

Coefficient estimates from model on truncated data appear to be quite similar to those in table 11. Similarly to the short model, the long model on truncated data yields lower reduction in deviance from the intercept-only model than the model estimated on full data sample, indicating a slightly worse fit.

Table 12: In-sample performance of the long model for the Czech Republic

In-sample performance of the long model for the Czech Republic							
Model	U	Threshold	PCP	% crises predicted	NtS ratio	ROC area	p-value
Long full data	0.5	0.638	97.30	100	0.042	1	2.81E-10
Long truncated till 2011	0.5	0.593	96.97	100	0.05	1	1.74E-09

According to performance measures, the long model on both samples performs very well for the Czech Republic. Within the sample both models reach the maximum utility value of 0.5, predict 100% of systemic events and thus maximize area under ROC curve to 1 for which p-value is quite low. Based on ROC area measure it can be said that the long model on Czech data yields perfect in-sample predictions. However, according to PCP there is some noise within the forecast as the model on full data successfully predicts only 97.3% observations and its Noise-to-Signal ratio is not 0 either, though it is very low. As for the slightly worse performing model, the one on truncated data, it correctly predicts 0.3% of observations less than the full data model while its NtS ratio is 19% higher.

Figure 7: ROC curves for in-sample performance of the long logit model on full data and truncated data for the Czech Republic

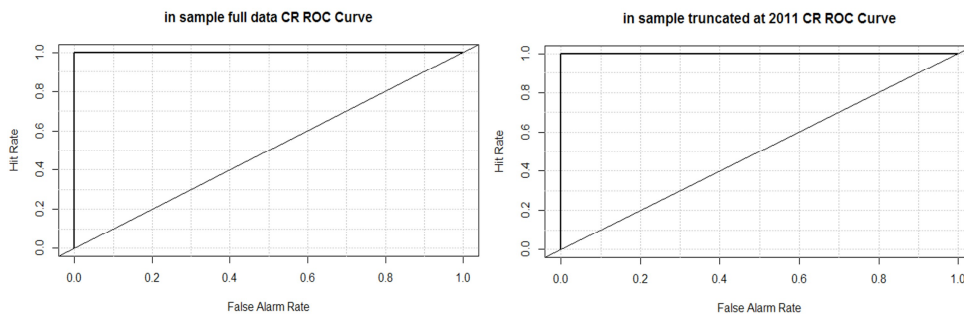


Table 13: In-sample performance of logit models for the Czech Republic

In-sample performance of logit models for the Czech Republic							
Model	U	Threshold	PCP	%crisis predicted	NtS ratio	ROC area	p-value
Long full data	0.5	0.638	97.30	100	0.042	1	2.81E-10
Long truncated till 2011	0.5	0.593	96.97	100	0.05	1	1.74E-09
Short full data	0.484	0.783	94.74	100	0.065	0.9954	1.58E-07
Short truncated till 2011	0.481	0.75	93.94	100	0.077	0.9945	4.68E-07

The highest ranking model for the Czech Republic is thus the long model on all available data followed by the long model on truncated data. The short model on all data performs as third best while its estimation on truncated data ranks last.

Ultimately, the long model, designed to be able to anticipate crises within long horizon of 12 quarters performs better than the short model with the horizon of 1.5 years. Overall both models perform very well in-sample with the difference between the long and the short model on full data in terms of utility of 3.3%, PCP of 2.7%, percentage of crises predicted of 0%, NtS ratio of 35.4% and finally area under ROC curve of 0.5%.

Figure 8: In-sample, out-of-sample predictions comparison of the long and the short model for the Czech Republic

