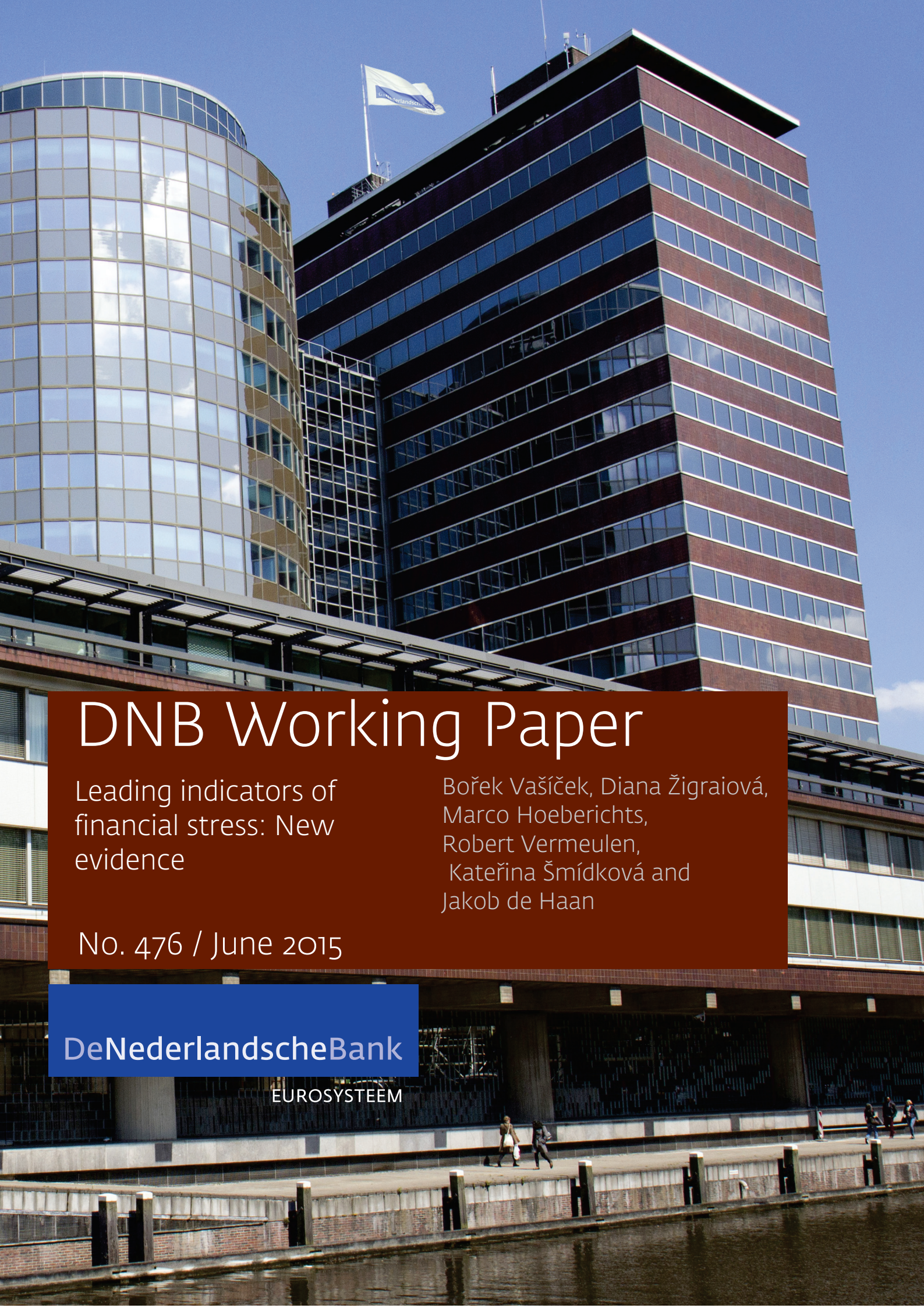




DNB Working Paper

Leading indicators of
financial stress: New
evidence

Bořek Vašíček, Diana Žigraiová,
Marco Hoeberichts,
Robert Vermeulen,
Kateřina Šmídková and
Jakob de Haan

No. 476 / June 2015

DeNederlandscheBank

EUROSISTEEM

Leading indicators of financial stress: New evidence

Bořek Vašíček, Diana Žigraiová, Marco Hoeberichts, Robert Vermeulen, Kateřina Šmídková and Jakob de Haan *

* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 476

June 2015

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

Leading indicators of financial stress: New evidence *

Bořek Vašíček ^a, Diana Žigraiová ^{a,e}, Marco Hoeberichts ^b, Robert Vermeulen ^b,
Kateřina Šmídková ^{a†} and Jakob de Haan ^{b,c,d *}

^a *Czech National Bank, Prague, Czech Republic*

^b *De Nederlandsche Bank, Amsterdam, The Netherlands*

^c *University of Groningen, The Netherlands*

^d *CESifo, Munich, Germany*

^e *Institute of Economic Studies, Charles University in Prague*

1 June 2015

Abstract

This paper examines which variables have predictive power for financial stress in a sample of 25 OECD countries, using a recently constructed Financial Stress Index (FSI). First, we employ Bayesian model averaging to identify leading indicators of our FSI. Next, we use those indicators as explanatory variables in a panel model for all our countries and in models at the individual country level. It turns out that panel models can hardly explain FSI dynamics. Although better results are achieved in models estimated at the country level, our findings suggest that (increases in) financial stress is (are) hard to predict out-of-sample.

Keywords: financial stress index; Bayesian model averaging; early warning indicators.

JEL classifications: E5, G10.

* Corresponding author: DNB, Research Department, PO Box 98, 1000 AB, Amsterdam, The Netherlands;
tel. + 31-20-5245657; email j.de.haan@dnb.nl.

1. Introduction

Financial stress indices (FSIs) are widely used by policymakers as an instrument for monitoring financial stability. A financial stress index measures the current state of stress in the financial system by combining several indicators of stress into a single statistic. According to Holló et al. (2012: 4-5), a FSI “not only permits the real time monitoring and assessment of the stress level in the whole financial system, but it may also be used to gauge the impact of policy measures aimed at alleviating financial instability.” From a policy perspective, reliably predicting increases in financial stress is crucial, as this would provide policymakers some time to take measures to alleviate stress. As shown by Vermeulen et al. (2015), spikes in financial stress may appear very abruptly. Since FSIs are now widely used in policy institutions for monitoring financial stability and even for activation of macro-prudential tools,¹ it would be very useful to identify leading indicators of financial stress so that policymakers may try to avoid increases in financial stress rather than responding to high levels of stress reactively.

So far, leading indicators of financial stress have received limited attention in the literature. This paper examines which variables have predictive power for financial stress in a sample of 25 OECD countries.² Only two earlier papers have examined leading indicators of financial stress. Their results are very mixed. Misina and Tkacz (2009) try to identify leading indicators for the financial stress index of Illing and Liu (2006) for Canada. They conclude that business credit and real estate prices emerge as important predictors of financial stress. Slingenberg and de Haan (2011) use a Financial Stress Index for 13 OECD countries to examine which variables help predicting financial stress. Their findings suggest that financial stress is hard to predict. Only credit growth turns out to have some predictive power for most countries. Several other variables have predictive power for some countries,

¹ For instance, the FSI of Holló et al. (2012) is the first item of the Risk Dashboard of the European Systemic Risk Board. In Sweden, the stress index plays a role in discussions of signals that can be used to activate and deactivate countercyclical capital buffers (Johansson and Bonthron 2013).

² One may wonder why we do not examine leading indicators of financial crises directly. There are two reasons. First, policy makers rely on FSIs in monitoring financial stability. Second, financial crises occur at low frequency in industrial countries, which makes it hard to examine regularities. Therefore, a FSI can be used as left-hand side variable in an early warning model (instead of a crisis dummy).

but not for others.

Our paper expands the analysis of Slingenberg and de Haan (2011) using the Financial Stress Index that was recently developed by Vermeulen et al. (2015) for 25 OECD countries. As a first step, we gather data for more than 20 potential early warning indicators of financial stress. These indicators have all been suggested in the literature on early warning models of financial crises (e.g. Frankel and Rose 1996; Kaminsky et al. 1998). Next, we employ Bayesian model averaging (BMA) to identify which of those variables are related to our FSI. BMA is a procedure that allows a subset of the most useful leading indicators of financial stress to be selected from the set of all possible combinations of potential leading indicators (Fernandez et al. 2001; Sala-i-Martin et al. 2004). This is a different approach from the common practice in early warning studies, where usually a limited number of (potential) leading indicators are selected on the basis of the authors' judgment, theory or previous empirical studies.³ The BMA approach allows us to identify the most important leading indicators of financial stress. Next, we use those variables as explanatory variables in a panel model for all our countries and in models at the individual country level (for the G7 countries only). Since policymakers are primarily interested in variables that may predict high levels of or increases in financial stress, we finally estimate our models using a variable that measures only high levels of FSI or increases in the FSI. It turns out that panel models can hardly explain FSI dynamics. Although better results are achieved for models estimated at the country level, our findings suggest that (increases in) financial stress is (are) hard to predict. Whereas the in-sample fit of the country level models is very decent (i.e. the models are able to track most of the FSI dynamics), the out-of-sample predictions are not very impressive.

The paper is structured as follows. Section 2 discusses the literature on financial stress and presents the Financial Stress Index used in our analysis. Section 3 describes our empirical framework. Section 4 presents the outcomes of panel and country-level models using leading indicators selected on the basis of a BMA as explanatory variables of (increases in) financial stress. Section 5 concludes.

