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Leading indicators of financial stress: New evidence

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ABSTRACT

This paper examines which variables have predictive power for financial stress in 25 OECD countries, using a recently constructed financial stress index (FSI). First, we employ Bayesian model averaging to identify leading indicators of stress. Next, we use those indicators as explanatory variables in a panel model for all 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 country models, our findings suggest that (increases in) financial stress is (are) hard to predict out-of-sample despite the reasonably good in-sample performance of the models.

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,[4] 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. However, there is an extensive line of research predicting financial (especially banking) crises in which several methodologies have been employed (summaries are provided by Demirgüc-Kunt and Detragiache, 2005, Demyanyk and Hasan, 2010 and Klomp, 2010). Although most of these “early warning” studies assume that crises are homogenously caused by identical factors across countries and that therefore standard panel models can be used, some studies depart from this assumption.

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[4] 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).

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For example, Klomp (2010), using a random coefficient logit model for about 130 banking crises between 1970 and 2007, concludes that there exists significant heterogeneity in the causes of banking crises. Although high credit growth, negative GDP growth and high real interest rates are, on average, the most important leading indicators of a banking crisis, none of these variables has a significant impact in more than 60% of the banking crises. Similarly, several studies apply binary regression trees (e.g. Davis and Karim, 2008), which allows explicitly for the fact that not all crises are alike and accommodates non-linearities by including conditional thresholds. However, it is a nonparametric approach that cannot estimate the marginal contributions of each explanatory variable or confidence intervals for the estimated thresholds.

Only three earlier papers have examined leading indicators of financial stress. Their results are very mixed. Misina and Tkacz (2009) try to identify leading indicators of 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, but not for others. Finally, Christensen and Li (2014) employ the signal-extraction approach to monitor the evolution of a number of economic indicators that tend to exhibit unusual behaviour in the period preceding a financial stress event. They combine these variables in three different indicators: the summed composite indicator, the extreme composite indicator and the weighted composite indicator. These composite indicators are used to predict the likelihood of the occurrence of financial stress events within a given period of time. Using the IMF financial stress index (Cardarelli et al., 2011) and 12 indicators for 13 OECD countries, the authors conclude that the composite indicator performs best in terms of out of sample predictions.

One important limitation of previous studies is that they look at a restricted set of countries and indicators and do not examine to what extent combinations of several leading indicators affect their results. The purpose of this paper is to examine which variables have predictive power for financial stress in a sample of 25 OECD countries and to examine whether these leading indicators have the same predictive power for different countries.[5] For this purpose we use the stress index recently proposed by Vermeulen et al. (2015).[6] The main reasons for choosing this index are that (i) the FSI can be consistently calculated for a large sample of countries, (ii) it is available for a relatively long time span and (iii) it covers a broad range of financial markets in a country. Furthermore, this index is fairly representative for other cross-country FSIs as explained in detail in Vermeulen et al. (2015).

As a first step, we gather data for more than 20 potential early warning indicators of financial stress. Since there is no theoretical literature on determinants of financial stress to guide our variable selection we consider indicators that have been suggested in the empirical literature on early warning models of financial and in particular banking crises (e.g. Frankel and Rose, 1996; Kaminsky et al., 1998; Klomp, 2010), which is the most common form of financial turmoil in our sample of OECD countries (Babecký et al., 2014). Next, we employ Bayesian model averaging (BMA) to identify which of those variables are related to our FSI. The systematic approach to select variables from a large set of potential financial stress predictors is a major improvement compared to previous studies that used smaller country samples and a narrower set of potential leading indicators (Misina and Tkacz, 2009; Slingenberg and de Haan, 2011; Christensen and Li, 2014). 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 also differs from common practice in early warning studies, where usually a limited number of (potential) leading indicators are selected on the basis of the authors' judgement, theory or previous empirical studies.[7] 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 also estimate our models using variables that measure only high levels of FSI or increases in the FSI. It turns out that panel models can hardly explain FSI dynamics suggesting that financial stress predictors might differ across countries. 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 far less 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.

2. Financial stress and economic outcomes

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 indexes for a single country combine more stress indicators into one statistic than multi-country stress indexes (for an extensive comparison of FSIs we refer to Kliesen et al., 2012).[8] 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 securitisation markets, even though there are good reasons for including these segments of the financial system in constructing a FSI (cf. Oet et al., 2012).

[5] 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). Duprey et al. (2015) combine the two approaches by converting a continuous measure of financial stress into a binary systemic stress dummy for 27 EU countries.

[6] The purpose of this paper is not to come up with yet another financial stress index. As will be explained in more detail in Section 2, several stress indexes have been suggested. The stress index used in our analysis captures indicators frequently included in multi-country stress indexes (see the online Appendix for a comparison of several widely used FSIs).

[7] 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. Christensen and Li (2014) use a different approach that does not allow identifying the predictive power of individual indicators.

[8] 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 that the lead with which market prices – on which most FSIs rely – point to distress is uncomfortably short from a policy perspective.

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 cov(return banking sector, total market)/variance(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).

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). This index is fairly representative of indexes used in cross-country analyses.[9] All variables included in the index are standardised, i.e. we subtract the mean and divide by the standard deviation. The index used is the non-weighted sum of the standardised variables included.[10] 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 using EViews 8.1 (see Fig. 1).

Financial stress indexes have been used for several purposes (see Vermeulen et al., 2015 for a more extensive discussion).[11] For instance, 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 characterised 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.

Fig. 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 −0.37, it is as high as −0.7 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. Yet, this finding is slightly weaker when we disregard the observations from recent financial crises. However, the correlation between FSI and GDP growth four quarters ahead is much lower and on average only −0.12. So, it seems unlikely that the current level of FSI will help policymakers to mitigate economic losses one year ahead.

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) who analyse a similar sample of OECD countries. After dropping some variables because of data availability, we are left with a set of 24 potential macroeconomic and financial variables (see Table A1 in the Appendix). These variables have all been argued to be linked to financial crises, although studies frequently report different findings for their significance, and sometimes even for their sign (see Table 1 in Klomp, 2010). For instance, Demirgüç-Kunt and Detragiache (1997) argue that high short-term interest rates affect bank balance sheets adversely if banks cannot increase their lending rates quickly enough. Furthermore, Calvo et al. (1993) conclude that capital flows are sensitive to changes in the level of the world interest rate. Large capital inflows and capital flight, particularly in the case of emerging countries, may affect the stability of the financial sector. Our list of variables also includes the credit gap and house prices. The motivation for these variables comes from recent research on financial cycles suggesting that they are driven by growth in credit and house prices (see, for instance, Drehmann et al., 2012). The turn of financial cycles comes along with financial instability. 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^{25} possible combinations of potential variables (Fernandez et al., 2001; Sala-i-Martin et al., 2004).[12]

Under BMA, many different models γ are estimated based on the following structure:

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

where $FSI_{i,t}$ is our continuous FSI, α_i^γ is a constant, β_t^γ is a vector of coefficients, $\varepsilon_{i,t}^\gamma$ is an error term and $X_{i,t}^\gamma$ is 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

[9] The online appendix compares the index of Vermeulen et al. (2015) and several other FSIs that recently have been proposed.

[10] 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.

