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Early Warning Indicators of Crisis Incidence: Evidence from a Panel of 40 Developed Countries

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Abstract:
We provide a critical review of the literature on early warning indicators of economics crises and propose methods to overcome several pitfalls of the previous contributions. We use a quarterly panel of 40 EU and OECD countries for the period 1970–2010. As the response variable, we construct a continuous index of crisis incidence capturing the real costs for the economy. As the potential warning indicators, we evaluate a wide range of variables, selected according to the previous literature and our own considerations. For each potential indicator we determine the optimal lead employing panel vector autoregression, then we select useful indicators employing Bayesian model averaging. We re-estimate the resulting specification by system GMM to account for potential endogeneity of some indicators. Subsequently, to allow for country heterogeneity, we evaluate the random coefficients estimator and illustrate the stability among endogenous clusters. Our results suggest that global variables rank among the most useful early warning indicators. In addition, housing prices emerge consistently as an important domestic source of risk.

Keywords: Early warning indicators, Bayesian model averaging, panel VAR, dynamic panel, macro-prudential policies.

JEL: C33, E44, E58, F47, G01.

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1. Introduction

The recent economic crisis has brought the early warning literature back into the spotlight. In the several past rounds of the debate, this literature stream developed the concept of an early warning system (EWS) consisting of alternative early warning models (EWMs) that should be able to identify and warn against various costly events, such as currency, banking or financial crises. The EWS should be able to warn early enough for policy makers to be able to implement measures reducing the costs for the economy. Despite the noticeable progress in the theoretical and empirical literature on this subject in previous decades, the recent crisis has demonstrated that there is still ample room for improving the EWS. First, while initial studies tried to offer EWMs to warn against currency and balance-of-payment crises in emerging economies, nowadays the research interest has shifted towards financial crises in developed economies. Second, the credibility of the initial EWMs was not always sufficient for policy makers to take the warnings seriously, owing to poor noise-to-signal ratios. Third, current risk factors may be very different, in particular due to the rising prominence of global factors and the interconnections between market segments and countries.

In this paper we construct a continuous EWM for a panel of 40 EU and OECD countries over the 1970–2010 period at quarterly frequency and sharing a common set of 50 potential leading indicators. Unlike the discrete EWMs of crisis occurrence much more common in the literature, the continuous approach does not require expert judgment whether a crisis occurred. The continuous model is designed to capture the real costs to the economy, where the key measure is the incidence of crises computed directly from data to reflect output and employment loss and fiscal deficit (the latter is used to characterize countries' propensity to prevent costly outcomes by debt accumulation). Although the real costs do not represent an immediate sign of an erupting crisis, they characterize better the ultimate measurable outcome for the economy.

We contribute to the early warning literature both in terms of scope of the study as well as in terms of estimation methodology. First, while previous contributions focused mainly on emerging markets or several selected developed countries, we use a broad panel of 40 developed countries, including the EU-27 over the past forty years. Second, we employ a number of advanced estimation techniques to build the continuous EWM. To our knowledge, most of them have not been applied in the early warning literature so far.

In particular, we relax the common assumption of a fixed horizon at which the early warning signals are issued (a fixed horizon of two years is often used in the literature) and examine the dynamic linkages between crisis incidence and leading indicators within the framework of panel vector autoregression (PVAR). Using a rich set of leading indicators, we classify them into three categories: 'early warning' (one to three years), 'ultra early warning' (more than three years), and 'late warning' (less than a year). We argue that proper accounting for the time lags of leading indicators is important for building an EWM.

Furthermore, we contribute to the methodological aspects of variable selection for the EWM. While it is a common practice in the early warning literature to use all available indicators based on the authors' judgment and/or theory, we refine the selection of leading indicators systematically using Bayesian model averaging (BMA). BMA is a procedure that selects a subset of the most useful leading indicators of crisis, from the set of all possible combinations of the potential warning indicators.

Finally, we use dynamic panel estimation techniques to reveal the marginal impact of each selected leading indicator on crisis incidence. The earlier applied BMA procedure allows us to estimate this model after removing indicators that have not been found useful, while the previous literature keeps all insignificant indicators inside the EWM. We also relax another typical assumption used in studies dealing with cross-section or panel EWMs, namely, the hypothesis of common parameters. To allow for country heterogeneity, we employ two methods: the random coefficient estimator and the tests of stability among endogenous clusters of countries. The results allow us to discuss the sources of risks to macroeconomic stability and, in particular, to compare the role of national versus global factors.

Our results show that the choice of time lead for each potential warning indicator as well as the choice of indicators that are included (all potential indicators or only the useful ones) matters for which factors are detected as the major sources of risk by the EWM. Nevertheless, the importance of certain factors seems to be robust across different specifications. We find that rising housing prices and external debt are important domestic risk factors for crisis incidence. We also find that while housing prices are a useful warning indicator for all clusters of countries, the role of external debt is not homogeneous across the sample. However, the main source of risk is represented by global factors, such as world credit growth and world output growth.

The paper is organized as follows. Section 2 motivates our design of the continuous model by identifying key lessons and challenges from the stock of the early warning literature. Section 3 describes our approach to the construction of the data set and shows some stylized facts. Section 4 presents the setting of the early warning model, including its main components, namely the optimal lag selection upon PVAR, the selection of variables employing BMA, dynamic panel estimations, assessment of model performance upon in-sample and out-of-sample fit, and sensitivity checks. Section 5 outlines the main sources of macroeconomic risks. Section 6 concludes. Two annexes attached to the paper contain data description and selected empirical results. More detailed data descriptions and all results are available from the online appendix (http://ies.fsv.cuni.cz/en/node/372). The content of the online appendix is listed in annex III to this paper.

2. Early Warning Literature: Lessons and Challenges

The recent financial crisis revived interest in the early warning literature among researchers as well as policy makers (Galati and Moessner, 2010; Trichet, 2010). The literature dates back to the late 1970s, when several currency crises generated interest in leading indicators (Bilson, 1979) and theoretical models (Krugman, 1979) explaining such crises. Nevertheless, it was only in the 1990s—the first golden era of the early warning literature—when a wide-ranging methodological debate started, including studies on banking and balance-of-payments problems (Kaminsky and Reinhart, 1996) and currency crashes (Frankel and Rose, 1996). This methodological debate served as a starting point for the current stream of literature that has been mainly motivated by the recent financial crisis. The early warning literature offers many useful lessons on how to approach the new generation of the EWMs. However, important challenges still prevail. In this paper, we attempt to tackle some of them, such as how to measure the crises, which countries to include into the EWM, how to find useful early warning indicators and how to select time lags.

2.1. Costly events

There are different types of costly events, such as currency crises, banking crises, and costly imbalances, for example on asset markets. Although the ultimate goal of each EWM is to warn against these costly events, there is no consensual approach in the literature on how to define them. Systemic events are typically identified as dramatic movements of nominal variables, such as large currency depreciations (Frankel and Rose, 1996; Kaminsky and Reinhart, 1999), stock market crashes (Grammatikos and Vermeulen, 2010), and rapid decreases in asset prices (Alessi and Detken, 2009). These studies either assume that systemic events are costly in real terms, citing stylized facts from previous crises, or select those systemic events which subsequently burdened the economy with real costs. The costly event is represented either by one variable (Frankel and Rose, 1996), or by several variables combined into one index (Burkart and Coudert, 2002; Slingenberg and de Haan, 2011) with the use of alternative weighting schemes (equal weights, weights adjusted for volatility, or principal components). Alternatively, other studies specify costly events by directly measuring their real costs (Caprio and Klingebiel, 2003; Laeven and Valencia, 2008), such as loss of GDP and loss of wealth approximated by the large fiscal deficits that are run to mitigate the real costs. Some studies look at variables representing both real costs and dramatic nominal movements (Rose and Spiegel, 2009; Frankel and Saravelos, 2010).