³ Misina and Tkacz (2009) and Slingenberg and de Haan (2011) follow the procedure common in the early warning literature. They only consider a limited set of potential leading indicators.

2. Financial stress and economic outcomes⁴

Several papers have come up with a FSI for one country (e.g. Illing and Liu 2006) or for several countries (e.g. Cardarelli et al. 2011). In general, stress indices for a single country combine more stress indicators into one statistic than multi-country stress indices (for an extensive comparison of FSIs we refer to Kliesen et al. 2012).⁵ This is not surprising in view of data availability. For this reason, the index used in our analysis does not include some sectors, notably the real estate sector and securitization markets, even though there are good reasons for including these segments of the financial system in constructing a FSI (cf. Oet et al. 2012).

We employ the FSI developed by Vermeulen et al. (2015), which consists of 5 widely used variables to capture stress in several segments of the financial system (see Table 1 for details). All variables included in the index are standardized, i.e. we subtract the mean and divide by the standard deviation. The index used is the non-weighted sum of the standardized variables included.⁶ The interpretation of the FSI is very straightforward. If the index rises above 0, it indicates an increase in stress; if it is below 0, the financial system is stable. The FSI is calculated for 25 OECD countries (see Figure 1).

⁴ The beginning of this section draws on Vermeulen et al. (2015).

⁵ As pointed out by Vermeulen et al. (2015) FSIs have several limitations. First, they generally do not capture interconnectedness. The same holds for certain other characteristics of the financial system, like the systemic importance of certain financial institutions. Finally, Borio and Drehmann (2009) argue that the lead with which market prices—on which most FSIs rely—point to distress is uncomfortably short from a policy perspective.

⁶ Vermeulen et al. (2015) show that using the weighting method proposed by Holló et al. (2012) does not lead to very different results. We therefore prefer giving all the variables the same weight as that makes the index easy to interpret.

Table 1. Indicators considered and FSI

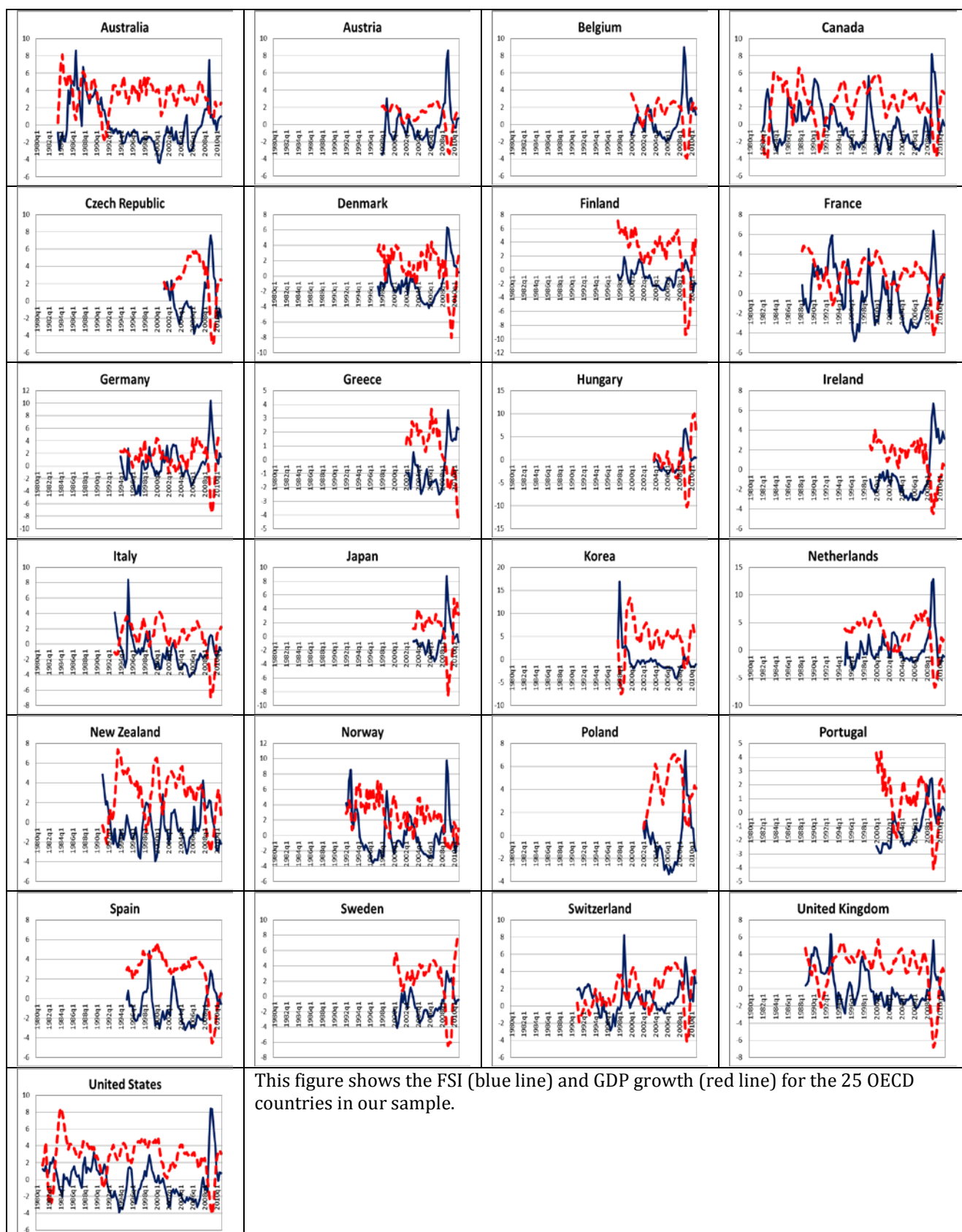
FSI1	Stock price volatility derived from a one year rolling GARCH(1,1) specification
FSI2	Volatility of monthly changes in the nominal effective exchange rate as calculated by a one year rolling GARCH(1,1) specification
FSI3	Beta of the banking sector, calculated as $\text{cov}(\text{return banking sector, total market})/\text{variance}(\text{total market})$
FSI4	Long-term interest rate - US long-term interest rate (measure of sovereign risk). This variable is zero for the US
FSI5	Inverse yield curve - (long-term interest rate – short-term interest rate), i.e. short-term interest rate – long-term interest rate
FSI	Financial stress index is the non-weighted sum of each financial stress indicator (FSI = FSI1 + FSI2 + FSI3 + FSI4 + FSI5).

Source: Vermeulen et al. (2015).

Cardarelli et al. (2011) use their stress index for 17 advanced economies to examine the relationship between financial stress and economic slowdowns. Their findings suggest that episodes of financial turmoil characterized by banking distress are more likely to be associated with deeper and longer downturns than episodes of stress mainly in securities or foreign exchange markets.

Figure 1 shows the FSI used in this paper and year-on-year changes in real GDP (both at quarterly frequency) in 25 OECD countries. Availability of the FSI differs across countries in the time dimension. There is almost an inverse pattern between these two variables in most countries. This pattern is not driven solely by the recent global financial crisis. Periods of above-average financial stress are commonly accompanied by below-average economic growth and vice versa. This inverse pattern is also apparent from Table 2 showing the correlation coefficient between the two series at the country level. While the average contemporaneous correlation between FSIs and GDP growth across countries amounts to -0.51, it is as high as -0.8 for some countries. Moreover, the temporal lead of FSI (vis-à-vis GDP growth) is confirmed by the dynamic correlations. Indeed, it seems that FSI is even more correlated with GDP growth one quarter ahead. This finding is slightly weaker when we disregard the observations from recent financial crises.

Figure 1. FSI vs. GDP growth, 1980Q1-2010Q4 (country-level effective samples)



This figure shows the FSI (blue line) and GDP growth (red line) for the 25 OECD countries in our sample.

Table 2. Correlation between GDP growth and financial stress

	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample (1980-2010)			Subsample until Q4 2006		
Country:	t	t+1	t+2	t	t+1	t+2
Australia	-0.12	-0.20	-0.24	-0.07	-0.14	-0.18
Austria	-0.66	-0.81	-0.81	-0.38	-0.52	-0.52
Belgium	-0.60	-0.76	-0.78	-0.31	-0.50	-0.64
Canada	-0.47	-0.50	-0.47	-0.36	-0.40	-0.41
Czech Rep.	-0.76	-0.81	-0.83	-0.68	-0.64	-0.59
Denmark	-0.68	-0.76	-0.74	-0.32	-0.35	-0.27
Finland	-0.30	-0.37	-0.46	-0.13	-0.01	-0.16
France	-0.44	-0.51	-0.50	-0.30	-0.40	-0.46
Germany	-0.57	-0.64	-0.53	-0.31	-0.39	-0.39
Greece	-0.78	-0.73	-0.59	-0.11	-0.01	0.27
Hungary	-0.31	-0.37	-0.21	-0.43	-0.56	-0.35
Ireland	-0.83	-0.78	-0.67	-0.15	-0.27	-0.32
Italy	-0.27	-0.32	-0.29	-0.22	-0.31	-0.32
Japan	-0.73	-0.77	-0.61	0.03	0.07	0.20
Korea	-0.49	-0.49	-0.38	-0.52	-0.56	-0.47
Netherlands	-0.44	-0.63	-0.72	-0.32	-0.39	-0.42
New Zealand	-0.55	-0.56	-0.53	-0.62	-0.58	-0.44
Norway	-0.37	-0.34	-0.35	-0.26	-0.25	-0.22
Poland	-0.69	-0.66	-0.75	-0.70	-0.64	-0.63
Portugal	-0.48	-0.56	-0.61	-0.80	-0.69	-0.50
Spain	-0.46	-0.47	-0.42	-0.06	-0.04	-0.06
Sweden	-0.75	-0.63	-0.43	-0.71	-0.51	-0.25
Switzerland	-0.18	-0.32	-0.38	-0.17	-0.26	-0.33
UK	-0.41	-0.39	-0.38	-0.35	-0.37	-0.42
US	-0.41	-0.36	-0.03	-0.03	-0.04	-0.07
Mean	-0.51	-0.55	-0.51	-0.33	-0.35	-0.32

Note: This table shows the correlation between GDP growth and: contemporaneous FSI (columns 1 and 4), FSI one period lagged (columns 2 and 5) and FSI two periods lagged (columns 3 and 6). In columns (1)-(3) the full sample period is used, while in columns (4)-(6) the sample runs until the financial crisis.