[11] Several recent papers are worth mentioning. Cevik et al. (2013) construct a FSI for Bulgaria, the Czech Republic, Hungary, Poland, and Russia and examine the relationship between financial stress and economic activity. Martin and Milas (2013) estimate Taylor rules in which they include a FSI to model UK monetary policy. Likewise, Baxa et al. (2013) examine whether and how central banks of the USA, the UK, Australia, Canada, and Sweden responded to episodes of financial stress over the last three decades. Mallick and Sousa (2013) analyse the real effects of financial stress in the Euro-zone using VARs. Blot et al. (2015) use the Federal Reserve Bank of St. Louis FSI and the index of Holló et al. (2012) to analyse the relationship between price stability and financial stability. Apostolakis and Papadopoulos (2014) examine financial stress co-movements and spillovers among the G7 economies for the 1981–2009 period, while Apostolakis and Papadopoulos (2015) use the FSI of Balakrishnan et al. (2009) to analyse financial stress spillovers among the banking, securities and foreign exchange markets.

[12] Similarly, Crespo-Cuaresma and Slacik (2009) and Babecký 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. Babecký and Havránek, 2014; Havránek and Rusnák, 2013). Raftery (1995) and Eicher et al. (2011) provide further details on BMA.

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.

BMA gives each model γ a weight, which captures the model's fit (similar to an adjusted R2) and reports weighted averages of the models' regression parameters and standard deviations, using posterior model probabilities from Bayes' theorem:

$$p(M^{\gamma}|\mathrm{FSI}_{i,t}, X^{\gamma}_{i,t-4}) \propto p(\mathrm{FSI}_{i,t}|M^{\gamma}, X^{\gamma}_{i,t-4})p(M^{\gamma}), \tag{2}$$

where $p(M^{\gamma}|\mathrm{FSI}_{i,t}, X^{\gamma}_{i,t-4})$ is the posterior model probability, $\propto$ is a sign of proportionality, $p(y|M^{\gamma}, X^{\gamma}_{i,t-4})$ 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:

$$p(\theta|M^{\gamma}, \mathrm{FSI}_{i,t}, X^{\gamma}_{i,t-4}) = \sum_{\gamma=1}^{2^K} p(\theta|M^{\gamma}, \mathrm{FSI}_{i,t}, X^{\gamma}_{i,t-4}) \frac{p(M^{\gamma}|\mathrm{FSI}_{i,t}, X^{\gamma}_{i,t-4})p(M^{\gamma})}{\sum_{j=1}^{2^K} p(y|M_j, X^{\gamma}_{i,t-4})p(M_j)}. \tag{3}$$

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:

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

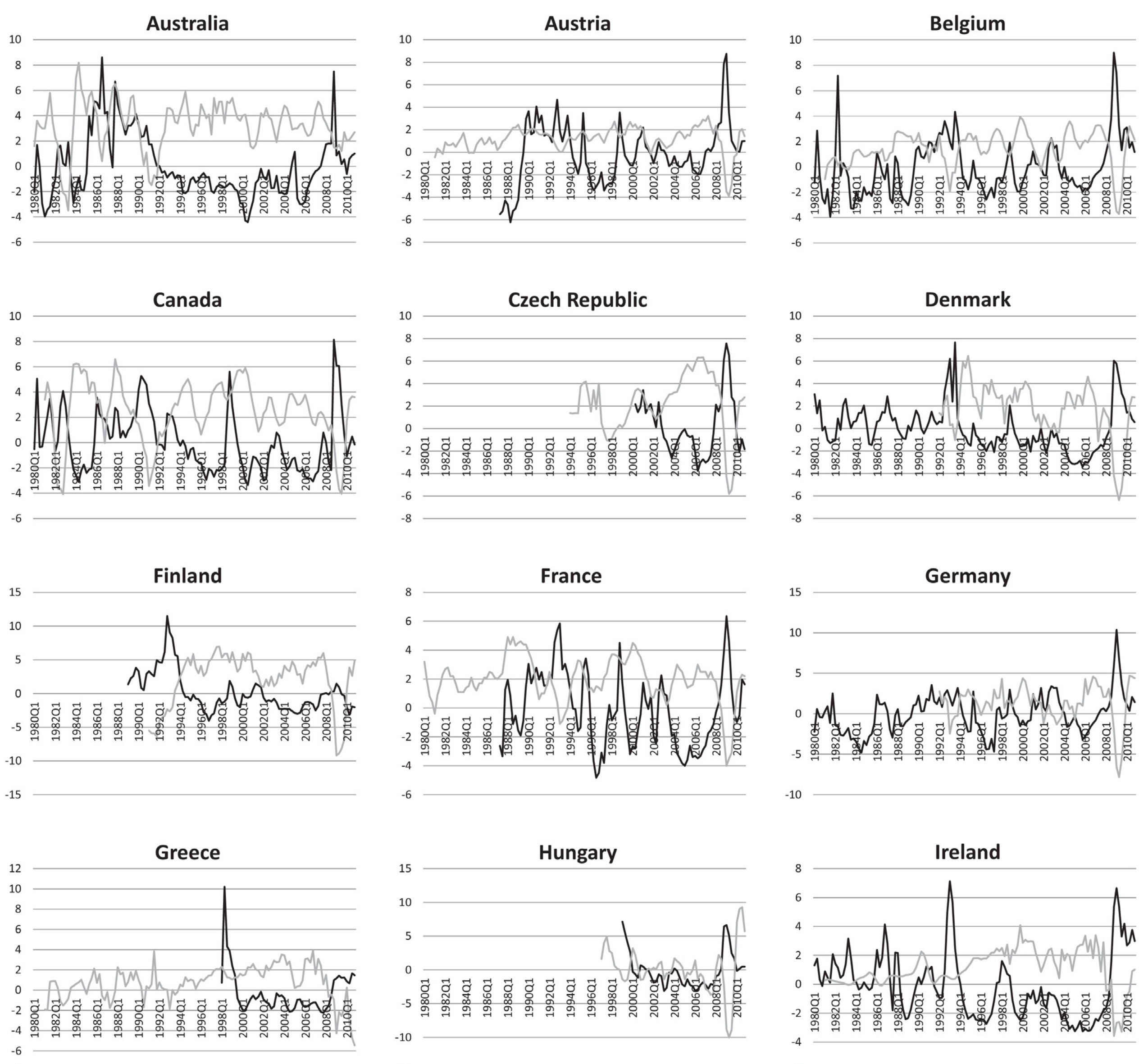

Fig. 1. FSI vs. GDP growth, 1980Q1–2010Q4. *Note*: This figure shows the FSI (black line) and real GDP growth (light grey line) for the 25 OECD countries in our sample.