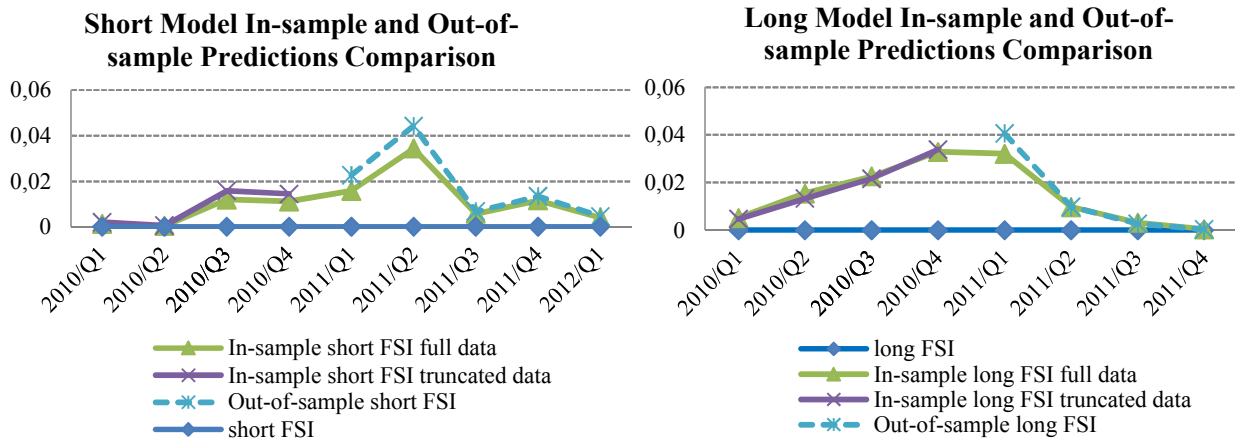


Figure 8 depicts systemic event probabilities estimated by both models not only in sample on full Czech data and on truncated data until 2011 but also out-of-sample systemic event probability estimates from 2011 onwards. The out-of-sample estimates do not diverge substantially from in-sample probabilities indicating good out-of-sample performance of EWS over both horizons for the Czech Republic.

Conclusions

The aim of this study is to develop EWS framework for predicting systemic events for the Czech Republic. We develop two models on the panel of 14 countries, i.e. the short model to allow prediction of events over the horizon of 1.5 years and the long one over the horizon of 3 years. We validate the models' performance on the panel and subsequently observe their skill when applied to the Czech data.

First, the Financial stress index (FSI), measuring the level of financial stress within the financial system, is constructed for each country within the panel. To aggregate individual subindices from equity, foreign exchange, money and securities markets into FSI, a market-equal weighting is employed due to the cross-country nature of the analysis. FSI thus reports average level of systemic stress in the economy at each point in time (quarter). Moreover, FSI transformed into binary form is used for identification of starting dates of country-specific systemic events.

Second, uncertainty in regards to the inclusion of potential leading indicators that best explain crisis occurrences into EWS is resolved by Bayesian model averaging (BMA) technique. We relax the assumption of a common fixed horizon at which all potential indicators issue early warning signals and detect indicators' relevant lags for signal emission by univariate logit models. Overall, the selected indicators for both horizons are in accordance with the literature which identifies credit indicators as the most useful (Alessi and Detken 2011; Borio and Lowe 2004) as well as their domestic and their global and domestic interactions (Peltonen and Lo Duca, 2011).

Third, the binary logit model containing BMA selected indicators is estimated for both horizons on the panel. Over the short horizon the best performing model, both in-sample as well as out-of-sample, is the one estimated on data till 2006 with its out-of-sample performance tested over the pre-crisis period of the global recent crisis (2006Q1-2008Q1).

The best performing long model in-sample is the one estimated on data till 2005 while out-of-sample it is the one estimated on data until 2011 and projected over the last two years till present. However, out-of-sample performance of the model estimated on data until 2011 comparatively deteriorates less than that of the model estimated on data up till 2005, which makes the model with better out-of-sample performance more stable.

Fourth, applied to the Czech data, the highest ranking model in-sample is the model over the long horizon estimated on full data. The model manages to correctly predict 100% of systemic events, maximizes the utility measure for the Czech Republic as well as the area under ROC curve which indicates perfect in-sample predictive skill of the model. Moreover, the model over the horizon of 1.5 years also performs very well in-sample for the Czech Republic with only negligible decline in performance compared to the long model.

To conclude, we observe also out-of-sample performance of the constructed EWS over both horizons on the Czech data from 2011 onwards. The out-of-sample estimates of systemic event probabilities do not deviate substantially from their in-sample estimates indicating good out-of-sample performance of the built EWS for the Czech Republic.