Another aspect of defining costly events is the scale of real costs or nominal movements. The scale can be looked at in either a discrete or a continuous way. The former approach, according to which crises are yes/no events, has been more common in the early warning literature so far. Real costs or nominal movements correspond to a 'yes' value when their scale exceeds a certain threshold (Kaminsky et al., 1998). Alternatively, the coding can be taken from the previous literature. Under the discrete representation of crises, two main empirical approaches commonly applied are the discrete choice approach and the signaling approach. In the class of discrete choice models, the probability of crisis is investigated. A crisis alarm is issued when the probability reaches a certain threshold. The originally applied binary logit or probit models (Berg and Pattillo, 1998) have been replaced with multinomial models (Bussiere and Fratzscher, 2006, Babecký et al., 2011) that extend the discrete choice from two (yes/no) to more states, such as crisis, post-crisis, and tranquil periods. Under the signaling approach proposed by Kaminsky et al. (1998), a crisis alarm is issued if the warning indicator reaches a certain threshold. The threshold can be defined based on the signal-to-noise ratio to minimize type I errors (missed crises) and type II errors (false alarms).

Recently, continuous indicators of crisis have been proposed (Rose and Spiegel, 2009; Frankel and Saravelos, 2010) that allow the EWM to explain the actual scale of real costs or nominal movements without the need to decide whether the scale is sufficiently high to produce a 'yes' value. Another advantage is that continuous indicators do not suffer from a lack of variation of the dependent variable when too few crisis events are observed in the data sample. Moreover, there is no problem with dating the exact start and end periods of costly events, a problem that is difficult to overcome in discrete approaches. The disadvantage of this approach lies in its limited capacity to send straightforward ('yes/no') signals to policy makers regarding the probability of crises. However, in the case of discrete indicators poor signal-to-noise ratios can limit this capacity as well.

In our paper, we follow several recent studies and we build a continuous EWM. It does not rely on the discrete indication of crisis occurrence that, as our related research noted (Babecký et al., 2011), can be rather subjective.[1] For the purposes of the continuous EWM,

[1] Babecký et al. (2011) construct a discrete EWM with crisis occurrence index that aggregates indices obtained from the survey of literature and expert opinion as the dependent variable. It is been noted that the academic studies often disagree whether a particular country had a crisis in a particular period. Moreover, the discrepancies are also common when the academic studies are confronted with expert opinion from national central banks that were collected by an ad-hoc survey.

we define systemic stress as an event that is costly for the real economy in terms of high output loss, high unemployment, and/or a high fiscal deficit (caused by fiscal expansion that mitigates the recession). We follow this approach since maintaining output and unemployment at their potential levels could be viewed as policy makers' ultimate objective. Also, this EWM reduces to some extent the judgment necessary to define the dependent variable. Specifically, it captures the consequences of any type of crisis for the real economy so there is no need to decide ax ante which type of costly events to consider. By looking directly at real costs, we avoid the problem of measuring which tail nominal events were costly. Moreover, there is no need to decide whether the scale is sufficiently high to produce a 'yes' value. The decision whether or not to act is left to the policy makers. There is one additional benefit of the continuous EWM. It supports policy makers in steering policy continuously instead of reacting only to very rare warnings issued by the discrete EWM.

2.2. Countries in the sample

The literature of the 1990s was concerned primarily with developing economies that had suffered from currency or twin crises (see, among others, Kaminsky et al., 1998; Kaminsky, 1999). The recent literature has focused on the identification of crises and imbalances for large samples of countries, including both developing and developed economies (Rose and Spiegel, 2009; Frankel and Saravelos, 2010). Alternatively, attention has been given to developing countries and emerging markets (Berg et al., 2004; Bussiere, 2007; Davis and Karim, 2008) or the OECD countries (Barrell et al., 2009; Alessi and Detken, 2009).

The assessment is typically done in a cross-section framework, under the assumption of homogeneity of the sample despite the fact that large samples of more than 100 countries are likely to form a rather heterogeneous group. Also, developing countries are not likely to be at the same level of convergence, and hence the homogeneity assumption might be too restrictive. The only exception is a set of studies focusing solely on the OECD group. In this case, however, the studies face the challenge of too few observed costly events in their sample (see Laeven and Valencia, 2010, to compare the frequency of costly events, such as currency crises and debt crises, in various countries). To sum up, there is a trade-off between a sufficient number of observed costly events and sample homogeneity.

To our knowledge, studies focusing on the group of all EU-27 and OECD countries, for which the trade-off between observed costly events and heterogeneity is relatively favorable, and which are of more interest to European policy makers, are not available. Moreover, homogeneity tests of the sample—in terms of both indicators and their elasticities—are quite rare in the studies using large samples. To reflect that, we build EWM for a sample consisting of EU-27 and OECD countries only, from which Malta and Cyprus were excluded for most parts of our analysis due to data limitations. In addition, to see how sensitive our results are to the homogeneity assumption, we employ several techniques, such as cluster analysis and random-slope modeling, which allow the estimated parameters for individual warning indicators to vary across countries. This approach might reduce the problems with finding at least some useful leading indicators reported by studies using large heterogeneous samples (Rose and Spiegel, 2009).

2.3. Potential leading indicators

There are three approaches to determining which variables should be included among the potential leading indicators. First, some studies survey theoretical papers to identify potential leading indicators. These theory-based studies (Kaminsky and Reinhart, 1999) usually work with a relatively narrow set of potential indicators, but sometimes this set is enlarged to include various transformations of the same data series (Kaminsky et al., 1998). Second, more recent studies often rely on systematic literature reviews. They scrutinize previously published research for useful leading indicators and create extensive data sets by including all detected indicators, and sometimes also various transformations thereof (Rose and Spiegel, 2009; Frankel and Saravelos, 2010). Third, some studies take all the variables available in a selected database and add various transformations. All of these approaches are subject to the risk of missing important potential indicators. Theory-based studies are limited in their search for indicators by a lack of theoretical models that are able to comprehensively capture the reasons for various types of crises and imbalances. Systematic literature reviews inherit various omissions from the surveyed research, unless they add indicators of their own. Studies relying on one database may miss indicators available elsewhere. Research that explicitly tackles the problem of non-available data series is very rare (Cecchetti et al., 2010). The recent crisis revealed that various financial indicators, such as liquidity ratios, might carry useful information regarding future costly events. Nevertheless, the data series needed to compute such indicators are not available, or are only available for some countries and limited time periods. For example, the ratio of regulatory capital to risk-weighted assets, credit to households, and the deposit-loan ratio for households are examples of variables that we could not include because of this problem.

In our paper, we follow the second approach and rely on a systematic literature survey. Nevertheless, we strive to reduce the risk of missing important potential indicators from our analysis by adding potential leading indicators, such as the total tax burden and several global variables, according to our own judgment. In addition, we combine several data sources, such as International Financial Statistics, OECD, World Bank, BIS, and NIGEM.

2.4. Time lags

The common approach to determining the time lags of potential leading indicators in EWMs is expert judgment. Most EWMs simply assume that the appropriate time horizon to look at is one or two years (Kaminsky and Reinhart, 1999). This assumption is rooted in stylized facts that describe how important economic indicators develop in the pre-crisis, crisis, and post-crisis period (Kaminsky et al., 1998; Grammatikos and Vermeulen, 2010). The assumption is also related to the fact that most EWMs do not try to predict the exact timing of crises because it is a too complex task. Instead, they assess the likelihood of crises over a one-year horizon, given the currently observed values of all potential leading indicators.

Such a fixed-lag assumption may be too limiting. Individual indicators may have completely different dynamics with respect to crisis occurrence, and so considering only their current values (and not lags) may yield suboptimal explanatory power for a given dataset. Therefore, we relax this assumption and we explicitly test for the optimal time lag for each potential leading indicator separately using panel vector autoregression (Holtz-Eakin et al., 1988). Once the one-year lag assumption is relaxed, it is possible to distinguish between several horizons that might be of interest to policy makers. Specifically, we can see which variables issue a 'late warning' for a 1–3Q horizon, which ones issue an 'early' warning for a 4–12Q horizon, and which ones issue an 'ultra early' warning for a 13+Q horizon. We try to focus on the early warning and ultra warning horizons, within which policy actions still have a significant chance to reduce the likelihood of costly events.

2.5. Early warning indicators

The EWM is constructed from potential leading indicators to give the best prediction of the dependent variable. Studies using the discrete representation of the dependent variable and the signaling approach usually evaluate each indicator separately by minimizing either the signal-to-noise ratio (Kaminsky, 1999) or the loss function (Bussiere and Fratzscher, 2008; Alessi and Detken, 2009). Alternatively, some studies combine potential indicators into composite indexes using judgmental approaches to select index components and computing thresholds for the corresponding variables simultaneously (Borio and Lowe, 2002). Both studies applying the discrete choice approach and studies using the continuous dependent variable work with a set of indicators that is also transformed into an early warning index (EWI). The weights of the potential leading indicators are estimated, and insignificant indicators (with zero weight) remain part of the index.