3. Empirical framework

Given the lack of studies that aim to predict financial stress, we select our list of potential leading indicators from studies on early warning indicators of financial crises following Babecký et al. (2013; 2014). After dropping some variables because of data availability, we are left with a set of more than 20 potential macroeconomic

and financial variables (see Table A1 in the Appendix). Most of our original variables are available at quarterly frequency; for those that are not we use linear interpolation.

Due to the absence of a theoretical framework that links our potential leading indicators to FSI dynamics, the choice of leading indicators to be included in the model needs to be addressed. In principle, we would like to run a regression with our continuous FSI as the dependent variable and all leading indicators as explanatory variables. However, including all potential indicators into one regression is infeasible and would likely lead to many redundant regressors in the specification. We therefore employ Bayesian model averaging (BMA) that deals with the issue of model uncertainty by running many regressions with different subsets of 2^{24} possible combinations of potential variables (Fernandez et al. 2001; Sala-i-Martin et al. 2004).⁷ Thus, under the BMA, many different models γ are estimated based on the following structure:

$$FSI_{i,t} = \alpha_i^\gamma + X_{i,t-4}^\gamma \beta^\gamma + \varepsilon_{i,t}^\gamma \quad \varepsilon_{i,t}^\gamma \sim (0, \sigma^2 I) \quad (1)$$

where $FSI_{i,t}$ is our continuous FSI, α_i^γ a constant, β^γ a vector of coefficients, $\varepsilon_{i,t}^\gamma$ an error term and $X_{i,t}^\gamma$ a subset of all potential leading indicators. So, each model γ contains a different subset of explanatory variables in $X_{i,t-4}^\gamma$. Specifically, all potential leading indicators are lagged by 4 quarters (alternatively by 8 and 12 quarters), which is the common forecasting horizon employed in early warning studies. The aim is to balance the need to be potentially informative (the information a variable provides is likely to decline with a longer prediction horizon) and the need to allow for timely policy action. Therefore, we want to identify the overall macroeconomic conditions that precede financial stress one (alternatively two and three) year(s) ahead. Whereas more complicated lag structures might potentially improve the predictive performance of our models, we prefer to keep our setting simple in order to have a more straightforward interpretation.

⁷ Similarly, Crespo-Cuaresma and Slacik (2009) and Babecky et al. (2014) apply BMA in the context of discrete models of financial crisis occurrence. Furthermore, BMA has also been applied to solve model uncertainty in the field of meta-analysis (e.g. Babecky and Havranek, 2014; Havranek and Rusnak, 2013). Raftery et al. (1997) and Eicher et al. (2011) provide further details on BMA.

BMA gives each model γ a weight, which captures the model's fit (similar to an adjusted R^2) and reports weighted averages of the models' regression parameters and standard deviations, using posterior model probabilities from Bayes' theorem:

$$p(M^\gamma | FSI_{i,t}, X_{i,t-4}^\gamma) \propto p(FSI_{i,t} | M^\gamma, X_{i,t-4}^\gamma) p(M^\gamma) \quad (2)$$

where $p(M^\gamma | FSI_{i,t}, X_{i,t-4}^\gamma)$ is the posterior model probability, $\propto$ a sign of proportionality, $p(y | M^\gamma, X_{i,t-4}^\gamma)$ the marginal likelihood of the model and $p(M^\gamma)$ the prior probability of the model. The posterior model distribution of any statistic θ is then obtained from model weighting as follows:

$$p(\theta | M^\gamma, FSI_{i,t}, X_{i,t-4}^\gamma) = \sum_{\gamma=1}^{2^K} p(\theta | M^\gamma, FSI_{i,t}, X_{i,t-4}^\gamma) \frac{p(M^\gamma | FSI_{i,t}, X_{i,t-4}^\gamma) p(M^\gamma)}{\sum_{j=1}^{2^K} p(y | M_j, X_{i,t-4}^\gamma) p(M_j)} \quad (3)$$

To express the lack of prior knowledge about the parameters and models, uniform priors are used. For the vector of coefficients β^γ Zellner's g prior is used as Eicher et al. (2011) have shown that the application of the uniform model prior and the unit information prior to the parameters in the model performs well for forecasting. Moreover, a posterior inclusion probability (PIP) is reported for each variable to show the probability with which the variable is included in the true model:

$$PIP = p(\beta^\gamma \neq 0 | y) = \sum_{\beta^\gamma \neq 0} p(M^\gamma | y) \quad (4)$$

The large number of potential variables entering into our BMA renders enumeration of all potential combinations of variables not only time consuming but even infeasible (Feldkircher and Zeugner, 2009). Therefore, we use the Markov Chain Monte Carlo (MCMC) sampler developed by Madigan and York (1995) to obtain results for the most important part of the posterior model distribution. The quality of the MCMC approximation of the actual posterior distribution is linked to the number of draws the sampler is set to go through during the estimation process (iterations). However, the MCMC sampler might start sampling from models that do not yield the best results and only after some time converges to models with high

posterior model probabilities. Hence, we discard initial iterations of the sampler (burn-ins).

In our calculations, we set the number of iterations to 5 million after the initial 1 million iterations are discarded as burn-ins. The correlation obtained between iteration counts and analytical posterior model probabilities exceeds 0.95, which we consider as sufficient convergence. This measure indicates the quality of approximation by showing to what extent the MCMC sampler converged to a good approximation of posterior model probabilities. The use of the uniform model prior means that the 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 the uniform model prior puts more importance on parsimonious models. We prefer parsimonious models, as policy makers can more easily monitor models with fewer variables. We perform the BMA exercise in R using the `bms` package developed by Feldkircher and Zeugner (2009).

We select all leading indicators that have a posterior inclusion probability larger than 50% and use those variables as explanatory variables in a panel model for all our countries. Next, we run the BMA at the individual country level (for the G7 countries only). Again, we select for each country the variables with a posterior inclusion probability larger than 50% and estimate an OLS model based on the variables that the BMA selects for the respective countries.

4. Empirical Results

4.1 Panel analysis with FSI

Figure 2 presents the results of the BMA exercise for the panel of 25 OECD countries using a lag of four quarters for the leading indicators. So we test whether an indicator is related to our FSI one year ahead. The indicators used are explained in Table A1 of the Appendix. The figure depicts the ranking of the variables according to their post inclusion probability (PIP), i.e. the probability that the variable belongs to the “true” model (right-hand side axis). The colours indicate the sign of the coefficient (blue – positive, red – negative, blank – the variable is missing from the model). This model detects seven variables with a PIP higher than 0.5, which is our rule of thumb to select a variable to further analysis.⁸ The coefficient of these seven variables is consistent across the different models, although these signs are not necessarily in line with theoretical priors.

As a robustness check we have estimated the model using lags of the indicators of 8 and 12 quarters. The results show that different variables are selected by the BMA-procedure when we look at crises 8 or 12 quarters ahead. The BMA-procedure selects 10 variables with a PIP higher than 0.5 for 8 quarters ahead and 9 variables for 12 quarters ahead. Only the money market rate and unemployment rate are selected for all three forecast horizons.

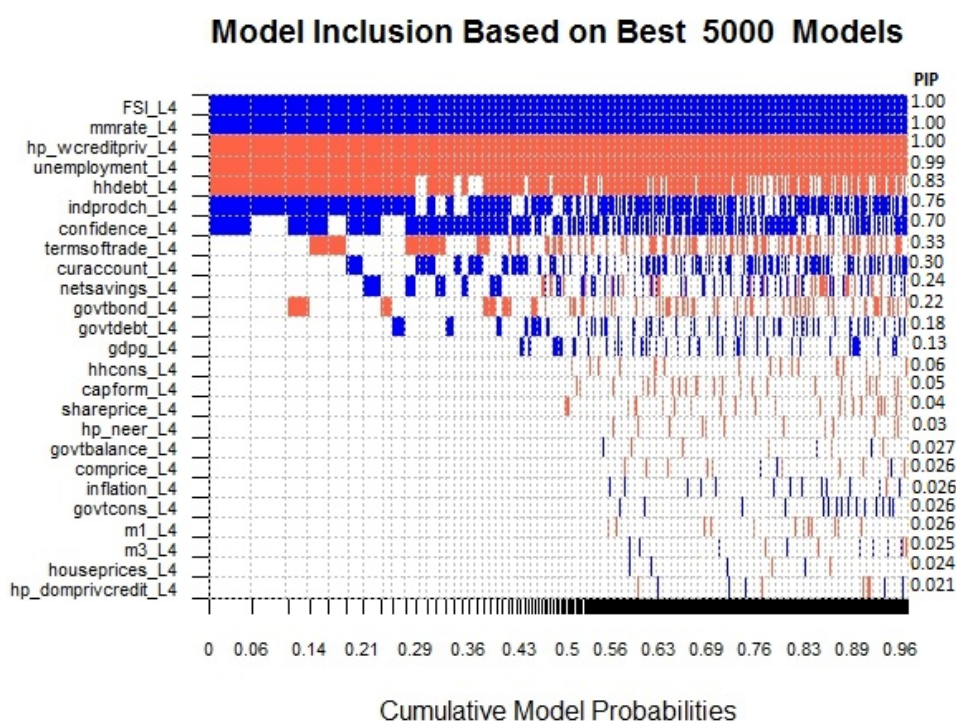
To evaluate the relationship between the seven BMA-preselected variables and our FSI in more detail, we next estimate a panel model with country fixed effects. The first column in Table 3 reports the results. It turns out that only four variables are statistically significant, namely the lag of the FSI, the money market rate, the world private credit gap, and the unemployment rate. Most notably, the overall fit of the model is relatively low. Only the money market rate keeps its significance at 8 and 12 quarters ahead (see columns (2) and (3) of Table 3). Note that different variables become significant at the different forecast horizons, e.g. M3 growth in the eight and twelve quarters ahead forecast. The overall fit of the model

⁸ Note that the PIP of a variable is a *relative* probability conditional on the other variables in the model. We deem 0.5 as conservative threshold to disregard irrelevant variables whereas there is no guarantee that the variable with PIP higher than that will be statistically significant at conventional confidence levels in normal regressions.

further deteriorates. We therefore keep the horizon of four quarters as our benchmark.