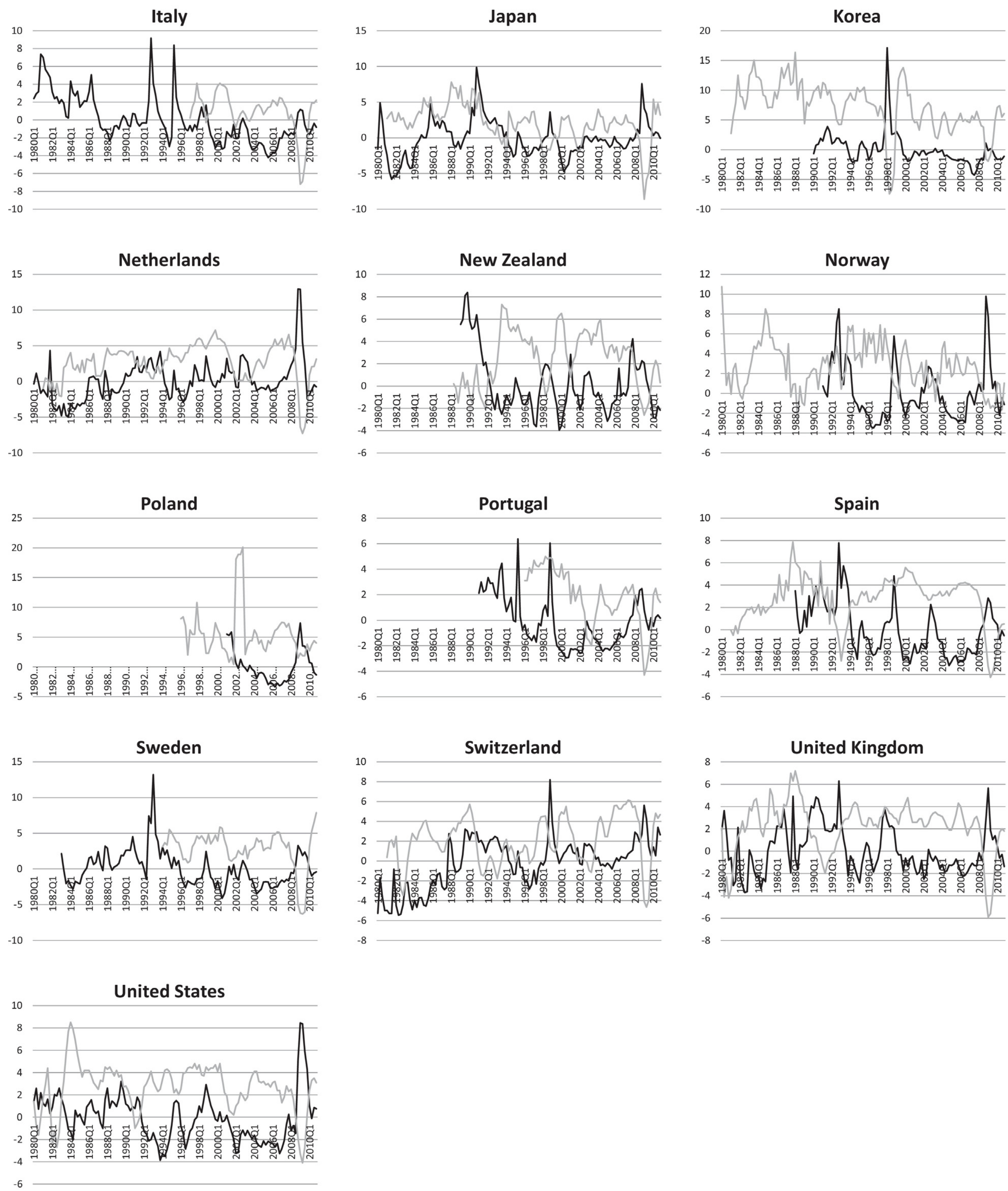

Fig. 1. (*Continued*).

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

Table 2
Correlation between GDP growth and (lagged) financial stress.

Country	Full sample			Sub-sample until 4.Q 2006		
	t	$t+1$	$t+4$	t	$t+1$	$t+4$
AUS	−0.15	−0.21	−0.09	−0.13	−0.18	−0.05
AUT	−0.38	−0.54	−0.40	−0.16	−0.29	−0.32
BEL	−0.40	−0.46	−0.23	−0.25	−0.28	−0.20
CAN	−0.45	−0.48	−0.16	−0.39	−0.40	−0.22
CZE	−0.73	−0.84	−0.57	−0.60	−0.63	−0.74
DNK	−0.59	−0.54	0.00	−0.37	−0.33	0.12
FIN	−0.54	−0.53	−0.34	−0.68	−0.65	−0.44
FRA	−0.39	−0.47	−0.26	−0.24	−0.35	−0.33
GER	−0.56	−0.64	−0.14	−0.35	−0.43	−0.27
GRC	−0.32	−0.30	−0.14	−0.19	−0.28	−0.29
HUN	−0.29	−0.29	0.41	−0.20	0.02	0.39
IRL	−0.67	−0.65	−0.43	−0.55	−0.58	−0.55
ITA	−0.45	−0.51	−0.12	−0.20	−0.33	−0.11
JAP	−0.09	−0.10	0.04	0.13	0.12	0.09
KOR	−0.30	−0.33	0.24	−0.38	−0.43	0.16
NLD	−0.20	−0.36	−0.32	0.08	0.03	−0.10
NZL	−0.55	−0.59	−0.45	−0.65	−0.66	−0.44
NOR	−0.34	−0.33	−0.08	−0.25	−0.25	0.10
POL	−0.25	−0.19	0.41	−0.10	−0.02	0.82
PRT	−0.06	−0.11	−0.01	0.28	0.31	0.40
SPA	−0.37	−0.41	−0.27	−0.39	−0.44	−0.37
SWE	−0.48	−0.40	0.05	−0.14	−0.05	0.05
SWI	0.02	−0.03	−0.04	0.07	0.05	−0.01
UK	−0.29	−0.30	−0.22	−0.20	−0.22	−0.32
US	−0.42	−0.38	0.03	−0.19	−0.22	−0.01
Mean	−0.37	−0.40	−0.12	−0.24	−0.26	−0.11

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.

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

Fig. 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, while Table A2 shows the availability of the data used. The figure depicts the ranking of the variables according to their posterior 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.[13] The coefficients of these seven variables are consistent across the different models, although the signs are not always in line with theoretical priors.

As a robustness check we have estimated the model using lags of 8 and 12 quarters for the leading indicators. The results show that different variables are selected by the BMA-procedure for financial stress 8 or 12 quarters ahead. The BMA-procedure selects 11 variables with a PIP higher than 0.5 for 8 quarters ahead and 8 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 different forecast horizons, e.g. M3 growth in the eight and twelve quarters ahead forecast. The overall fit of the model 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). Apart from the money market rate the only other

[13] 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.

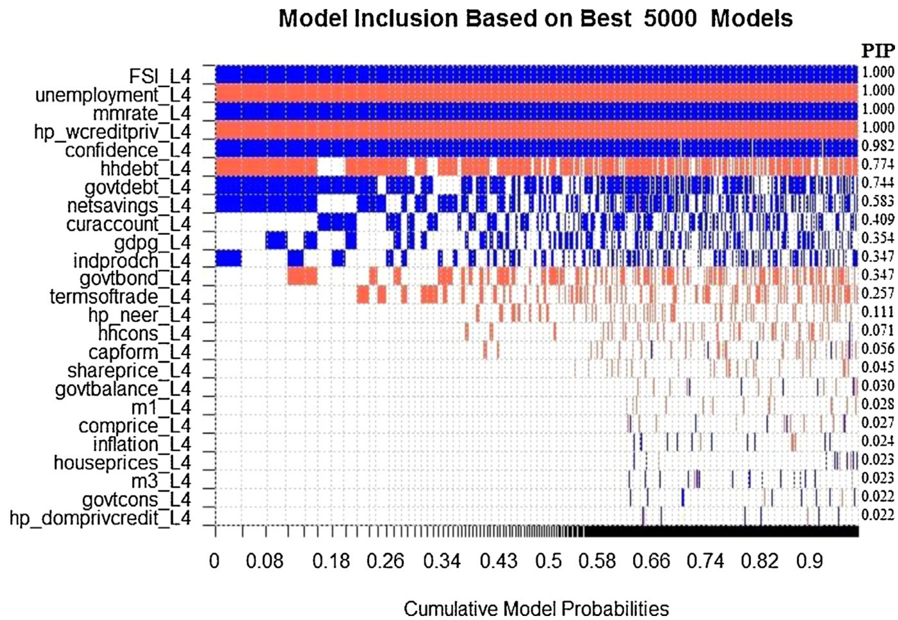

Fig. 2. Bayesian model averaging: leading indicators of FSI, 4Q ahead. *Note*: Rows = potential FSI predictors. Columns = best models according to marginal likelihood, ordered from left. Full cell = variable included in model, blue = positive sign, red = negative sign. Variables are described in Table A1 in the Appendix. L4 means that four lags have been used. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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.