In the case of working with one early warning indicator, the challenge rests in choosing the threshold values above which the potential indicator (or composite index) should be used to form the EWM. The threshold values are determined ex ante by judgment or in line with previously published studies. Studies employing the discrete choice approach have to decide about the probability threshold. In the case of loss functions, a balanced trade-off between missed crises and false alarms has become the standard. Interactions between individual indicators pose another challenge. In the case of single-indicator EWMs, the information about interactions of indicators is fully omitted. Although policy makers can use several EWMs in parallel, there is a risk of underestimating the probability of a crisis if more indicators are close to, but below, their individual threshold values (Borio and Lowe, 2002). In the case of composite-index EWMs, this risk is reduced to the extent possible, given the empirical methodology chosen. In the case of multiple-indicator EWMs, it is often the case that the model is estimated and many potential indicators that are insignificant remain part of the model. Consequently, various biases may reduce the predictive power of these models. The resulting EWMs are typically assessed according to their out-of-sample performance by comparing one- or two-year-ahead forecasts with the actual values. For example, when 20–30% of crises are predicted, the EWM may be considered well-performing. Also, traditional mean squared errors are used to judge the EWMs' performance relative to naive models such as random walk. Sometimes the EWMs are also compared to a benchmark EWM selected from the available literature.

Designing the continuous EWM we employ a methodology that, to our knowledge, has not been applied in the early warning literature so far: Bayesian model averaging (BMA). BMA allows us to select the best performing combination from all combinations of potential indicators (and their lags, as explained above). Subsequently, we estimate the weights of the useful indicators that are part of the best combination and create the EWI. This EWI does not contain insignificant variables. It follows that this newly proposed approach has several advantages. It reduces the problem of neglected variable interactions faced by studies working with each indicator separately. Also, it eliminates judgment from the process of creating the index from potential indicators. To test performance of our EWM, we employ the pseudo-out-of-sample evaluation technique. Note that we understand our early warning indicators as being identified risk factors that make countries vulnerable to crises rather than variables that will be able to forecast the timing of the next crisis. This is in the spirit of the early warning literature (Kaminsky and Reinhart, 1999) and also in the spirit of the very few practical guides to conducting early warning exercises (IMF, 2010).

3. Data Set and Stylized Facts

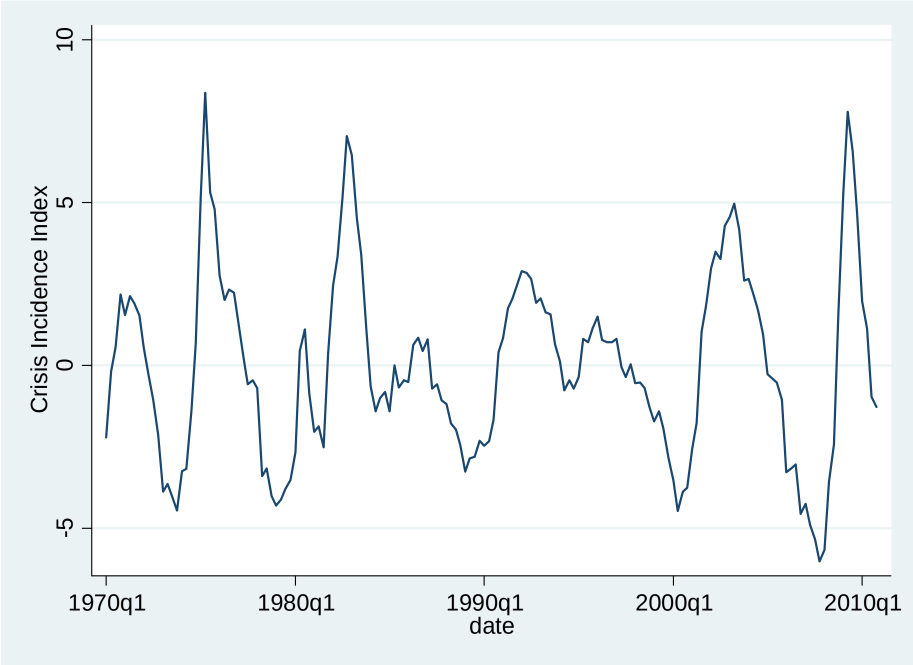
As outlined in the previous section, there is a certain trade-off in the early warning literature between country coverage, the time dimension, the choice of variables, and data availability. One unique feature of our data set is that it focuses on a panel of developed countries which are members of the EU-27 and/or the OECD. In total, the data set covers 40 countries, listed in Annex I.1. Another feature of our data set is a combination of a large time dimension and a rich informational content. The sample covers the period from 1970 through 2010 at quarterly frequency and includes the continuous indicator of crisis incidence and potential leading indicators. Most of the data come from commonly available sources.

3.1. Crisis Incidence Index

The Crisis Incidence Index (CII) is our continuous dependent variable which characterizes the consequences of any type of crisis for the real economy. Rose and Spiegel (2009) and Frankel and Saravelos (2010) use changes in GDP, industrial production, currency depreciation, and stock market performance to measure the incidence of the 2008/2009 crisis. We propose separating the nominal and real aspects and focusing on a real indicator of crisis incidence. Consequently, we construct the CII upon GDP growth, unemployment, and the fiscal deficit, by applying alternative weighting schemes. Since maintaining output and unemployment at their potential levels could be viewed as the ultimate objective of policy makers, a decline of GDP growth below, and a rise of unemployment above, the corresponding potential values characterize the costs for the real economy. The inclusion of the budget balance reflects a need to detect episodes where real costs have been prevented by fiscal deficits. Our definition is motivated by stylized facts according to which strong systemic events, such as the crisis of 2008/2009, are indeed characterized by a decline in output, a rise in unemployment, and large fiscal deficits that are run to mitigate the costs of the crisis.

The CII used in our analysis is obtained as a simple average of three standardized variables: the HP-filtered gaps of real GDP, the unemployment rate, and the government budget surplus (the series definitions and data sources are reported in the first three rows of Annex I.3). Real GDP and the budget surplus enter with negative signs to the average, so that an increase in the CII is associated with higher costs for the real economy. To take a country-specific example, the CII for the United States is shown in Figure 1. The plots of the CII for all 40 countries of the sample are illustrated in the online appendix. We also tried different weighting schemes (for example, principal components), but the results are qualitatively similar.

Figure 1. *Crisis Incidence Index, United States*



3.2. Leading indicators

As a starting point for the selection of useful leading indicators, we identified over 100 relevant macroeconomic and financial variables based on recent studies (e.g., Alessi and Detken, 2009; Rose and Spiegel, 2009; Frankel and Saravelos, 2010) as well as on our own judgment. We constructed a dataset covering 40 developed countries over 1970–2010 at quarterly frequency. Since for a number of countries the data only start in the early 1990s, the panel is unbalanced. In order to address the trade-off between sample coverage and data availability, as a rule of thumb we excluded series for which more than 50% of observations were missing. Moreover, some series were strongly correlated, differing only in statistical definition. As a result, our data set consists of 50 potential leading indicators listed on rows 9 through 58 in Annex I.3.[2] The majority of the series were originally available on a quarterly basis, from the IMF's IFS database. Some series were taken from the World Bank's WDI database, available on an annual basis only. Such series were converted to quarterly frequency using the standard cubic match method. Fiscal indicators were collected from the NIGEM database. Property price indices were provided by the Bank for International Settlements and

[2] Note that unlike some other studies we do not include among the crisis predictors any fiscal-policy-related variables. This is to avoid potential endogeneity as we use information on the on fiscal deficit to construct the crisis incidence index (i.e. the dependent variable of the regression).

the Global Property Guide. We standardized all variables[3] and used their stationary transformations; see Annex I.3 for details and data sources.

In order to facilitate the economic interpretation of the leading indicators in the subsequent text, we divide the individual variables into twelve groups: for example, monetary policy stance, capital market situation, and global variables. Annex I.2 shows the groups of variables; the classification of the individual variables into groups is provided in Annex I.3.