Finally, we use a pre-crisis sample period that ends in 2006 in order to discard the global financial crisis. As column (4) of Table 3 shows, the fit of this model is similar to the model reported in column (1). The only variable that is significant is again the money market rate.

Figure 2. Bayesian model averaging: leading indicators of FSI, 4Q ahead



Note: Rows = potential FSI predictors. Columns = best models according to marginal likelihood, ordered from left. Full cell = variable included in model, blue = positive sign, red = negative sign. Variables are described in Table A1 in the Appendix. L4 means that four lags have been used.

Table 3. Comparison of results of BMA preselected early warning indicators of FSI (PIP ≥ 0.5) 4, 8 and 12Q ahead for a panel of 25 OECD countries

	(1)	(2)	(3)	(4)
Lags:	4	8	12	4 (pre-crisi
Constant	-3.62 (2.23)	-8.04*** (2.01)	-2.12*** (0.66)	-2.40*** (0.61)
Lag FSI	0.17*** (0.04)		-0.23*** (0.047)	
Money market rate	0.35*** (0.04)	0.49*** (0.08)	0.20*** (0.04)	0.34*** (0.04)
World credit gap	-0.18*** (0.02)			
Unemployment	-0.15*** (0.05)	-0.05 (0.09)	-0.05 (0.09)	-0.06 (0.04)
Private debt	-0.03* (0.02)			
Production	0.018 (0.01)			
Confidence	0.03 (0.02)	0.07*** (0.02)		
Govt. bond yield		-0.30** (0.13)		
Commodity prices		0.03*** (0.01)		-0.02 (0.01)
Exchange rate		-0.08*** (0.02)		-0.03 (0.02)
Current account		0.01 (0.06)	0.09 (0.06)	-0.08 (0.07)
Capital formation		0.03 (0.02)	0.03** (0.01)	
Stock market		0.01 (0.00)	0.02 (0.01)	
M3 growth		0.05** (0.02)	0.11*** (0.02)	-0.01 (0.02)
Terms of trade			-0.04 (0.03)	
Govt. balance			-0.08 (0.08)	
Net savings				0.03 (0.03)
R²	0.20	0.07	0.13	0.23
Obs.	1521	1421	1394	1194
Count.	25	25	25	25

Note: This table shows results from a panel regression with country fixed effects. *** indicates significance at 1%, ** at 5% and * at 10% level. Variables in column 1 are explained in Table A1 in the Appendix.

This panel exercise suggests that it is very difficult to find a set of robust predictors of financial stress across different countries. We have therefore performed a number of other panel exercises, such as allowing for nonlinear effects by using

squares and cubes and estimating models for each subcomponent of the FSI, but fail to detect a specification with a substantially higher fit than the benchmark case (these results are available upon request). Apparently, within a panel context financial stress is very hard to predict. Forecasting models at the national level may do a better job as not all leading indicators considered may be equally important for all countries (Slingenberg and de Haan, 2011). Next, we therefore turn our attention to individual countries. In this exercise, we limit ourselves to the G7 countries.

4.2 Country level analysis with FSI

There are different ways how to tackle potential heterogeneity of leading indicators of FSI across countries. The simplest option is to assume that the set of indicators is homogeneous across countries, i.e. to keep the indicators preselected by the panel BMA (as in Figure 2), but allow for different marginal effects. The estimation results for these country-specific models (available on request) only give a marginally better fit than the results for the panel model as reported in Table 3.

As the next step we therefore estimate country models using a country-specific set of leading indicators (based on the BMA results reported in Figure A1 in the Appendix). For each G7 country, the BMA identifies 8 to 10 variables with a PIP above 0.5. The most striking result is that the fit of the country-level models is substantially better than that of the panel model. It is also apparent that there is a lot of cross-country heterogeneity. Interestingly, the lag of the FSI is not significant anymore. Indeed, Figure 1 suggests that the persistence of the FSI is relatively low as the index can abruptly change from one quarter to the next.

There are several variables that are significant across various countries although the sign of the coefficients is not always the same. Specifically, we find that falling house prices, decreasing unemployment, decreasing household debt, increasing government bond yields, and increasing government consumption are statistically significant leading indicators of financial stress in at least three out of the seven countries. As our results are derived from a purely statistical approach, we refrain from interpreting them from a theoretical perspective. In contrast to Borio and Lowe (2002), we do not find that credit is a good leading indicator of financial stress. Similarly, Rose and Spiegel (2009, 2010) do not find strong

evidence that credit growth is a leading indicator for the recent financial crisis in their cross-country study. Our finding that residential real estate prices frequently have good leading-indicator properties is in line with the results of some previous studies, including Adalid and Detken (2007) and Goodhart and Hoffman (2008).

Even allowing for country-heterogeneity, the present approach might be seen as restrictive, as it allows only for a linear relation between each leading indicator and our FSI. Unfortunately, adding squared and cubed transformed variables in the BMA resulted in convergence problems. The number of variables is too large relative to the number of observations. In order to still address the issue of nonlinearity we estimated for the US and UK an extended model where we allow for a non-linear relationship between FSI and each leading indicator by including the square of each indicator.

Tables A2a and A2b in the Appendix compare the results of a linear and a non-linear model for two countries where we find some evidence in favour of non-linearities, namely the US and the UK. Specifically, in both countries there seems to be a parabolic relationship between our FSI and house prices. For the US, we also find a non-linearity for M3 growth and for the UK for the world private credit gap. While including these terms further improves the fit of the model, the improvement is only very marginal. We therefore conclude that the linear model seems to be a reasonable approximation of the relationship between the selected leading indicators and financial stress.

Table 4. Comparison of results of BMA preselected early warning indicators of FSI (PIP ≥ 0.5) 4 Q ahead for individual G7 countries

	USA	UK	JAP	GER	FRA	ITA	CAN
Constant	3.31*** (1.08)	-11.79*** (1.45)	-6.00*** (2.07)	10.73*** (2.19)	217.45*** (48.29)	-39.82** (18.06)	-3.47*** (0.46)
M3 growth	0.34*** (0.08)						0.41*** (0.08)
House prices	-0.16*** (0.04)	0.19*** (0.04)		-1.04*** (0.12)	-0.33*** (0.05)		
Domestic credit gap	-0.05 (0.05)				0.23*** (0.07)	0.14*** (0.04)	
Unemployment	-1.29*** (0.20)			-1.54*** (0.24)	-2.38*** (0.40)		
Govt. balance	-0.42*** (0.10)	0.09 (0.06)				0.44*** (0.13)	
Production	0.14 (0.09)	-0.26*** (0.06)					
Private debt	-0.18** (0.08)	-0.30*** (0.08)			0.18* (0.11)	-0.39*** (0.09)	-0.14*** (0.08)
GDP growth	-0.13 0.15						
Govt. bond yield	0.57*** (0.10)	1.00*** (0.10)				0.24** (0.12)	
World credit gap		-0.29*** (0.07)				-0.22*** (0.07)	
Net savings		0.83*** (0.17)	-1.33*** (0.28)				
Capital formation		-0.13*** (0.03)	-0.82*** (0.08)				
Current account		-0.98*** (0.23)	3.97*** (0.51)				-0.40*** (0.09)
Exchange rate		0.10** (0.04)					0.09** (0.04)
Govt. consumption			0.98*** (0.21)			0.46*** (0.13)	0.27*** (0.10)
Terms of trade			-0.16*** (0.03)				-0.16*** (0.06)
Inflation				1.68*** (0.31)	-0.72* (0.39)		
Commodity prices				-0.01 (0.02)	-0.08*** (0.02)	-0.09*** (0.02)	
Production					0.66*** (0.09)	0.22*** (0.05)	
Confidence					-1.95*** (0.46)	0.42*** (0.18)	
Stock market					0.04*** (0.01)		
Household cons.							0.36*** (0.13)
R²	0.57	0.73	0.80	0.56	0.64	0.61	0.49
Obs.	120	89	31	68	91	72	116

Note: This table shows results from OLS regressions. *** indicates significance at 1%, ** at 5% and * at 10% level. Variables in column 1 are explained in Table A1 in the Appendix.

4.3 In-sample and out-of-sample fit

Even though the previous section shows that the in-sample fit of the country level models is relatively decent, the real test of these models is of course how well they predict financial stress out of sample. We therefore re-run the BMA and the regressions for each country using a subsample that ends in 2006. For most countries but the US (Japan could not be considered due to too few observations) we find a similar or even slightly better in-sample fit of the models using data up to 2006 compared to the models using data up to 2010 (see Table 5). Moreover, Figure 3 shows that the in-sample fit of the models using data up to 2006 is quite good.