Lags:	(1) 4	(2) 8	(3) 12	(4) 4 (pre-crisis)
Constant	−4.75**	−8.35***	−2.12***	−2.4
	(2.21)	(2.16)	(0.59)	(2.29)
Lag FSI	0.14***			
	(0.04)			
Money market rate	0.37***	0.48***	0.13***	0.41***
	(0.04)	(0.08)	(0.04)	(0.03)
World credit gap	−0.17***			
	(0.02)			
Unemployment	−0.15***	−0.06	0.02	0.01
	(0.05)	(0.09)	(0.09)	(0.05)
Private debt	−0.03			
	(0.02)			
Confidence	0.04	0.07***		−0.00
	(0.02)	(0.02)		(0.02)
Govt. debt	0.01	0.01		
	(0.00)	(0.01)		
Govt. bond yield		−0.28**		
		(0.11)		
Commodity prices		0.04***		−0.02*
		(0.01)		(0.01)
Exchange rate		−0.06***		−0.07***
		(0.01)		(0.02)
Current account		0.01	0.03	−0.03
		(0.06)	(0.06)	(0.05)
Capital formation		0.03	0.06***	
		(0.02)	(0.02)	
Stock market		0.01	0.02***	
		(0.00)	(0.00)	
M3 growth		0.05***	0.11***	−0.01
		(0.02)	(0.02)	(0.01)
Terms of trade			−0.06**	
			(0.03)	
Govt. balance			0.01	0.08**
			(0.06)	(0.03)
Net savings	0.02			
	(0.03)			
R^2	0.22	0.07	0.09	0.19
Obs.	1586	1486	1386	1186
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. Explanatory variables are explained in Table A1 in the Appendix.

significant variables are commodity prices, exchange rate and government balance.

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, which suggests that predictors of financial stress may differ across countries. Consequently, 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, which also partially reflects data availability.

4.2. Country level analysis with FSI

There are different ways to tackle potential heterogeneity of leading indicators of FSI across countries. The simplest option is to assume that the set of indicators is homogenous across countries, i.e. to keep the indicators preselected by the panel BMA (as in Fig. 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.

We therefore estimate country models using a country-specific set of leading indicators (based on the BMA results reported in Fig. A1 in the Appendix). For each G7 country, except Germany, the BMA identifies 7 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 (see Table 4). It is also apparent that there is a lot of cross-country heterogeneity. Interestingly, the lag of the FSI is not significant anymore, except for Japan. Indeed, Fig. 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

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

	USA	UK	JAP	GER	FRA	ITA	CAN
Constant	3.31***	−11.79***	0.05	10.73***	217.45***	−39.82**	−3.47***
	(1.08)	(1.45)	(0.26)	(2.19)	(48.29)	(18.06)	(0.46)
M3 growth	0.34***						0.41***
	(0.08)						(0.08)
House prices	−0.16***	0.19***	0.25***	−1.04***	−0.33***		
	(0.04)	(0.04)	(0.06)	(0.12)	(0.05)		
Domestic credit gap	−0.05		−0.15***		0.23***	0.14***	
	(0.05)		(0.02)		(0.07)	(0.04)	
Unemployment	−1.29***			−1.54***	−2.38***		
	(0.20)			(0.24)	(0.40)		
Govt. balance	−0.42***	0.09				0.44***	
	(0.10)	(0.06)				(0.13)	
Production	0.14	−0.26***					
	(0.09)	(0.06)					
Private debt	−0.18**	−0.30***			0.18*	−0.39***	−0.14***
	(0.08)	(0.08)			(0.11)	(0.09)	(0.08)
GDP growth	−0.13						
	0.15						
Govt. bond yield	0.57***	1.00***				0.24**	
	(0.10)	(0.10)				(0.12)	
World credit gap		−0.29***				−0.22***	
		(0.07)				(0.07)	
Net savings		0.83***					
		(0.17)					
Capital formation		−0.13***	−0.17***				
		(0.03)	(0.03)				
Current account		−0.98***					−0.40***
		(0.23)					(0.09)
Exchange rate		0.10**	−0.07***				0.09**
		(0.04)	(0.02)				(0.04)
Lag FSI			−0.27***				
			(0.08)				
Money market rate			0.32***				
			(0.10)				
Inflation			0.69***	1.68***	−0.72*		
			(0.17)	(0.31)	(0.39)		
Commodity prices				−0.01	−0.08***	−0.09***	
				(0.02)	(0.02)	(0.02)	
Production					0.66***	0.22***	
					(0.09)	(0.05)	
Confidence					−1.95***	0.42***	
					(0.46)	(0.18)	
Stock market					0.04***		
					(0.01)		
Govt. consumption						0.46***	0.27***
						(0.13)	(0.10)
Terms of trade							−0.16***
							(0.06)
Household cons.							0.36***
							(0.13)
R^2	0.57	0.73	0.70	0.56	0.64	0.61	0.49
Obs.	120	89	96	68	91	72	116

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

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. Still, some findings deserve some attention. First, 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. Second, 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 Hofmann (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. Tables A3 and A4 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.

Finally, we have re-estimated our model for the US using two alternative financial stress indexes, namely those of the

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

	USA	UK	JAP	GER	FRA	ITA	CAN
R^2 (full sample)	0.57	0.73	0.70	0.56	0.64	0.61	0.49
R^2 (subsample)	0.38	0.78	0.78	0.64	0.77	0.70	0.52