4. Early Warning Indicators in the Continuous Model

4.1. Optimal lag selection upon panel VAR

In order to set the horizon at which leading indicators send a warning of a potential crisis, the early warning literature commonly applies expert judgment. In our evaluation of the CII, we relax this assumption and perform an explicit test for the optimal time lag, employing the panel vector autoregression (PVAR) framework developed originally by Holtz-Eakin et al. (1988) for disaggregated data with a limited time span and a larger cross-sectional dimension. PVAR departs from traditional VAR estimation in the sense that it deals with individual heterogeneity potentially present in the panel data. In particular, it allows for nonstationary individual effects and is estimated by applying instrumental variables to quasi-differenced autoregressive equations in the spirit of Anderson and Hsiao (1982). The specification of PVAR can be written as follows:

$$Y_{i,t} = f_i + B(L)Y_{i,t} + u_{i,t}$$

where *i* stands for cross section and *t* time period, $Y_{i,t}$ is a 2 x 1 endogenous variable vector $Y_{i,t} = \left[predictor_{i,t}, CII_{i,t} \right]'$, $predictor_{i,t}$ represents each of the leading indicator, and the cross section heterogeneity is controlled for by including fixed effects f_i. Given that the lags of dependent variables are correlated with the fixed effects, forward mean-differencing (Helmert transformation) is used following Arellano and Bover (1995) to eliminate the means of all future observations for each variable-country-year combination. The estimation is performed by the GMM using untransformed variables as instruments.[4] While the optimal VAR lag length in a standard VAR can be determined by statistical criteria, this is not straightforward for PVAR due to the cross-sectional heterogeneity. Balancing the need to allow a sufficient number of lags given the nature of the EWS exercise and to try to avoid over-parametrization,

[3] The standardization is done for each country separately and is carried out by subtracting the mean from the series and dividing the series by the standard deviation. Such standardization makes the regression results for each variable comparable, but does not affect the inference concerning the sources of risk.

[4] The Helmert-transformed variables are orthogonal to the lagged regressors and the latter can be used as instruments for the GMM estimation.

we set the number of lags to eight. The error bands are generated by a Monte Carlo simulation with 500 repetitions (Love and Zicchino, 2006).

The advantage of this approach is that it allows for complex dynamics and accounts for potential bi-directional causality between the CII and potential leading indicators. We apply PVAR on the variable pairs represented by the CII and each of the 50 potential leading indicators available. Orthogonalized impulse-response functions are then used to determine the optimal horizon at which leading indicators warn about a crisis. Observing the response of the CII to a shock in each potential indicator, we set the lag of each indicator equal to the lead where the response function reaches its maximum with no prior on its response sign and no consideration of its statistical significance.[5] In addition, we allow for a minimum lag length of four quarters, assuming that a variable only provides an early warning if it predicts crisis incidence at least one year ahead so that timely policy action can still be taken.

The impulse-response analysis determined the leads of all the tested variables between 4 (our threshold value for a variable to qualify as an early warning) and 16 quarters. A full set of impulse responses for all leading indicators is available in the online appendix. To illustrate the lead selection logic, three examples of impulse responses are reported in Figures 2 and 3 below. Each figure corresponds to the bivariate PVAR consisting of the CII and one selected leading indicator, specifically, the nominal effective exchange rate (NEER) and house prices (HOUSPRIC). For the NEER we observe that the maximum response of the CII to a one-standard-deviation shock to the NEER (an increase means domestic currency appreciation) appears within 3 quarters and is negative; i.e., domestic currency appreciation reduces crisis incidence, and currency depreciation increases crisis incidence correspondingly (Figure 2). Nevertheless, as noted previously we assume that a variable qualifies as an early warning indicator only if it points to a crisis at least one year ahead. Moreover, the negative sign of the CII response to a positive shock to the NEER suggests that it is rather a short-term effect in the run-up to the crisis. In particular, the fact that the domestic currency is on a depreciation path a few quarters before the peak of the crisis represents a late rather than an early warning. Consequently, for an early warning we make use of the other CII response peak with a positive sign (domestic currency appreciation implies in the long term an increase in crisis incidence) and we set the lag of the NEER equal to 12. The maximum response of the CII to a shock to housing prices appears within 5 quarters and is negative, indicating that an increase

[5] The coefficient estimates and the impulse-response functions are conditioned on the variables included in the PVAR and, given the Choleski decomposition, also on the ordering of the variables. Given that PVAR estimates an elevated number of coefficients and there are numerous potential crisis indicators, they had to be included one by one. Nevertheless, the omission bias is in principle controlled for by including several lags of the CII, which arguably trace the effects of omitted variables. We tested ordering where the CII appears in the system before each potential crisis predictor but failed to find any different pattern.

(decrease) in housing prices reduces (increases) crisis incidence. In other words, housing prices start decreasing sharply before the peak of a crisis and can be potentially considered an early rather than an ultra-early warning indicator.

We also performed alternative robustness checks such as estimating the model with a subpanel of G7 countries where the data series are longer, as well as excluding these countries, but failed to find any systematic differences in terms of the impulse-response functions.

Figure 2. *Impulse responses for bivariate panel VAR (NEER, CII)*

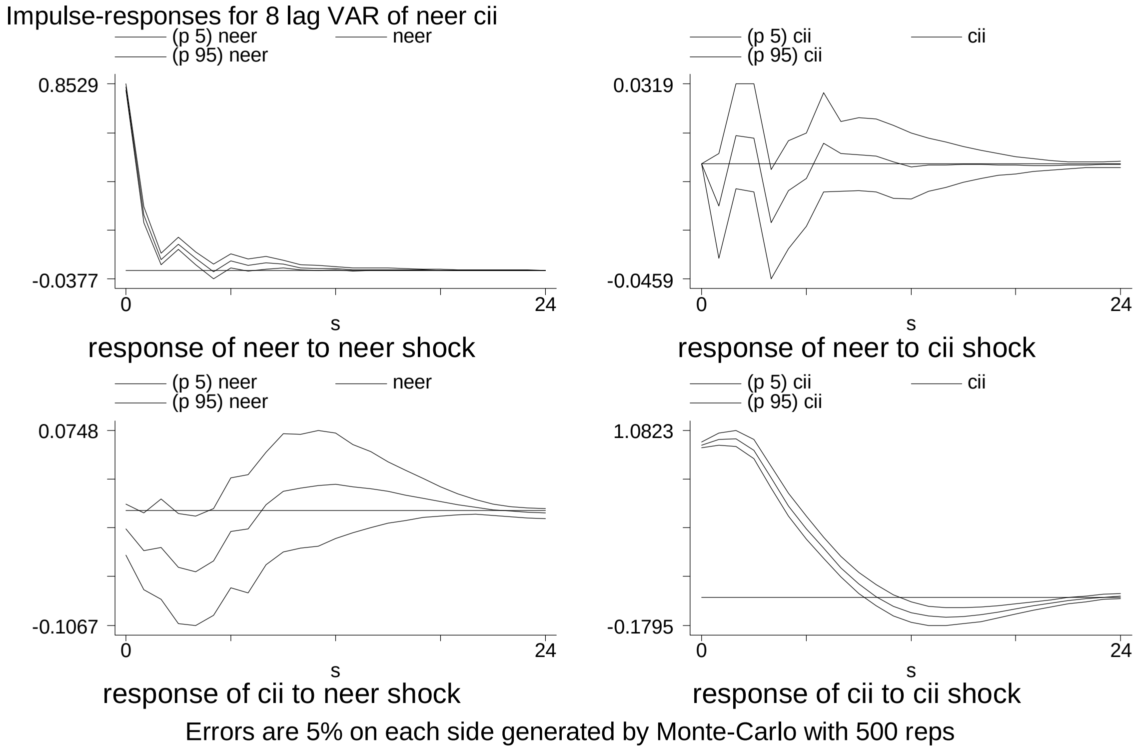
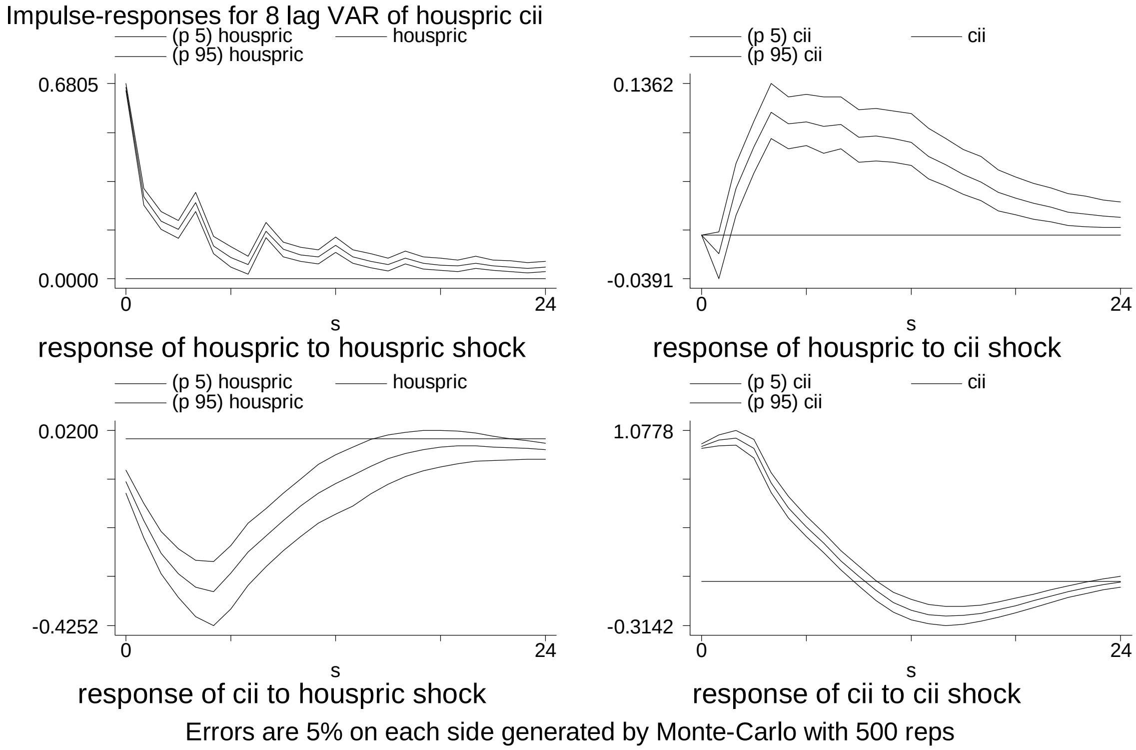