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Appendix

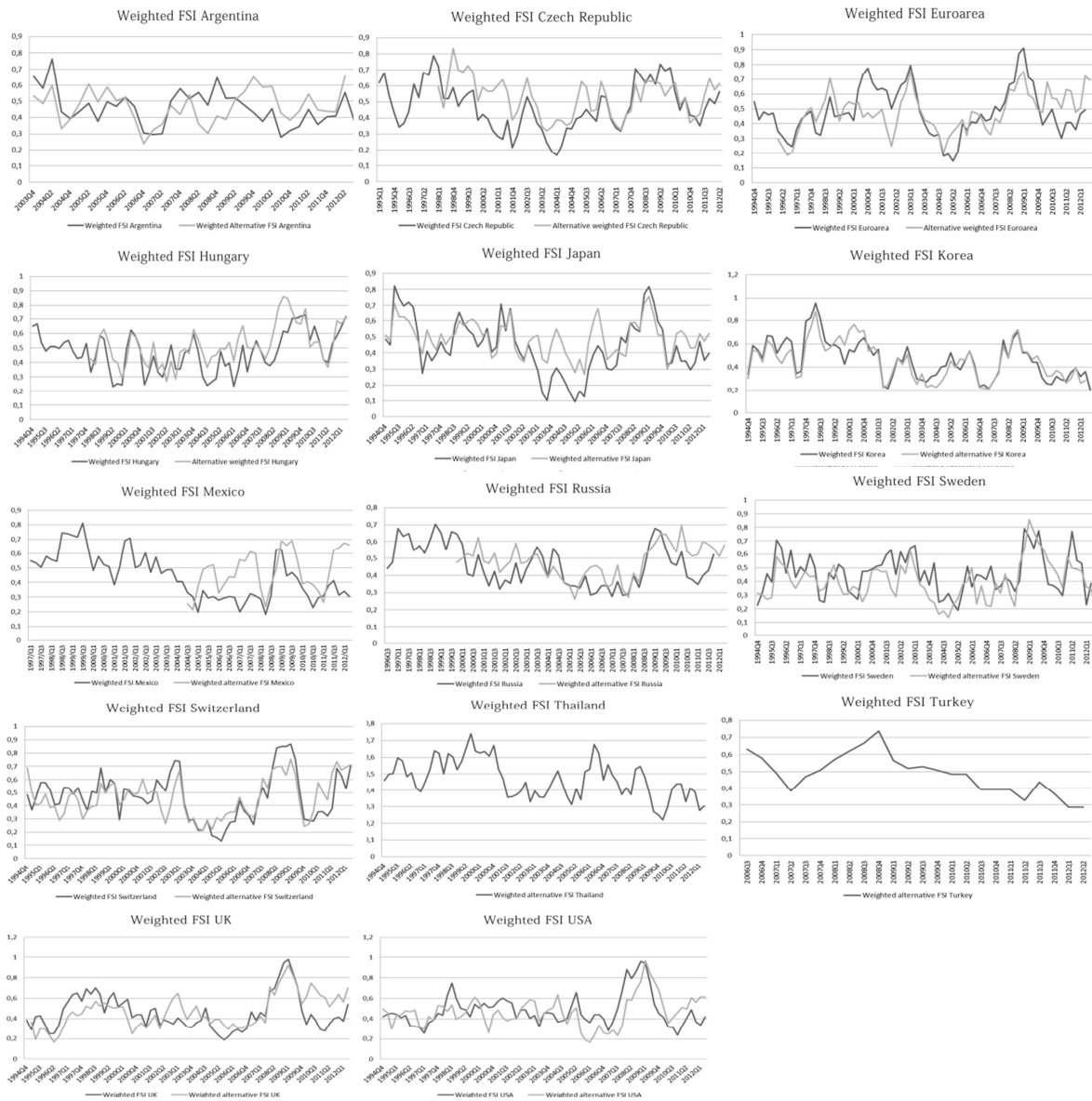


Figure 1: Equal- market Weighted FSI (in dark gray) and Alternative Equal – market weighted FSI (in light gray) Development

Notes:

Argentina: FSI registers the highest stress in 2004 in the wake of debt, systemic banking and currency crises with starting dates of 2001, 2001 and 2002, respectively. *Czech Republic:* The FSI peaks in 1997 following systemic banking crisis starting in 1996. *Euro area:* FSI attains its highest values during crisis period in 2008/2009. *Hungary:* FSI identifies higher stress levels during the recent global crisis than during the Hungarian systemic banking crisis of 1991. *Japan:* FSI registers increased stress during the recent global crisis and before the outbreak of the Japanese systemic banking crisis in 1997. *South Korea:* FSI peaks during the Korean systemic banking crisis of 1997. *Mexico:* Due to data restrictions FSI omits Mexican banking crisis of 1994 but reflects major insolvency of Mexican banks by the year 2000. *Russia:* The FSI captures the highest stress levels during the Russian crisis of 1998. *Sweden:* FSI peaks during the recent global crisis and also reflects increased stress in 1995, in the aftermath of the Swedish systemic banking crisis. *Switzerland:* FSI indicates high stress during the recent global crisis. *Thailand:* Only alternative FSI is constructed due to data restrictions, it reflects well the high stress during the Asian crisis of 1997/1998. *Turkey:* Only alternative FSI is constructed covering the shortest time period of all indices due to data restrictions. *United Kingdom and United States:* Both FSIs peak during the recent global crisis.