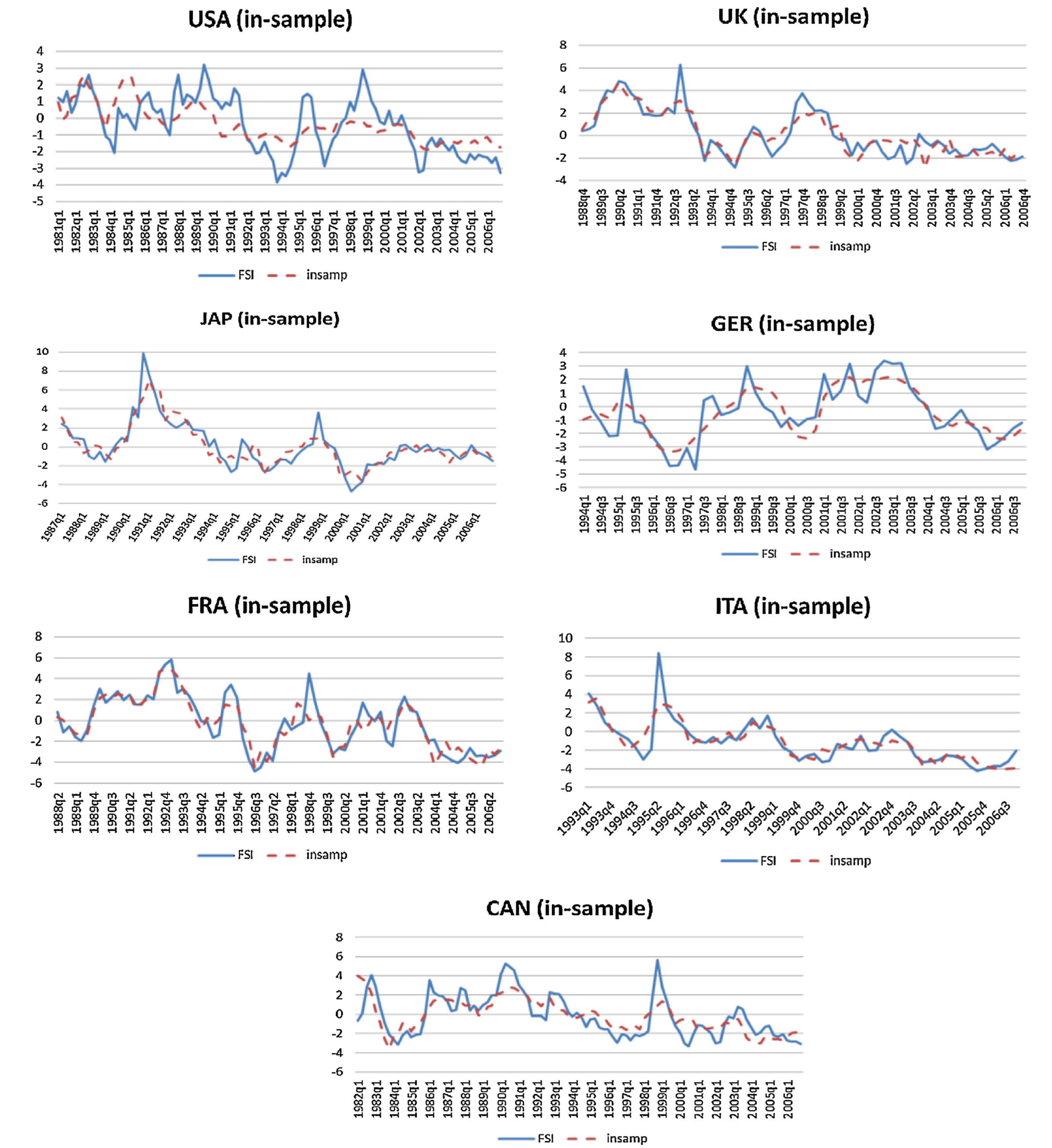

Fig. 3. In-sample fit of country level models. *Note*: The figures compare the actual level of the FSI with the predicted value (in-sample) according to the models based on BMA-selected variables.

Federal Reserve Bank of Cleveland and of the Federal Reserve Bank of Kansas. Both indices are much broader than our FSI as they do not face the restriction that data should be available for all countries for which we have constructed our FSI. Table A5 in the Appendix shows that the estimates are fairly similar to those reported in Table 4, so that we conclude that our results are not driven by the use of the FSI proposed by Vermeulen et al. (2015).

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 all countries but the US we find a similar or even slightly better in-sample fit of the

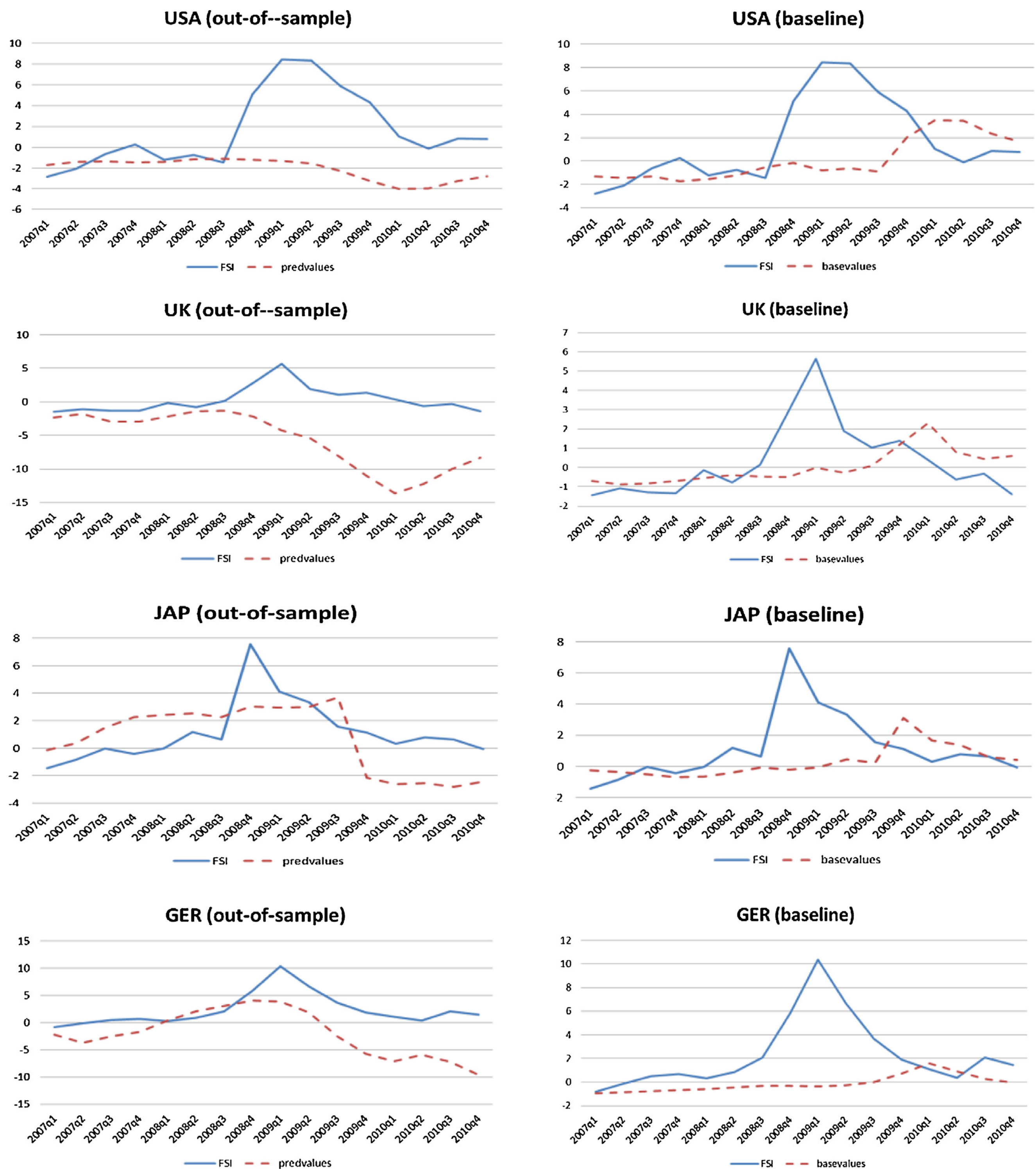

Fig. 4. Out-of-sample fit: country level models vs. autoregressive models. *Note*: The figures compared the predicted FSI from models based on BMA-selected variables (left panel) and autoregressive models based on the FSI 4th lag only (right-hand side panels).