Figure 3. *Impulse responses for bivariate panel VAR (HOUSPRIC, CII)*



4.2. Selection of useful indicators employing Bayesian model averaging

As the discussion of the literature relating to early warning systems in Section 2 suggests, there is large uncertainty about the correct set of variables that should be included in a credible EWM. Consequently, there is a need to account systematically for this model uncertainty. In the presence of many candidate variables, traditional approaches suffer from two important drawbacks (Koop, 2003). First, putting all of the potential variables into one regression is not desirable, since the standard errors inflate if irrelevant variables are included. Second, if we test sequentially in order to exclude unimportant variables, we might end up with misleading results since there is a possibility of excluding the relevant variable each time the test is performed. A vast literature uses model averaging to address these issues (Sala-i-Martin et al., 2004; Feldkircher and Zeugner, 2009; Moral-Benito, 2010). Bayesian model averaging takes into account model uncertainty by going through all the combinations of models that can arise within a given set of variables.

We consider the following linear regression model:

$$y = \alpha_\gamma + X_\gamma \beta_\gamma + \varepsilon \qquad \varepsilon \sim (0, \sigma^2 I) \tag{1}$$

where y is the crisis incidence index, α_γ is a constant, β_γ is a vector of coefficients, and ε is a white noise error term. X_γ denotes some subset of all available relevant explanatory variables X. K potential explanatory variables yield 2^K potential models. Subscript γ is used to refer to one specific model out of these 2^K models. The information from the models is then averaged using the posterior model probabilities that are implied by Bayes' theorem:

$$p(M_\gamma \mid y, X) \propto p(y \mid M_\gamma, X) p(M_\gamma) \tag{2}$$

where $p(M_\gamma \mid y, X)$ is the posterior model probability, which is proportional to the marginal likelihood of the model $p(y \mid M_\gamma, X)$ times the prior probability of the model $p(M_\gamma)$. We can then obtain the model weighted posterior distribution for any statistics θ:

$$p(\theta \mid y, X) = \sum_{\gamma=1}^{2^K} p(\theta \mid M_\gamma, y, X) \frac{p(M_\gamma \mid y, X) p(M_\gamma)}{\sum_{i=1}^{2^K} p(y \mid M_i, X) p(M_i)} \tag{3}$$

We elicit the priors on the parameters and models as follows. Since α_γ and σ^2 are common to all models we can use uniform priors ($p(\alpha_\gamma) = 1, p(\sigma^2) \propto \frac{1}{\sigma^2}$) to reflect a lack of knowledge. As for the parameters β_γ, we follow the literature and use Zellner's g prior $\beta_\gamma \mid \sigma^2, M_{\gamma,} g \sim N(0, \sigma^2 g (X_\gamma' X_\gamma)^{-1})$. Following Fernandez et al. (2001), the prior for g is set as $g = \max(N, K^2)$. When choosing priors for the model space, we follow the advice of Ley and Steel (2009), who suggest using the Binomial-Beta prior.

The robustness of a variable in explaining the dependent variable can be captured by the probability that a given variable is included in the regression. We refer to it as the posterior inclusion probability (PIP), which is computed as follows:

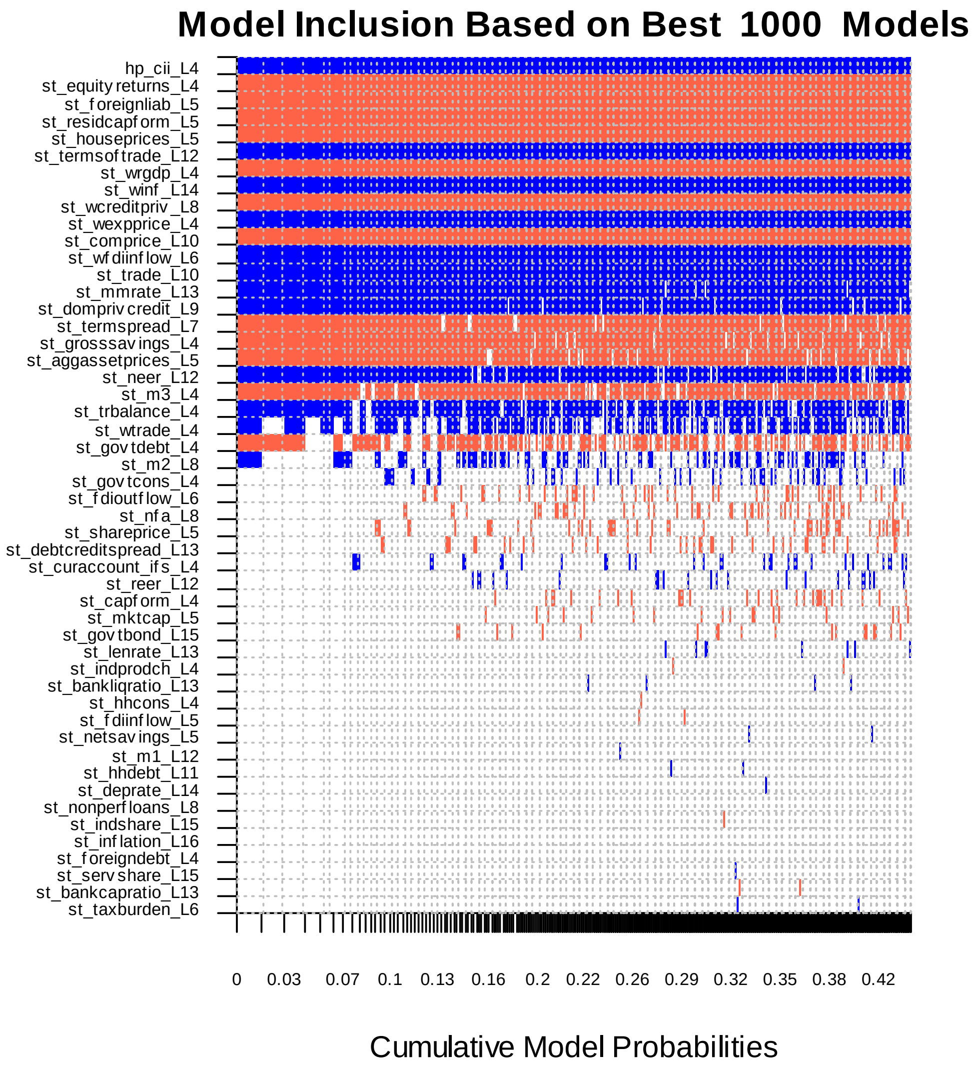
$$PIP = p(\beta_\gamma \neq 0 \mid y) = \sum_{\beta_\gamma \neq 0} p(M_\gamma \mid y) \tag{4}$$

Finally, since it is usually not possible to go through all of the models if the number of potential explanatory variables is large (in our case with 50 variables, the model space is almost 10^{15}), we employ the Markov Chain Monte Carlo Model Comparison (MC^3) method developed by Madigan and York (1995). The MC^3 method focuses on model regions with high posterior model probability and is thus able to approximate the exact posterior probability in a more efficient manner. The technical details of the BMA procedure can be found in Feldkircher and Zeugner (2009).