Table 5. Comparison of model fit for whole sample and pre-crisis subsample

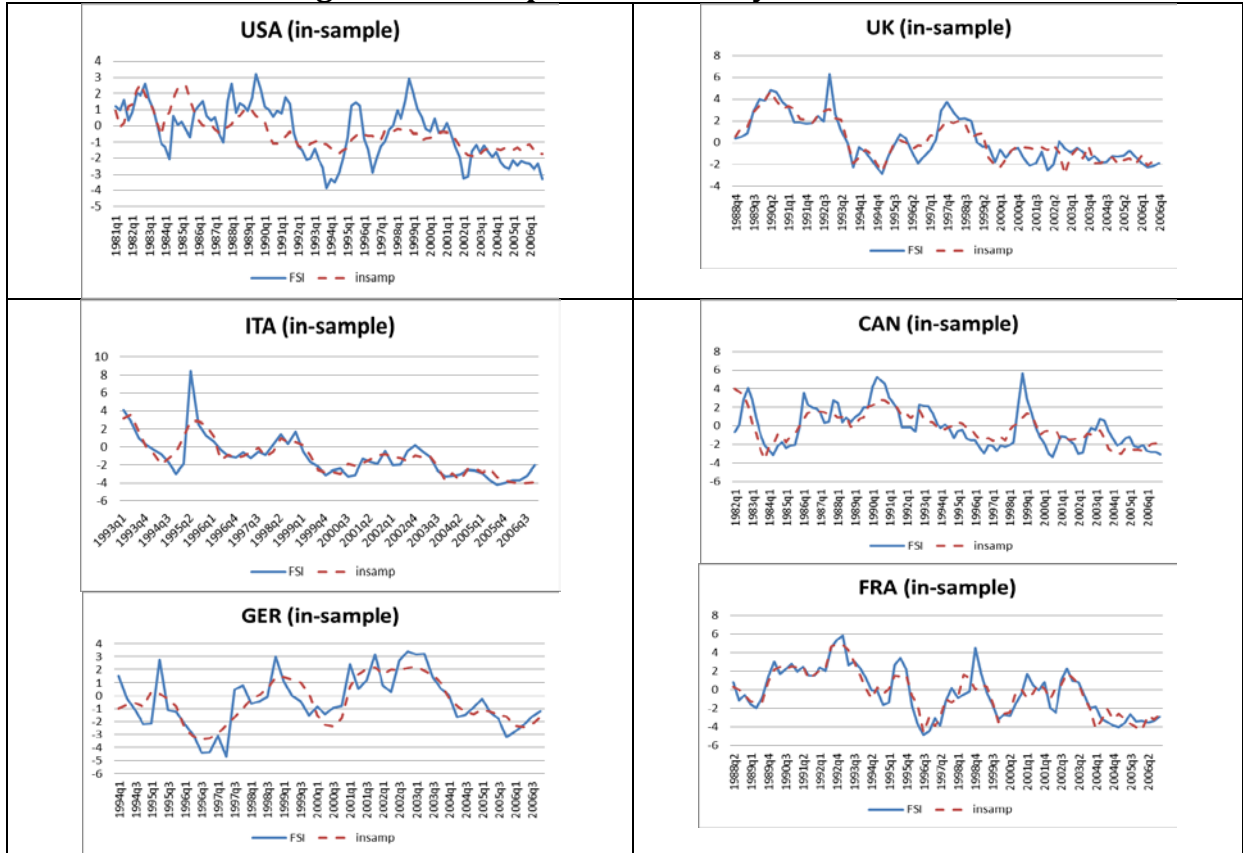
	USA	UK	JAP	GER	FRA	ITA	CAN
R² (full sample)	0.57	0.73	0.80	0.56	0.64	0.61	0.49
R² (subsample)	0.38	0.78	-	0.64	0.77	0.70	0.52

Figure 4 compares the predicted FSI (based on the parameters of the pre-crisis subsample) and an autoregressive model based on the 4th lag of the FSI.⁹ The figure compares out-of-sample rolling forecasts using the coefficients of the model estimated on the subsample ending in 2006 and the respective values of the leading indicators from period 2006Q1 till 2009Q4, i.e. corresponding to the prediction horizon from 2007Q1 till 2010Q4 (left-hand side panels in Figure 4). The right-hand side panels depict similar out-of-sample forecasts for the autoregressive model.

The results shown in Figure 4 are not very encouraging. In fact, for none of the countries does the model adequately capture the increase in financial stress during 2008-2009. This result is quite disappointing in view of the decent in-sample fit of the country models. It seems that different variables need to be taken into account than those selected for the pre-crisis sample to forecast the rise in the FSI.

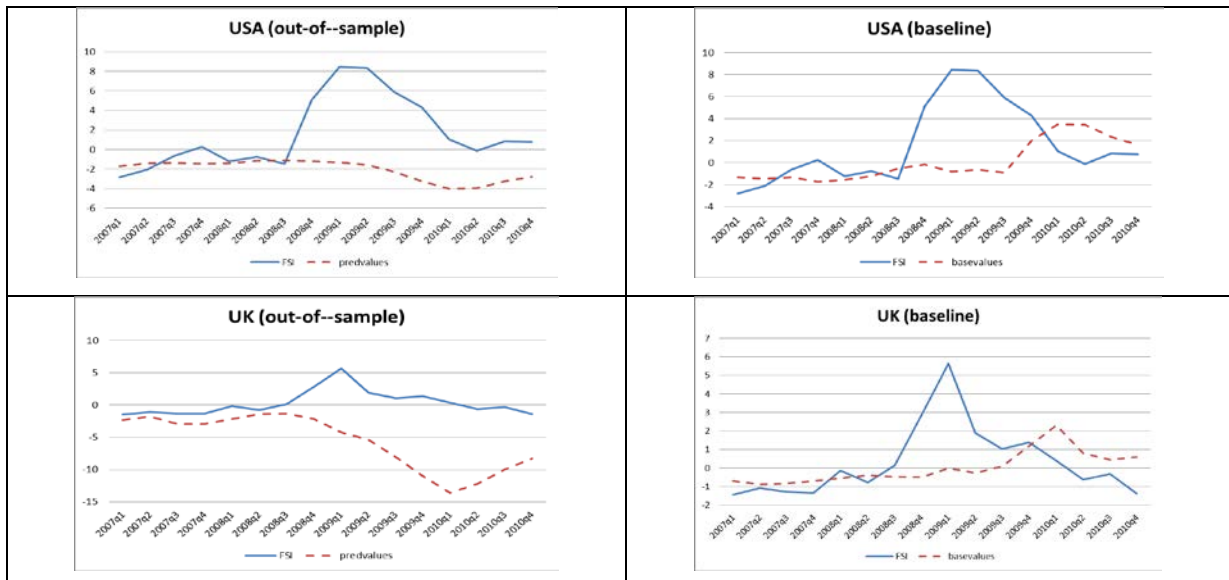
⁹ Alternatively, one can choose a random walk as an alternative benchmark model. However, this would be in contrast with the stationary, i.e. mean-reverting, behaviour of the FSI. We opt for the 4th lag because this is a fair comparison with the one year in advance predictive criterion we use in the BMA variable selection procedure.

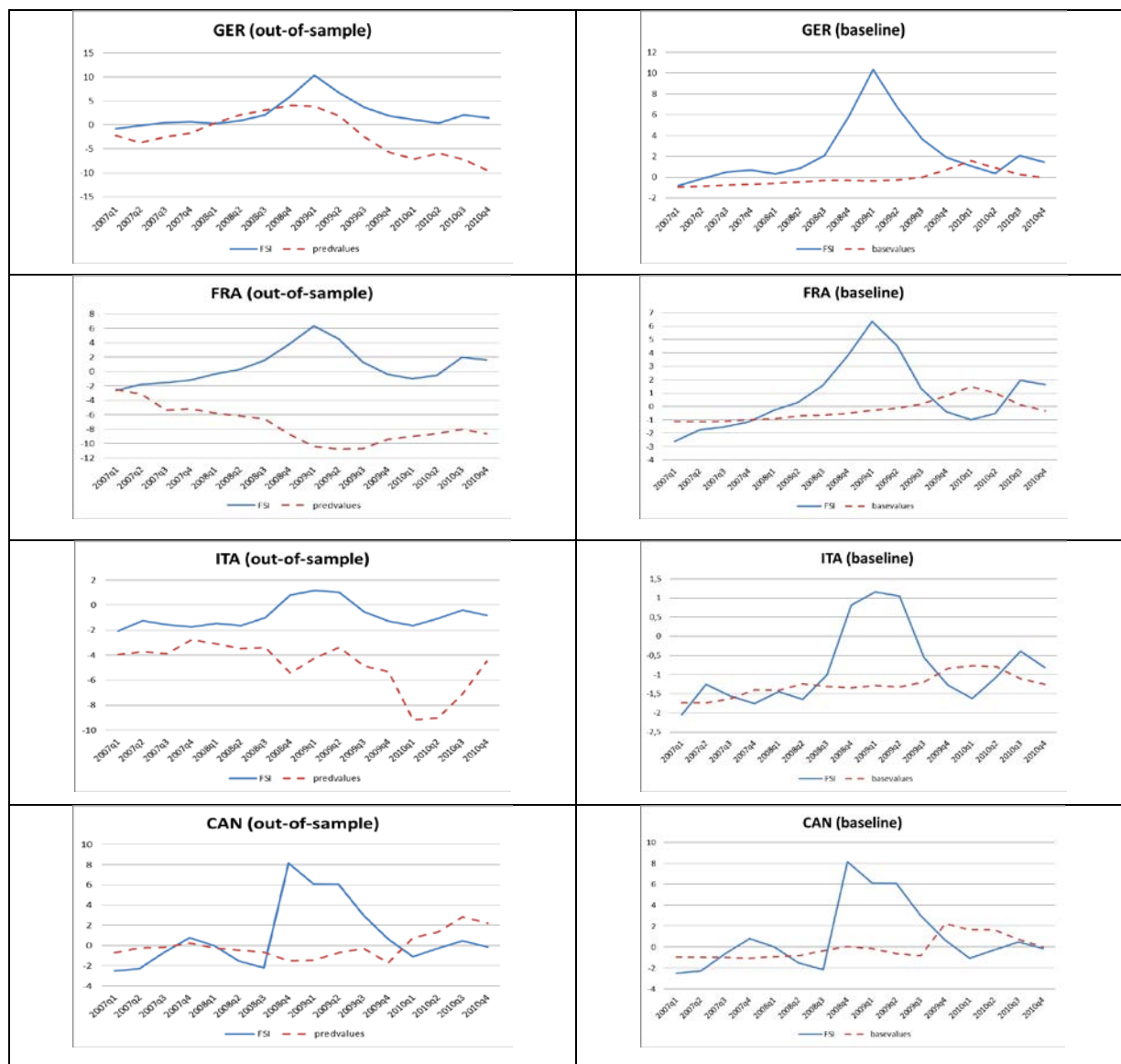
Figure 3. In-sample fit of country level models