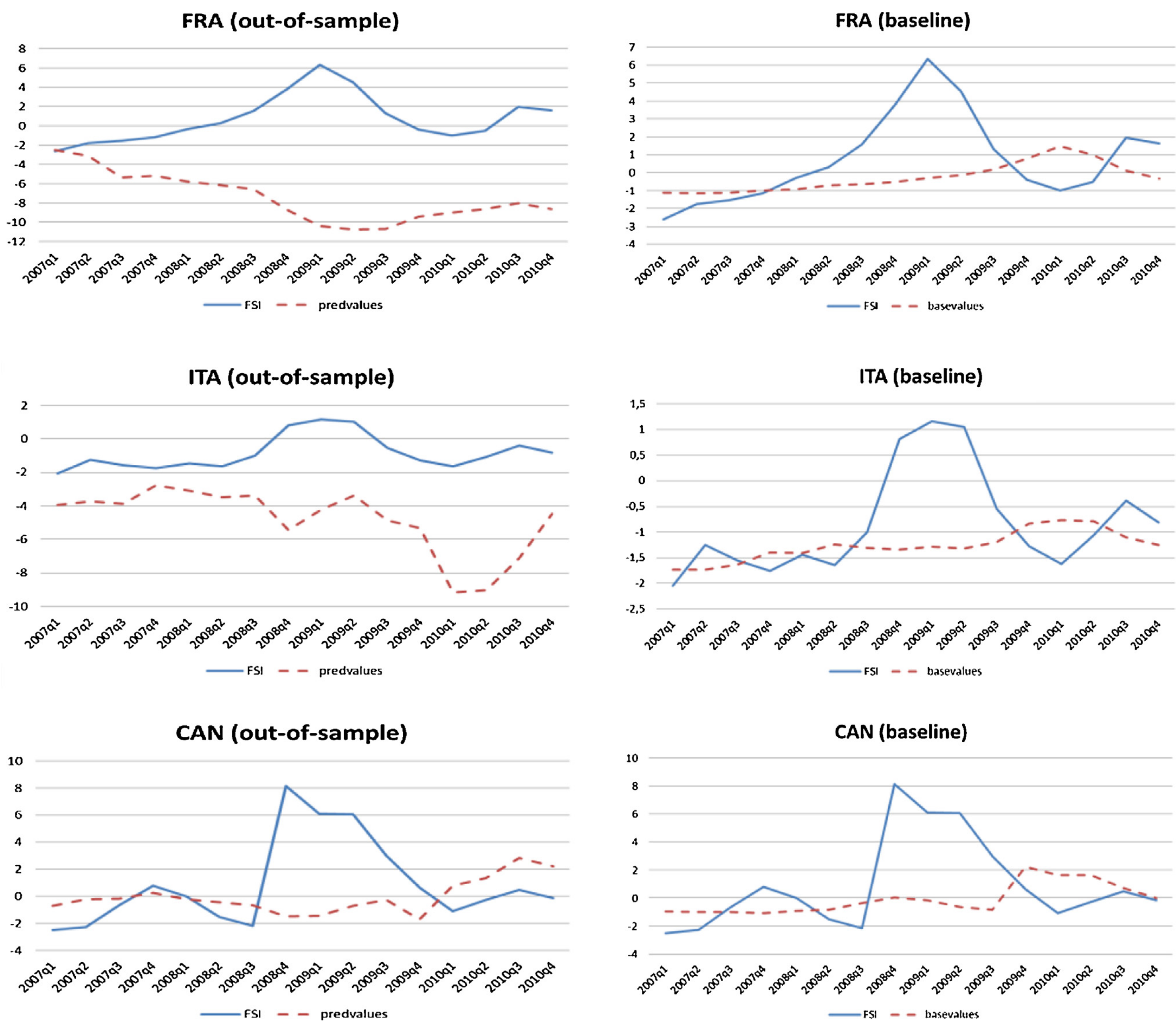

Fig. 4. (*Continued*).

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	2.47	5.65	9.36	4.53	3.88
RMSE (AR 4th lag)	4.15	1.94	2.50	3.82	2.65	1.09	3.44

models using data up to 2006 compared to the models using data up to 2010 (see Table 5). Moreover, Fig. 3 shows that the in-sample fit of the models using data up to 2006 is quite good.

Fig. 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.[14] 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 the 2006Q1–2009Q4 period, i.e. corresponding to the prediction horizon from 2007Q1 until 2010Q4 (left-hand side panels in Fig. 4). The right-hand side panels depict similar out-of-sample forecasts for the autoregressive model.

The results shown in Fig. 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 the drivers of financial stress during the global financial crisis are different variables than those selected for the pre-crisis sample to forecast the rise in the FSI.

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

[14] 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.

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.

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 on the left-hand side a variable that measures whether the FSI is above a particular threshold (in line with Lo Duca and Peltonen, 2011) 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 Fig. 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 analyse 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) which is fairly representative of stress indices used in cross-country analyses. 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. Our models generally do not predict an increase in financial stress before the recent financial crisis. Although the unprecedented nature of the financial crisis may play a role here, our results are in line with most previous studies suggesting that in general it is hard to predict financial stress out-of-sample. 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, even though the in-sample performance of our models is quite acceptable.

The results in this paper show that policymakers will face difficulties when trying to proactively avoid potential stress in financial markets. It is a challenging task for models to predict the abrupt changes in financial stress. Furthermore, the potential drivers of financial stress differ across countries and may differ as well across stress episodes. The lack of predictability implies that policymakers need to be equipped with flexible tools to respond quickly to emerging financial stress, since long policy implementation lags may aggravate the financial stress episode and the negative effects on the real economy.

Acknowledgements

The authors would like to thank two anonymous referees for their very helpful comments on a previous version of this paper. The views expressed are those of the authors and do not reflect the views of the European Commission, the Czech National Bank or De Nederlandsche Bank. We dedicate this paper to the memory of Kateřina Šmídková.