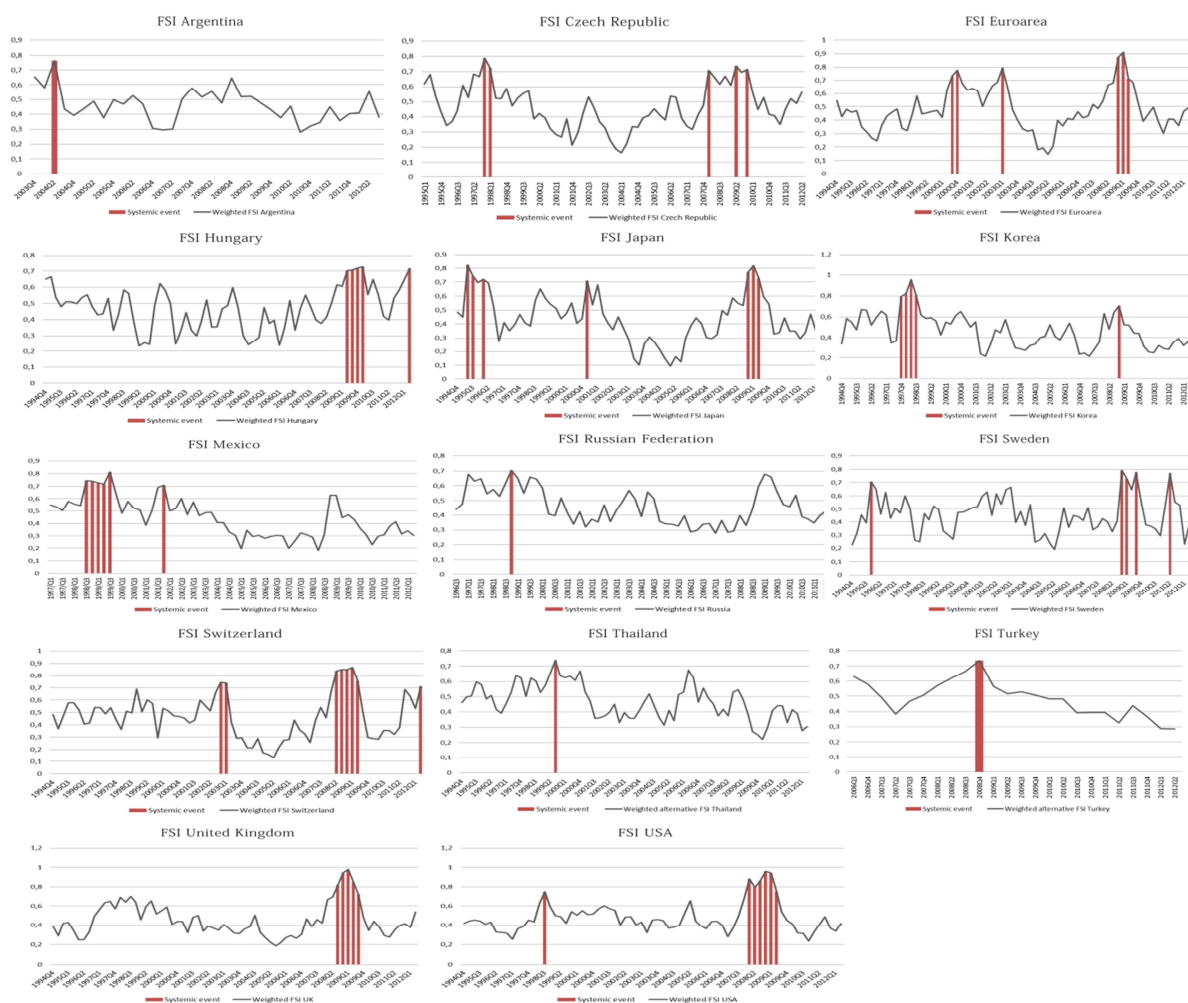


Figure 2: Systemic Events Identification by Means of FSI Threshold Value of 0.7

Notes:

Argentina: Systemic event taking place in 2004Q2, near the time of the Argentinian systemic banking crisis. *Czech Republic*: The threshold exceeded in 1997Q4 and 1998Q1 during the country-specific systemic banking crisis and during the recent global crisis. *Euro area*: The threshold exceeded in the second half of 2000, the beginning of 2003 and during the recent crisis. *Hungary*: Event episodes recognized during the global crisis. *Japan*: The threshold exceeded in periods around the Japanese systemic banking crisis and during the global crisis. *South Korea*: The threshold identifies the presence of systemic events in the Korean crisis period and during the global crisis. *Mexico*: Events are identified in the wake of the Mexican systemic banking and currency crises. *Russia*: The recognized systemic event falls into the Russian crisis period. *Sweden*: The threshold exceeded in the country-specific systemic banking and the global crisis periods. *Switzerland*: Systemic events mainly recognized during the global crisis. *Thailand*: The threshold exceeded after the Asian crisis outburst. *Turkey*: Due to data constraints the systemic event recognized during the global crisis only. *United Kingdom* and *United States*: Both indices exceed the threshold during the global crisis.

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