Note: The figures compare the actual level of the FSI with the predicted value (in-sample) according to the models based on BMA-selected variables.

Figure 4. Out-of-sample fit: country level models vs. autoregressive models





Note: The figures compared the predicted FSI from models based on BMA-selected variables (left panel) and autoregressive models based on the FSI 4th lag only (right-hand side panels).

Table 6 compares the RMSE of the two models. The out-of-sample performance of the BMA-based leading indicators model is not better than that of the autoregressive model showing the limits of using the selected variables for out of sample forecasts. So even though the explanatory power of the variables selected by the BMA is quite good pre-crisis, trying to predict financial stress during the crisis years using these variables is doing more harm than good.

Table 6. Comparison of model fit: Country level models vs. autoregressive models

	USA	UK	JAP	GER	FRA	ITA	CAN
RMSE (BMA):	5.20	7.49	-	5.65	9.36	4.53	3.88
RMSE (AR 4th lag)	4.15	1.94	-	3.82	2.65	1.09	3.44

4.4 Thresholds of FSI and increases of FSI

So far, our analysis has been based on predicting the level of our FSI. Since policymakers are primarily interested in variables that may predict high levels or increases in financial stress, we also estimate our models using as left-hand side a variable that measures whether the FSI is above a particular threshold (in line with Lo Duca and Peltonen, 2013) or the increase of the FSI. First, we transform the FSI into a binary indicator taking value 1 whenever the FSI value is higher than the 80% quantile and 0 otherwise. We estimate logit models with the same country-specific leading indicators as in Table 3. Table A3 and Figure A2 in the Appendix report the results. The findings are largely in line with those in Tables 3 and 4, i.e. even when we aim at peaks of FSI only, most of the variables are still significant and the model has a decent in-sample fit. However, the out-of-sample performance is poor and also when threshold effects are considered it is difficult to outperform a simple autoregressive model.

An alternative approach is to focus on increases in FSI. We compute year-on-year changes in the FSI and use a Tobit-model to analyze whether the BMA-preselected variables are able to predict increases in the FSI 4 quarters ahead. Table A4 in the Appendix presents the results of the Tobit-regressions. Since we transform the data from levels to changes, it is not surprising that the in-sample fit, as measured by Pseudo- R^2 , is slightly worse than in previous regressions. The signs and significance of the variables are largely in line with the logit-regressions and confirm our earlier results. Again, the out-of-sample performance is relatively poor (not shown).

5. Conclusion

Rose and Spiegel (2010: 15) conclude that “Despite a broad search, we have been unable to find consistent strong linkages between pre-existing variables that are plausible causes of the Great Recession and the actual intensity of the recession.” Similarly, our results suggest that it is hard to identify leading indicators of financial stress. We have examined which variables have predictive power for financial stress in a sample of 25 OECD countries, using the Financial Stress Index (FSI) of Vermeulen et al. (2015). First, we have used Bayesian model averaging to identify leading indicators of our FSI. Next, we have used those indicators as explanatory variables in a panel model for all our countries and in models at the individual country level. It turns out that panel models can hardly explain FSI dynamics. Although better results are achieved in models estimated at the country level, our findings suggest that (increases in) financial stress is (are) hard to predict.

References

- Adalid, R., Detken, C., 2007. Liquidity shocks and asset price boom/bust cycles. ECB Working Paper 732.
- Babecký J., Havránek T., 2014. Structural reforms and growth in transition: A meta-analysis. *Economics of Transition* 22 (1), 13–42.
- Babecký J., Havránek T., Matějů J., Rusnák M., Šmídková K., Vašíček B., 2013. Leading indicators of crisis incidence: Evidence from developed countries. *Journal of International Money and Finance* 35, 1–19.
- Babecký J., Havránek T., Matějů J., Rusnák M., Šmídková K., Vašíček B., 2014. Banking, debt and currency crisis: early warning indicators for developed countries. *Journal of Financial Stability* 15, 1–17.
- Borio C., Drehmann, M. 2009. Towards an operational framework for financial stability: 'Fuzzy' measurement and its consequences. BIS Working Paper 284.
- Borio, C., Lowe, P., 2002. Asset prices, financial and monetary stability: Exploring the nexus. BIS Working Paper 114.
- Cardarelli, R., Elekdag, S., Lall, S., 2011. Financial stress and economic contractions, *Journal of Financial Stability* 7, 78–97.
- Crespo-Cuaresma, J., Slacik, T., 2009. On the determinants of currency crisis: the role of model uncertainty. *Journal of Macroeconomics* 31 (4), 621–632.
- Eicher, T.S., Papageorgiou, C., Raftery, A.E., 2011. Default priors and predictive performance in Bayesian model averaging, with application to growth determinants. *Journal of Applied Econometrics* 26 (1), 30–55.
- Feldkircher, M., Zeugner, S., 2009. Benchmark priors revisited: On adaptive shrinkage and the supermodel effect in Bayesian model averaging. IMF Working Paper 09/202.
- Fernandez, C., Ley, E., Steel, M., 2001. Benchmark priors for Bayesian model averaging. *Journal of Econometrics* 100 (2), 381–427.
- Frankel, J.A., Rose, A.K., 1996. Currency crashes in emerging markets: an empirical treatment. *Journal of International Economics* 41 (3–4), 351–366.
- Goodhart, C., Hofmann, B. 2008. House prices, money, credit and the macroeconomy. ECB Working Paper 888.
- Havránek, T., Rusnák, M., 2013. Transmission lags of monetary policy: A meta-analysis. *International Journal of Central Banking* 9(4), 39–76.
- Holló, D., Kremer, M., Lo Duca, M., 2012. CISS – A “Composite Indicator of Systemic Stress” in the financial system. ECB Working Paper 1426.
- Illing, M., Liu, Y., 2006. Measuring financial stress in a developed country: An application to Canada. *Journal of Financial Stability* 2 (3), 243–65.
- Johansson, T., Bonthron, F., 2013. Further development of the index for financial stress for Sweden. *Sveriges Riksbank Economic Review* 2013:1, 1–20.
- Kaminsky, G.L., Lizondo, S., Reinhart, C.M., 1998. The leading indicators of currency crises. *IMF Staff Papers* 45 (1), 1–48.

- Kliesen K.L., Owyang M.T., Vermann E.K., 2012. Disentangling diverse measures: A survey of financial stress indexes. Federal Reserve Bank of St. Louis Economic Review September/October 2012: 369-397.
- Lo Duca M., Peltonen T., 2011. Macro-financial vulnerabilities and future financial stress – assessing systemic risks and predicting systemic events. ECB Working Paper 1311.
- Madigan, D., York, J., 1995. Bayesian graphical models for discrete data. International Statistical Review 63 (2), 215-232.
- Misina, M., Tkacz, G., 2009. Credit, asset prices, and financial stress. International Journal of Central Banking 5 (4), 95-122.
- Oet, M.V., Bianco, T., Gramlich, D., Ong, S. 2012. Financial Stress Index: A Lens for Supervising the Financial System Federal Reserve Bank of Cleveland Working Paper 12-37.
- Raftery, A.E., 1995. Bayesian model selection in social research. Sociological Methodology 25, 111-163.
- Rose, A.K., Spiegel, M., 2009. Cross-country causes and consequences of the 2008 crisis: International linkages and American exposure. NBER Working Paper 15358.
- Rose, A.K., Spiegel, M., 2010. Cross-country causes and consequences of the crisis: An update. CEPR Discussion Paper 7901.
- Sala-i-Martin, X., Doppelhofer, G., Miller, R., 2004. Determinants of long-term growth: a Bayesian averaging of classical estimates (BACE) approach. American Economic Review 94 (4), 813-835.
- Slingenberg, J.W., de Haan, J. 2011. Forecasting financial stress. De Nederlandsche Bank Working Paper 292.
- Vermeulen, R., Hoeberichts, M., Vašíček, B., Žigraiová, D., Šmídková, K., de Haan, J., 2015. Financial stress indices and financial crises. Open Economies Review, forthcoming.