To obtain the posterior distributions of the parameters we use 2,000,000 draws from the MC^3 sampler after discarding the first 1,000,000 burn-in draws. All computations are performed in the R-package BMS (Feldkircher and Zeugner, 2009). To account for any unobserved (constant) country heterogeneity, we perform fixed effects estimation.

Our dependent variable in the Bayesian model averaging exercise is the crisis incidence index as defined above. We use the whole sample of countries and include all of the 50 potential leading indicators described in Section 3. In addition, we include the fourth lag of the dependent variable in order to control for persistence of crises in time. In what follows we present the results for the main model when the lags of the variables are chosen according to the results of the PVAR discussed in the previous subsection.[6]

Figure 4. *Inclusion of variables in 1,000 best models in exact lag dynamic specification*



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[6] In principle, one could choose directly the appropriate lags within the BMA model but a number of issues make it unfeasible. First, since BMA weighs the models according to their fit and the number of variables included, it does not account for the potential multicollinearity of different lags of the same variable. Second, including a number of lags for each variable would yield an enormous model space even by model-averaging standards (e.g. including 16 lags of each variable would yield 2800 possible models). Third, one could also attempt to choose from the models where only one lag from each variable appears; nevertheless, to our knowledge there are no available off-the-shelf algorithms that would allow us to do this in a straightforward manner. The last reason for choosing the optimal lag length within the PVAR framework is that BMA would not allow dynamic interrelations between the variables. In addition, as sensitivity check we performed two more sets of BMA estimations, namely, when all the variables are lagged by three years, and when the lag length for all variables is set to six years.

In Table A1 in Annex II.1, we report for each indicator its posterior inclusion probability, posterior mean, posterior standard deviation, and conditional posterior sign (the posterior probability of a positive coefficient conditional on its inclusion). The correlation between the analytical posterior model probability (PMP) and the PMP from the Markov Chain Monte Carlo Model Comparison (MC^3) method for the 5,000 best models is higher than 0.99, suggesting sufficient convergence of the underlying algorithm. Out of the 50 explanatory variables, 23 have a posterior inclusion probability higher than 0.5; we retain these variables. The results are discussed in more detail below, when we perform the frequentist check of the BMA exercises, but it is worth noting that all the global variables are important, which might be partly explained by the contagion effects and the worldwide nature of some crises.

Figure 4 reports the best 1,000 models arising from the main model. The models are ordered according to their posterior model probabilities, so that the best model is the one on the left. The blue color indicates a positive coefficient, the red color indicates a negative coefficient, while the white color indicates that the variable is not included in the respective model. Figure 4 shows that most of the model mass includes variables that have a posterior inclusion probability (PIP) higher than 0.5.

As a robustness check (detailed results are reported in Babecký et al., 2011) we have tested two alternative specifications with a fixed lag length set to 3 years and 6 years, respectively. The convergence is satisfactory as the correlation between the analytical and MC^3 PMPs is higher than 0.99 for both exercises. It is important to note that these results differ relative to the exact lag specification for each variable. Interestingly, variables belonging to the group of housing prices experience the largest drop in PIPs in the model with lags fixed at 3 years. When using the variables with a fixed lag of 6 years, only 11 of the potential variables have PIPs higher than 0.5. Notice that for this ultra long lag length, global variables turn out to be the most important in explaining crisis incidence. The development of global variables could thus be informative for crisis incidence even at the horizon of six years.

4.3. Dynamic panel estimations

As the last step, we re-estimate the model with the 23 indicators with PIP higher than 0.5 (with exact lag for each indicator selected by PVAR) to obtain the marginal effect of each indicator, while controlling for all other indicators. We use GMM estimator to account for potential endogeneity. We opt for dynamic panel estimations since the dependent variable—the CII—is time dependent. Given that crises are time-persistent, past realizations of the CII turn out to be significant determinants of the contemporaneous CII values according to our

BMA exercise. We set the lag of the CII variable on the righ-hand side equal to 4, consistently with the logic that an early warning must be issued at least one year ahead. Notice that our empirical specification has one important refinement compared to the existing studies. While it is common practice to use all available indicators, some of them being insignificant, we construct our model based on the pre-selected variables which are the outcome of the BMA.

We start with a fixed effects specification as a natural benchmark for the panel framework. Nevertheless, since we employ a dynamic panel data model, the simple fixed effects estimator may deliver incorrect results. In dynamic panels the lagged dependent variable on the right-hand side is correlated with the error term; this is called dynamic panel bias (Nickell, 1981). Moreover, with the macroeconomic data we use, no regressors can be expected to be strictly exogenous, and the possible endogeneity should be taken into account. We treat all regressors as predetermined, because they enter the regression with lags (predetermined variables are independent of current disturbances but influenced by past ones).

To tackle both the dynamic panel bias and the possible endogeneity of regressors, we employ the system generalized method-of-moments estimator (GMM) developed by Arellano and Bover (1995) and Blundell and Bond (1998). The system GMM is a refined version of the difference GMM (Holtz-Eakin et al., 1988; Arellano and Bond, 1991), allowing for greater estimation efficiency. Because our data set involves many time periods and regressors, we only use up to two lags of regressors as instruments and collapse the instrument sets to avoid proliferation of instruments. Moreover, because our data set is unbalanced, we use orthogonal deviations for the system GMM in order to maximize the sample size. It should be noted, however, that the dynamic panel bias dwindles with increasing time span of data, and with 160 quarters in our data set the bias is likely to be quite small (Roodman, 2009). Also, the endogeneity problem should not be too serious since the shortest lag we use on the right-hand side of the regression is four quarters. Despite these caveats that point in favor of the simple fixed-effects model, we believe that the system GMM is a useful robustness check.

As another sensitivity check, we allow for cross-country heterogeneity in the estimated parameters. Although our database only includes OECD and EU countries, and is thus substantially more homogeneous than the data set used by, for example, Rose and Spiegel (2009) and Frankel and Saravelos (2010) to explain crisis incidence, it would still be interesting to allow the coefficients on the individual warning indicators to vary across countries. To achieve that, we employ the mixed-effects multilevel estimator with random effects for each coefficient in the regression:

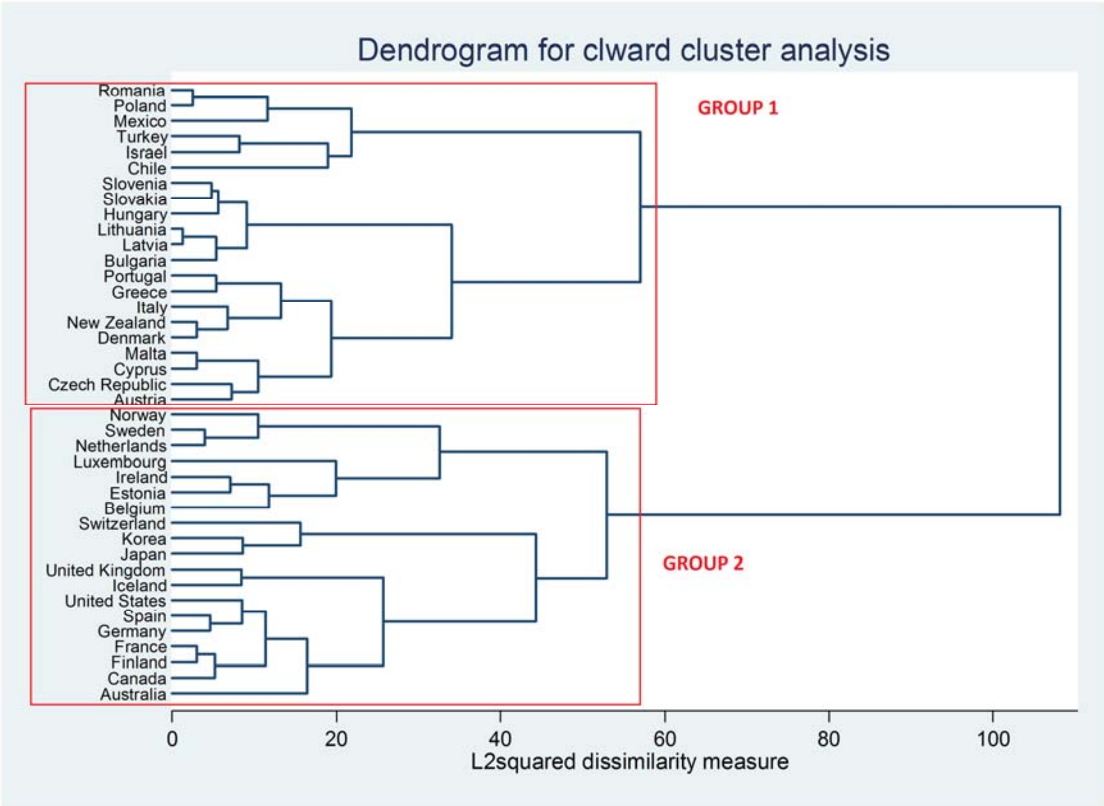
$$CII_{it} = \alpha_i + (\beta + \beta_i)CII_{it-4} + (\gamma + \gamma_{ij})X_{ijt} + \delta S_{kt} + u_{it} \qquad (5)$$

where β_i and γ_{ij} are country-specific, normally distributed random effects. Again, considering the large number of regressors, we have to collapse the number of coefficients to be estimated in the random-effects part of the specification. Therefore, we restrict all variances of random terms to be equal and all covariances to be zero. The resulting model is estimated by restricted maximum likelihood, which is more suitable for unbalanced panels than the usual generalized least squares method (Rabe-Hesketh and Skrondal, 2009). The assumption underlying the aforementioned specification is that the random effects are uncorrelated with the remaining regressors. While this is a strong assumption, it is difficult to test in this setting. Thus, large differences between the results of the mixed-effects multilevel model and the simple fixed-effects model may indicate either heterogeneity across countries in our sample or improper identification of the multilevel model.

Another way of tackling the problem of possible country heterogeneity is to divide the countries into several groups and then run the simple fixed-effects regression separately for each group. A systematic method for dividing the countries into groups is clustering. The goal is to create groups of countries that may be expected to share similar slope coefficients in the early warning exercise. Because it is difficult (and arbitrary) to select one dimension that would define country similarity in this respect, we use all the variables in our data set that are available for all 40 countries (the variables are used in a standardized form so that every variable has the same weight). The common clustering method is the hierarchical approach, which begins with each country considered as one group, then continues with combining the closest two groups, and again—until one general group comprising all countries is formed.

There are many methods for determining which groups are the closest ones, and therefore which groups should be merged at each step. One of the most appealing approaches is Ward's method (Ward, 1963), which merges the two groups that lead to the minimum increase in the error sum of the squares of the differences across all dimensions; in this respect, Ward's method is similar to ordinary least squares.

Figure 5. *Clusters of countries in our sample*



The results of the clustering exercise are depicted in Figure 5, and it is readily apparent that two main groups of countries are formed. Despite a few exceptions, Group 2 consists primarily of large, developed countries (the 'core' of the OECD and the EU), while Group 1 consists primarily of smaller or less developed countries. Countries inside these groups may be more homogeneous in terms of possible early warning indicators. Notice that although it is technically possible to form as many clusters as the number of countries in the sample, it is ultimately the researcher's choice of the optimum number of clusters given the trade-off between the number of clusters and the degrees of freedom available for the estimations. We present results for two clusters in addition to the results for all countries.

In our baseline specification the lags of the warning indicators are set upon the PVAR reported earlier; the results are reported in Table 1 and all three robustness checks (fixed effects, system GMM, and random coefficients) are broadly consistent with each other. The similarity of the estimated coefficients obtained by alternative methods suggests that the potential endogeneity of the regressors is not likely to be an issue. In addition, it should be noted that the signs of all the estimated coefficients are consistent in the panel and the BMA estimation as well as in the impulse response function (at the selected horizon) from the PVAR. This also rebuts the issue of potential omission bias in the bivariate PVAR. In fact, the examination of the impulse responses upon the PVAR brings extra information on how the effects of each selected variable change over time (from 'ultra early warning' to 'late warning'). The main differences in the results of the specifications reported in Table 1 emerge between the two clusters of countries. While residential capital formation is important for Cluster 1, it is not important for Cluster 2 (the 'core' countries). The worldwide inflow of FDI and trade is a significant warning indicator of crisis incidence for the core countries, but not for the countries included in Cluster 1. The same applies for the money market rate, domestic private credit, the term spread, aggregate asset prices, and the nominal effective exchange rate. On the other hand, M3 is important for the countries in Cluster 1, but not for the core countries. Our models are able to explain approximately 40% of the variation in the Crisis Incidence Index.[7]

Table 1. *Warning indicators for crisis incidence (lags set upon PVAR)*

	Fixed Effects	System GMM	Random Coefficients	Cluster 1 Fixed Effects	Cluster 2 Fixed Effects
L4.hp_cii	0.303***	0.369***	0.260***	0.265***	0.321***
L4.st_equityreturns	-0.390***	-0.431***	-0.410***	-0.323***	-0.451***
L4.st_wrgdp	-0.555***	-0.544***	-0.546***	-0.746***	-0.458***
L4.st_wexpprice	0.181***	0.167***	0.149**	0.248***	0.130**
L4.st_grosssavings	-0.268***	-0.205*	-0.307***	-0.350***	-0.193***
L4.st_m3	-0.151***	-0.105	-0.210***	-0.226***	-0.107
L4.st_trbalance	0.113***	0.114**	0.0994*	0.0967*	0.118**
L4.st_wtrade	0.0847	0.172**	0.206***	0.0254	0.240***
L4.st_govtdebt	-0.233***	-0.443***	-0.311***	-0.295*	-0.216***
L5.st_foreignliab	-0.237***	-0.345***	-0.325***	-0.276***	-0.222***
L5.st_residcapform	-0.223***	-0.182*	-0.252***	-0.397***	-0.0852
L5.st_houseprices	-0.390***	-0.404***	-0.482***	-0.482***	-0.335***
L5.st_aggassetprices	-0.264***	-0.314***	-0.388***	-0.0450	-0.422***
L6.st_wfdiinflow	0.276***	0.271**	0.181**	0.0470	0.395***
L7.st_termspread	-0.0971**	-0.0731	-0.171**	0.00400	-0.224***
L8.st_wcreditpriv	-0.383***	-0.360**	-0.455***	-0.530***	-0.309***
L9.st_domprivcredit	0.138***	0.242*	0.192**	0.0412	0.128*
L10.st_comprice	-0.373***	-0.429***	-0.407***	-0.368***	-0.336***
L10.st_trade	0.255***	0.317**	0.377***	0.208*	0.214**
L12.st_termsoftrade	0.232***	0.218**	0.284***	0.430***	0.172**
L12.st_neer	0.190***	0.182***	0.158**	0.0683	0.206***
L13.st_mmrate	0.146**	0.122*	0.226***	0.101	0.226***
L14.st_winf	0.271***	0.274**	0.256***	0.174*	0.280***
s1	-0.0541	0.00913	-0.0735	-0.365*	0.126
s2	0.137	0.157***	0.134	0.0440	0.247*
s3	0.0230	0.0379	-0.0114	-0.124	0.138
_cons	-0.178*	-0.174*	-0.194*	0.132	-0.333***
Observations	3558	3558	3558	1360	2198

[7] It may be argued that a warning four quarters before the crisis (for some variables) is not sufficiently 'early'. For this reason, we also provide results of the model where all the lags of the warning indicators are set to three years (Babecký et al., 2011, Table 2). Similarly to the previous case, we first run the BMA exercise and only select variables with an inclusion probability higher than 50%. Once again, the results of our robustness checks are consistent with the results of BMA. Because we model crisis incidence for the real economy, we also provide the results of an 'ultra early-warning' exercise where all lags of the indicator variables are set to six years. It is interesting to note that global variables are especially important in this case (Babecký et al., 2011, Table 3).