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

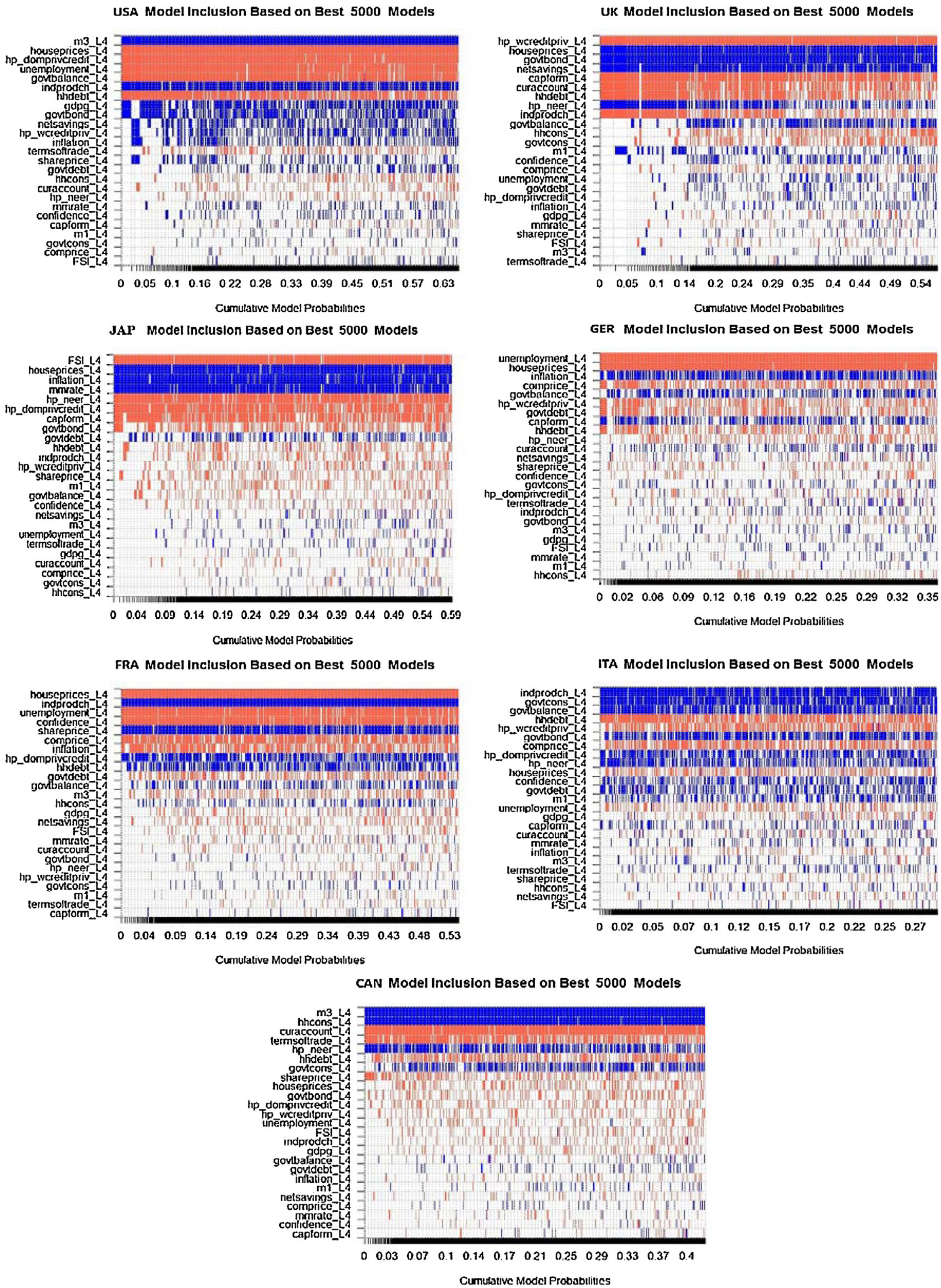

Fig. A1. Bayesian model averaging: early warning indicators of FSI for G7 countries, 4Q ahead.

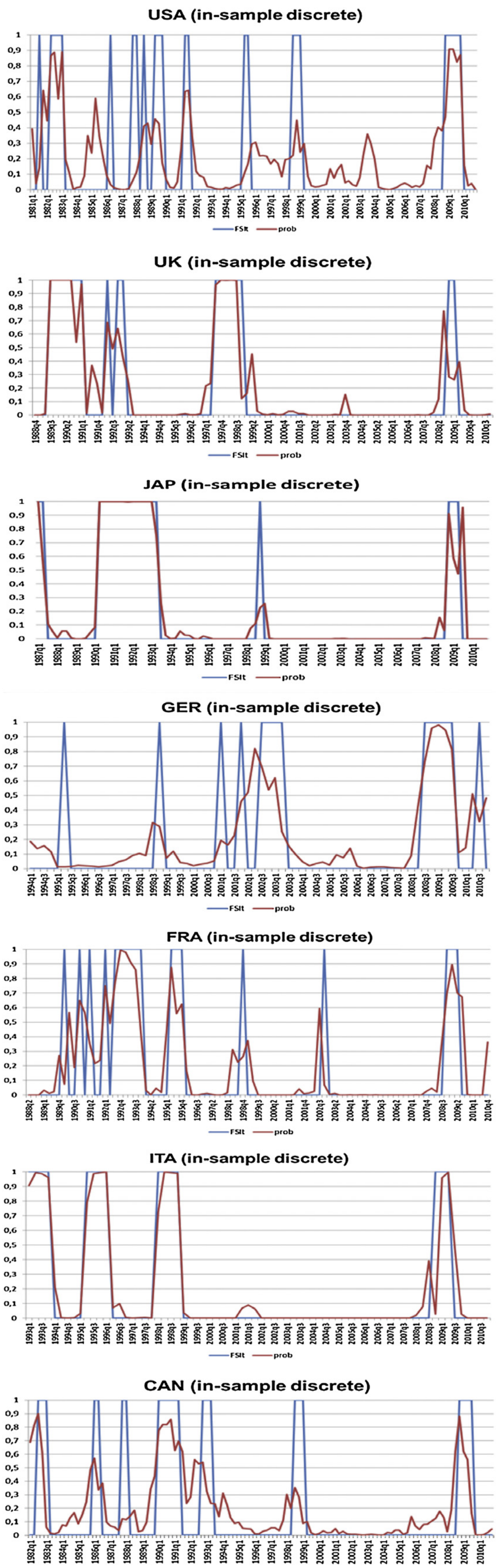

Fig. A2. In-sample fit of country level models logit model. (For interpretation of the references to colour in this figure citation, the reader is referred to the web version of this article.)

Table A2
Variable availability.

Country	FSI availability since:	Availability all predicting variables since:
Australia	1980Q1	1986Q1
Austria	1987Q2	1997Q1
Belgium	1980Q1	1999Q1
Canada	1980Q1	1986Q1
Czech Rep.	2000Q2	2000Q2
Denmark	1980Q1	1996Q1
Finland	1989Q1	1996Q4
France	1987Q2	1987Q2
Germany	1980Q1	1993Q1
Greece	1998Q1	2001Q1
Hungary	1999Q1	2002Q4
Ireland	1980Q1	1998Q1
Italy	1980Q1	1992Q1
Japan	1980Q2	1986Q1
Korea	1990Q1	1998Q4
Netherlands	1980Q1	1994Q1
New Zealand	1989Q1	1990Q1
Norway	1991Q1	1992Q3
Poland	2001Q1	2001Q2
Portugal	1991Q1	1999Q1
Spain	1988Q1	1994Q1
Sweden	1983Q1	1999Q1
Switzerland	1980Q1	1990Q1
UK	1980Q1	1987Q4
US	1980Q1	1986Q1

Table A3
Comparison of results of BMA preselected early warning indicators of FSI (PIP ≥ 0.5) 4Q ahead using linear and nonlinear model – the US.

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

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

Table A4
Comparison of results of BMA preselected early warning indicators of FSI (PIP ≥ 0.5) 4Q ahead using linear and nonlinear model – the UK.