Appendix

Table A1. Variables, transformations and data sources

Variable:	Description:	Transformation:	Main source:
Capital formation	Gross total capital formation (constant prices)	% yoy	Statistical offices, OECD
Commodity prices	Commodity prices	% yoy	Commodity Research Bureau
Confidence	Consumer confidence indicator	none	OECD
Current account	Current account (% of GDP)	none	OECD, WDI
GDP growth	Real GDP growth	% yoy	Statistical offices
Govt. balance	Government balance (% of GDP)	none	Statistical offices
Govt. bond yield	10Y government bond yield	none	National central banks
Govt. consumption	Government consumption (constant prices)	% yoy	OECD, statistical offices
Govt. debt	Government debt (% of GDP)	none	WDI, ECB
Household cons.	Private final consumption expenditure (constant prices)	% yoy	Statistical offices
Household debt	Gross liabilities of personal sector growth	% yoy	National central banks, Oxford Economics
House prices	House price inflation	% yoy	BIS, Eurostat, Global Property Guide
Domestic credit gap	Domestic credit to private sector to GDP gap	HP gap	BIS, WDI
World credit gap	Domestic credit to private sector to GDP gap	HP gap	BIS, WDI
Exchange rate	Nominal effective exchange rate gap	HP gap	IFS
Production	Industrial production growth	% yoy	Statistical offices
Inflation	Consumer price inflation	% yoy	Statistical offices, national central banks
M1 growth	M1 growth	% yoy	National central banks
M3 growth	M3 growth	% yoy	National central banks
Net savings	Net national savings (% of GNI)	none	WDI
Stock market	Stock market index growth	% yoy	Reuters, stock exchanges
Money market rate	Money market interest rate	none	IFS
Terms of trade	Terms of trade change	% yoy	Statistical offices
Unemployment	Unemployment rate	none	Statistical offices

Figure A1. Bayesian model averaging: early warning indicators of FSI for G7 countries, 4Q ahead

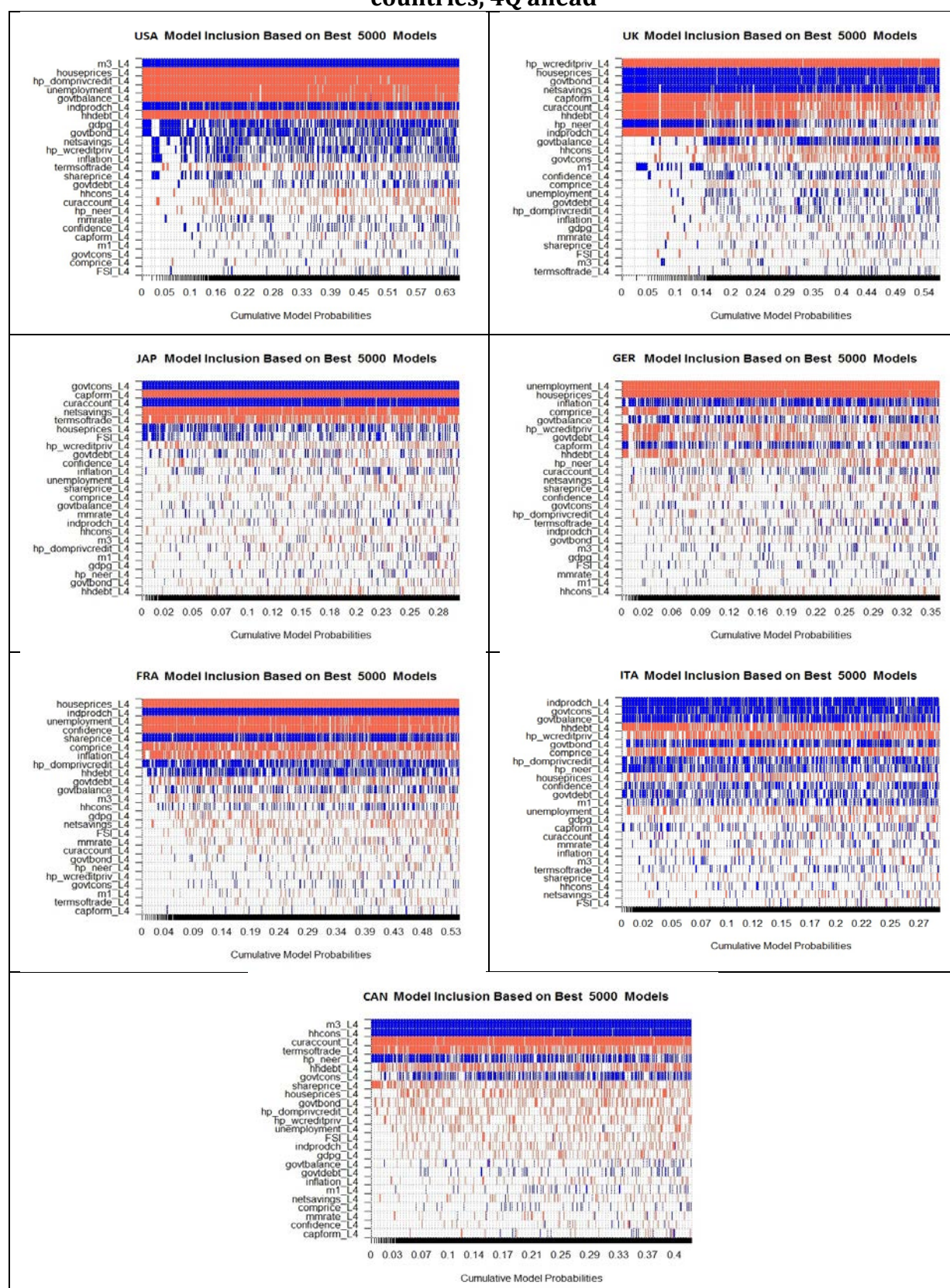


Table A2a. Comparison of results of BMA preselected early warning indicators of FSI (PIP ≥ 0.5) 4 Q ahead using linear and nonlinear model – the US

	USA linear	USA non- linear
Constant	3.31*** (1.08)	-11.91*** (3.97)
M3 growth	0.34*** (0.08)	0.75*** (0.22)
M3 growth^2		-0.04** (0.02)
House prices	-0.16*** (0.04)	-0.21*** (0.05)
House prices^2		0.01*** (0.00)
Domestic credit gap	-0.05 (0.05)	-0.07 (0.05)
Domestic credit gap^2		0.01 (0.01)
Unemployment	-1.29*** (0.20)	-0.91 (0.85)
Unemployment^2		0.02 (0.06)
Govt. balance	-0.42*** (0.10)	-0.14 (0.13)
Govt. balance^2		0.12 (0.03)
Production	0.14 (0.09)	0.24*** (0.09)
Production^2		0.00 (0.01)
Household debt	-0.18** (0.08)	0.55 (0.36)
Household debt ^2		-0.03* (0.02)
GDP growth	-0.13 0.15	0.10 (0.27)
GDP growth ^2		-0.09 (0.04)
Govt. bond yield	0.57*** (0.10)	2.26*** (0.44)
Govt. bond yield^2		-0.09*** (0.03)
R²	0.57	0.71
Adjusted R²		
Obs.	120	120
Count.	1	1

Note: This table shows results from OLS-regression. *** indicates significance at 1%, ** at 5% and * at 10% level. Variables in column 1 are explained in Table A1 in the Appendix.

Table A2b. Comparison of results of BMA preselected early warning indicators of FSI (PIP ≥ 0.5) 4 Q ahead using linear and nonlinear model – the UK

	UK linear	UK non-linear
Constant	-11.79*** (1.45)	-3.31 (5.14)
House prices	0.19*** (0.04)	0.22*** (0.07)
House prices^2		-0.01*** (0.00)
Govt. balance	0.09 (0.06)	-0.15 (0.19)
Govt. balance^2		-0.03 (0.03)
Production	-0.26*** (0.06)	-0.24*** (0.07)
Production^2		0.01 (0.01)
Household debt	-0.30*** (0.08)	-0.24 (0.31)
Household debt^2		0.01 (0.01)
Govt. bond yield	1.00*** (0.10)	0.73 (0.82)
Govt. bond yield^2		-0.00 (0.05)
World credit gap	-0.29*** (0.07)	-0.23* (0.12)
World credit gap^2		0.04** (0.01)
Net savings	0.83*** (0.17)	0.22 (0.36)
Net savings^2		-0.02 (0.09)
Capital formation	-0.13*** (0.03)	-0.08 (0.06)
Capital formation^2		-0.00 (0.00)
Current account	-0.98*** (0.23)	1.19 (0.94)
Current account^2		0.34** (0.13)
Exchange rate	0.10** (0.04)	0.13*** (0.04)
Exchange rate^2		0.01 (0.01)
R²	0.73	0.79
Adjusted R²	0.69	0.73
Obs.	89	89
Count.	1	1

Note: This table shows results from OLS regressions. *** indicates significance at 1%, ** at 5% and * at 10% level. Variables in column 1 are explained Table A1 in the Appendix.

Table A3. Results of BMA preselected early warning indicators for extreme values of FSI (PIP ≥ 0.5) 4Q ahead for individual G7 countries – logit model

	USA	UK	JAP	GER	FRA	ITA	CAN
M3 growth	0.52*** (0.18)						0.36** (0.17)
House prices	-0.28 (0.74)	1.41*** (0.50)		-1.04** (0.41)	-0.58** (0.28)		
Domestic credit gap	-0.21*** (0.08)				0.77*** (0.27)	0.05 (0.17)	
Unemployment	-1.77*** (0.59)			-1.74*** (0.53)	-4.47*** (1.26)		
Govt. balance	-0.42* (0.23)	1.08*** (0.40)				2.91*** (0.50)	
Production	0.57*** (0.19)	-0.26*** (0.06)			1.72*** (0.48)	0.98** (0.44)	
Household debt	-0.30 (0.29)	-1.19** (0.54)			0.06 (0.33)	-1.46*** (0.39)	-0.05 (0.17)
GDP growth	-0.98*** (0.33)						
Govt. bond yield	0.53** (0.25)	4.40*** (1.28)				2.04*** (0.56)	
World credit gap		-1.30*** (0.43)				-0.67 (0.48)	
Net savings		2.77*** (0.06)					
Capital formation		-0.46* (0.26)					
Current account		-5.10*** (2.23)					-0.51** (0.24)
Exchange rate		0.39** (0.19)					0.34*** (0.12)
Govt. consumption						1.92*** (0.70)	-0.11 (0.16)
Terms of trade							-0.08 (0.15)
Inflation				1.74** (0.72)	-2.76** (1.23)		
Commodity prices				-0.01 (0.03)	0.00 (0.71)	-0.03 (0.09)	
Confidence					-4.70*** (1.20)	-1.75* (1.04)	
Stock market					0.07** (0.03)		
Household cons.							0.22 (0.27)
Pseudo R²	0.33	0.72		0.40	0.55	0.82	0.36
Obs.	120	89		68	91	72	116

Note: This table shows results from Logit-regressions. *** indicates significance at 1%, ** at 5% and * at 10% level. Variables in column 1 are explained in Table A1 in the Appendix.

Figure A2. In-sample fit of country level models logit model

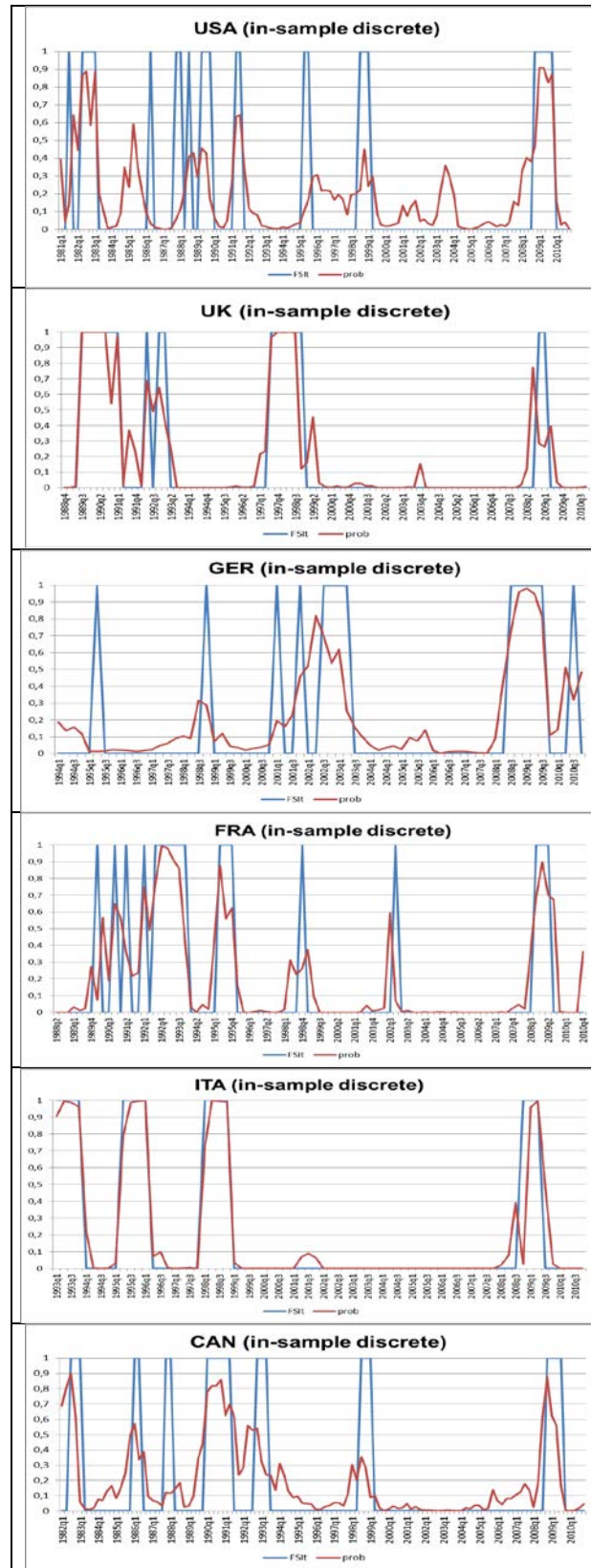


Table A4. Results of BMA preselected early warning indicators for increases of FSI (PIP $\geq$ 0.5) 4Q ahead for G7 countries – tobit model

	USA	UK	GER	FRA	ITA	CAN
M3 growth	0.471*** (0.12)					0.528*** (0.13)
House prices	-0.214*** (0.05)	0.242*** (0.07)	-0.803** (0.24)	-0.254** (0.08)		
Domestic credit gap	-0.353*** (0.08)			-0.037 (0.13)	0.218*** (0.06)	
Unemployment	-1.387*** (0.33)		-0.557 (0.37)	-2.380*** (0.55)		
Govt. balance	-0.180 (0.19)	0.329* (0.16)			0.079 (0.16)	
Production	0.479*** (0.13)	0.001 (0.15)		0.569*** (0.14)	0.486*** (0.11)	
Household debt	0.282 (0.16)	-0.325* (0.13)		0.256 (0.16)	-0.255 (0.13)	-0.344** (0.13)
GDP growth	-0.519* (0.24)					
Govt. bond yield	-0.092 (0.17)	0.702*** (0.16)			-0.175 (0.20)	
World credit gap		-0.596*** (0.11)			-0.362*** (0.10)	
Net savings		-0.063 (0.34)				
Capital formation		-0.028 (0.06)				
Current account		-0.565 (0.38)				0.179 (0.13)
Exchange rate		0.100 (0.07)				0.273*** (0.07)
Inflation			1.453* (0.56)	-1.425** (0.49)		
Commodity prices			0.056 (0.03)	0.009 (0.03)	-0.120*** (0.03)	
Confidence				-2.318*** (0.59)	0.572* (0.26)	
Stock market				0.075*** (0.01)		
Govt. consumption					0.644** (0.19)	0.197 (0.16)
Household cons.						1.079*** (0.24)
Terms of trade						-0.366*** (0.10)
pseudo R²	0.207	0.167	0.091	0.151	0.215	0.149
N	120	89	68	91	72	116

Note: This table shows results from Tobit-regressions for annual changes in FSI, where changes in FSI < 0 are censored. *** indicates significance at 1%, ** at 5% and * at 10% level. Variables in column 1 are explained in Table A1 in the Appendix.

Previous DNB Working Papers in 2015

- No. 454 **Mauro Mastrogiacomo and Rob Alessie**, Where are the retirement savings of self-employed? An analysis of 'unconventional' retirement accounts
- No. 455 **Clemens Bonner and Paul Hilbers**, Global liquidity regulation - Why did it take so long?
- No. 456 **Leo de Haan, Jan Willem van den End and Philip Vermeulen**, Lenders on the storm of wholesale funding shocks: Saved by the central bank?
- No. 457 **Wilko Bolt and David Humphrey**, Assessing bank competition for consumer loans
- No. 458 **Robert Beyer and Michael Stemmer**, From progress to nightmare - European regional unemployment over time
- No. 459 **Stijn Claessens and Neeltje van Horen**, The impact of the global financial crisis on banking globalization
- No. 460 **Francisco Blasques, Falk Bräuning and Iman van Lelyveld**, A dynamic network model of the unsecured interbank lending market
- No. 461 **Carin van der Crujsen, Lola Hernandez and Nicole Jonker**, In love with the debit card but still married to cash
- No. 462 **Koen van der Veer**, Loss shocks and the quantity and price of private export credit insurance: Evidence from a global insurer
- No. 463 **Cenkhan Sahin and Jakob de Haan**, Market reactions to the ECB's Comprehensive Assessment
- No. 464 **Melanie de Waal, Floor Rink and Janka Stoker**, How internal and external supervisors influence employees' self-serving decisions
- No. 465 **Andrea Colciago and Lorenza Rossi**, Firms entry, oligopolistic competition and labor market dynamics
- No. 466 **Peter Heemeijer and Ronald Heijmans**, Central bank intervention in large value payment systems: An experimental approach
- No. 467 **Natalya Martynova**, Effect of bank capital requirements on economic growth: a survey
- No. 468 **Melle Bijlsma and Robert Vermeulen**, Insurance companies' trading behaviour during the European sovereign debt crisis: Flight home or flight to quality?
- No. 469 **Robert Vermeulen, Marco Hoeberichts, Bořek Vašíček, Diana Žigraiová, Kateřina Šmídková and Jakob de Haan**, Financial stress indices and financial crises
- No. 470 **Nicole Jonker, Mirjam Plooi and Johan Verburg**, Does a public campaign influence debit card usage? Evidence from the Netherlands
- No. 471 **Carin van der Crujsen en Mirjam Plooi**, Changing payment patterns at point-of-sale: their drivers
- No. 472 **Christina Strobach and Carin van der Crujsen**, The formation of European inflation expectations: One learning rule does not fit all
- No. 473 **Jan Willem van den End and Christiaan Pattipeilohy**, Central bank balance sheet policies and inflation expectations
- No. 474 **Dirk Broeders, Arco van Oord and David Rijsbergen**, Scale economies in pension fund investments: A dissection of investment costs across asset classes
- No. 475 **Richhild Moessner, David-Jan Jansen and Jakob de Haan**, Communication about future policy rates in theory and practice: A Survey