	UK linear	UK non-linear
Constant	−11.79***	−3.31
	(1.45)	(5.14)
House prices	0.19***	0.22***
	(0.04)	(0.07)
House prices2̂		−0.01***
		(0.00)
Govt. balance	0.09	−0.15
	(0.06)	(0.19)
Govt. balance2̂		−0.03
		(0.03)
Production	−0.26***	−0.24***
	(0.06)	(0.07)
Production2̂		0.01
		(0.01)
Household debt	−0.30***	−0.24
	(0.08)	(0.31)
Household debt2̂		0.01
		(0.01)
Govt. bond yield	1.00***	0.73
	(0.10)	(0.82)
Govt. bond yield2̂		−0.00
		(0.05)
World credit gap	−0.29***	−0.23*
	(0.07)	(0.12)
World credit gap2̂		0.04**
		(0.01)
Net savings	0.83***	0.22
	(0.17)	(0.36)
Net savings2̂		−0.02
		(0.09)
Capital formation	−0.13***	−0.08
	(0.03)	(0.06)
Capital formation2̂		−0.00
		(0.00)
Current account	−0.98***	1.19
	(0.23)	(0.94)
Current account2̂		0.34**
		(0.13)
Exchange rate	0.10**	0.13***
	(0.04)	(0.04)
Exchange rate2̂		0.01
		(0.01)
R^2	0.73	0.79
Obs.	89	89
Count.	1	1

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

Table A5
Robustness: different Financial Stress Indexes for the United States.

	FSI	CFSI	KCFSI
Constant	1.58**	0.33	1.23
	(0.50)	(1.23)	(0.99)
M3 growth	0.16***	0.20**	0.15***
	(0.04)	(0.07)	(0.04)
House prices	−0.07***	−0.06*	−0.10**
	(0.02)	(0.02)	(0.03)
Domestic credit gap	−0.02	0.04	0.04
	(0.02)	(0.03)	(0.02)
Unemployment	−0.60***	−0.29	−0.43***
	(0.09)	(0.15)	(0.12)
Govt. balance	−0.19***	−0.18*	−0.15**
	(0.05)	(0.08)	(0.05)
Production	0.06	0.03	0.03
	(0.04)	(0.07)	(0.04)
Household debt	−0.08*	−0.02	−0.02
	(0.04)	(0.08)	(0.06)
GDP growth	−0.06	0.16	0.14*
	(0.07)	(0.10)	(0.06)
Govt. bond yield	0.27***	0.01	0.06
	(0.05)	(0.10)	(0.06)
R^2	0.57	0.55	0.65
N	120	78	84

Note: FSI is the financial stress index used in this paper, while CFSI and KCFSI are the financial stress indexes constructed by the Federal Reserve Bank of Cleveland and the Federal Reserve Bank of Kansas City, respectively. (The data are available at: https://research.stlouisfed.org/fred2/series/CFSI; https://research.stlouisfed.org/fred2/series/KCFSI.) Both the CFSI and KCFSI are constructed at the quarterly frequency by taking their mean value during a specific quarter. In order to ease the comparison of coefficients all FSI series are standardise with mean zero and standard deviation 1. *** indicates significance at 1%, ** at 5% and * at 10% level.

Table A6
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***						0.36**
	(0.18)						(0.17)
House prices	−0.28	1.41***	0.93**	−1.04**	−0.58**		
	(0.74)	(0.50)	(0.42)	(0.41)	(0.28)		
Domestic credit gap	−0.21***		−0.41*		0.77***	0.05	
	(0.08)		(0.23)		(0.27)	(0.17)	
Unemployment	−1.77***			−1.74***	−4.47***		
	(0.59)			(0.53)	(1.26)		
Govt. balance	−0.42*	1.08***				2.91***	
	(0.23)	(0.40)				(0.50)	
Production	0.57***	−0.26***			1.72***	0.98**	
	(0.19)	(0.06)			(0.48)	(0.44)	
Household debt	−0.30	−1.19**			0.06	−1.46***	−0.05
	(0.29)	(0.54)			(0.33)	(0.39)	(0.17)
GDP growth	−0.98***						
	(0.33)						
Govt. bond yield	0.53**	4.40***				2.04***	
	(0.25)	(1.28)				(0.56)	
World credit gap		−1.30***				−0.67	
		(0.43)				(0.48)	
Net savings		2.77***					
		(0.06)					
Capital formation		−0.46*	−0.88**				
		(0.26)	(0.37)				
Current account		−5.10***					−0.51**
		(2.23)					(0.24)
Exchange rate		0.39**	−0.24***				0.34***
		(0.19)	(0.09)				(0.12)
Lag FSI			−1.66*				
			(0.90)				
Money market rate			2.71**				
			(1.14)				
Inflation			3.13	1.74**	−2.76**		
			(2.30)	(0.72)	(1.23)		
Commodity prices				−0.01	0.00	−0.03	
				(0.03)	(0.71)	(0.09)	
Confidence					−4.70***	−1.75*	
					(1.20)	(1.04)	
Stock market					0.07**		
					(0.03)		
Govt. consumption						1.92***	−0.11
						(0.70)	(0.16)
Terms of trade							−0.08
							(0.15)
Household cons.							0.22
							(0.27)
Pseudo R^2	0.33	0.72	0.82	0.40	0.55	0.82	0.36
Obs.	120	89	96	68	91	72	116

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

Table A7
Results of BMA preselected early warning indicators for increases of FSI (PIP ≥ 0.5) 4Q ahead for G7 countries – Tobit model.

	USA	UK	JAP	GER	FRA	ITA	CAN
M3 growth	0.471***						0.528***
	(0.12)						(0.13)
Lag FSI			−1.56***				
			(0.24)				
House prices	−0.214***	0.242***	0.41***	−0.803**	−0.254**		
	(0.05)	(0.07)	(0.09)	(0.24)	(0.08)		
Domestic credit gap	−0.353***		−0.16***		−0.037	0.218***	
	(0.08)		(0.04)		(0.13)	(0.06)	
Unemployment	−1.387***			−0.557	−2.380***		
	(0.33)			(0.37)	(0.55)		
Govt. balance	−0.180	0.329*				0.079	
	(0.19)	(0.16)				(0.16)	
Production	0.479***	0.001			0.569***	0.486***	
	(0.13)	(0.15)			(0.14)	(0.11)	
Household debt	0.282	−0.325*			0.256	−0.255	−0.344**
	(0.16)	(0.13)			(0.16)	(0.13)	(0.13)
GDP growth	−0.519*						
	(0.24)						
Govt. bond yield	−0.092	0.702***				−0.175	
	(0.17)	(0.16)				(0.20)	
World credit gap		−0.596***				−0.362***	
		(0.11)				(0.10)	
Net savings		−0.063					
		(0.34)					
Capital formation		−0.028	−0.22***				
		(0.06)	(0.05)				
Current account		−0.565					0.179
		(0.38)					(0.13)
Exchange rate		0.100	−0.05**				0.273***
		(0.07)	(0.03)				(0.07)
Inflation			0.91***	1.453*	−1.425**		
			(0.21)	(0.56)	(0.49)		
Money market rate			0.22				
			(0.18)				
Commodity prices				0.056	0.009	−0.120***	
				(0.03)	(0.03)	(0.03)	
Confidence					−2.318***	0.572*	
					(0.59)	(0.26)	
Stock market					0.075***		
					(0.01)		
Govt. consumption						0.644**	0.197
						(0.19)	(0.16)
Household cons.							1.079***
							(0.24)
Terms of trade							−0.366***
							(0.10)
Pseudo R^2	0.21	0.17	0.38	0.09	0.15	0.22	0.15
N	120	89	92	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.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jfs.2016.05.005.

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