Countries	38	38		19	19
R-squared	0.371			0.399	0.377

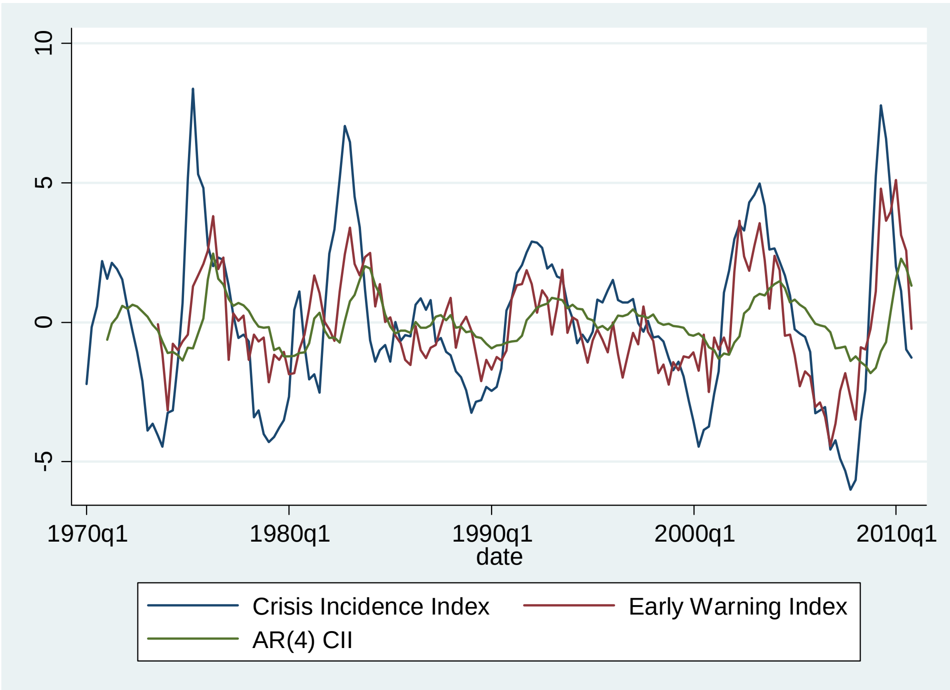
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Response variable: hp_cii. We select lag length using PVAR and only include variables with inclusion probability from BMA higher than 50%.

4.4. Assessment of model performance

In the next step we construct an Early Warning Index (EWI) from the fitted values of our model. We select the random coefficients model for this exercise and also add the extracted random effects to the estimated slope coefficients for each country; consequently, the index becomes country-specific. The EWI in quarter *t* can be interpreted as the prediction of crisis incidence for quarter *t* observed one year before.

To take a country-specific example, Figure 6 illustrates the in-sample fit of the EWI for the United States. The EWI is compared against a simple autoregressive function of the CII; it is readily apparent that the additional indicators included in the EWI significantly improve the prediction accuracy. The figures for other countries, available in Babecký et al. (2011), allow for similar inference. The EWI was able to predict quite precisely the incidence of all major US recessions across the last 40 years. However, it partially failed to predict the magnitude of the 1973–75 and 1982 recessions. A possible explanation is that the causes of these crises (the first oil shock and the Vietnam War for the former one, and the second oil shock and monetary policy tightening for the latter one) were too different from the rest of the sample.

Figure 6. *In-sample fit of crisis incidence, United States*



While the in-sample fit of the EWI is satisfactory, the out-of-sample performance of the model may be quite different. We conduct a pseudo-out-of-sample forecasting exercise and focus on the recent crisis. The model is re-estimated using data till 2007Q1, which means well before the real economy began to feel the latest crisis. The results for all specifications are summarized in Table 2; most variables hold their signs and only a few have now lost their statistical significance. To be specific, it appears that foreign liabilities, residential capital formation, oil prices, and world trade were more important predictors for the recent crisis than for previous crises in our data set.

Out-of-sample forecasting performance is not the focus of this paper, because, among other things, some of the variables included in the EWI are not available in real time and thus cannot be used for forecasting. The purpose of the following exercise is merely to show that our model can be expected to perform better than a naïve estimate, the simple autoregressive process of the CII. The pseudo-out-of-sample forecast for the case of the United States is depicted in Figure 7.[8] Even out-of-sample, the model is able to capture the beginning of the crisis in the real economy in 2008 and predicts the magnitude of the crisis quite well, as opposed to the simple autoregressive function of the CII. The picture is similar for other countries (reported in Babecký et al., 2011). In all cases the EWI seems to perform better than the simple autoregressive function.

Table 2. *Warning indicators for crisis incidence (exact lags, data till 2007Q1)*

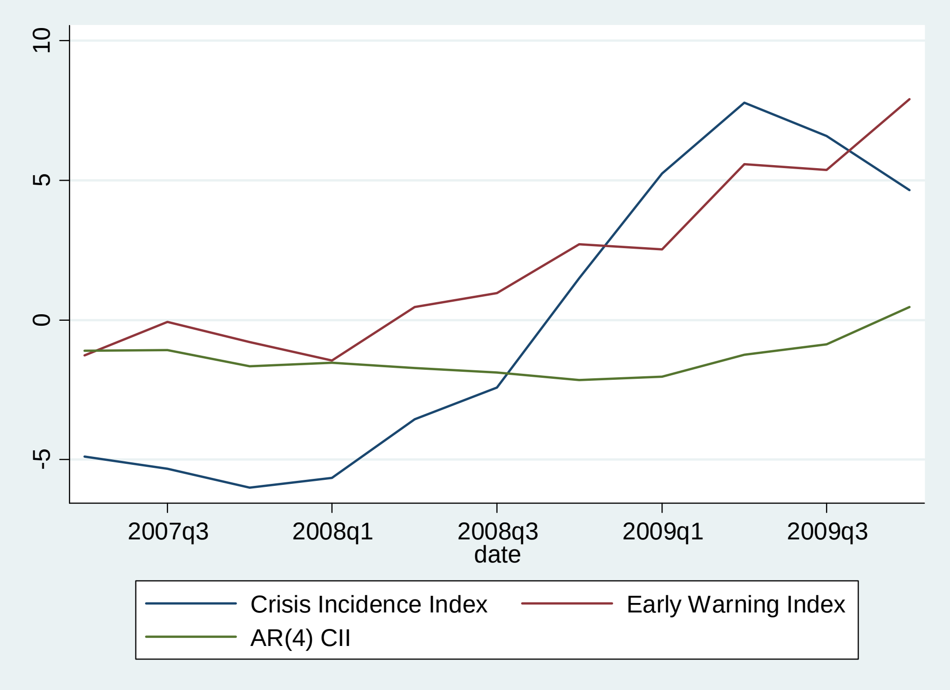
	Fixed Effects	System GMM	Random Coefficients	Cluster 1 Fixed Effects	Cluster 2 Fixed Effects
L4.hp_cii	0.360***	0.421***	0.267***	0.269***	0.384***
L4.st_equityreturns	-0.297***	-0.288***	-0.240***	-0.154*	-0.378***
L4.st_wrgdp	-0.178***	-0.232***	-0.192**	-0.308***	-0.123
L4.st_wexpprice	0.126**	0.112*	0.0956	0.0981	0.101
L4.st_grosssavings	-0.322***	-0.195**	-0.416***	-0.554***	-0.179**
L4.st_m3	-0.133**	-0.149**	-0.201**	-0.107	-0.190**
L4.st_trbalance	0.130**	0.130**	0.115	0.0738	0.199***
L4.st_wtrade	-0.121	-0.0124	-0.131	-0.159	-0.0295
L4.st_govtdebt	-0.286***	-0.207*	-0.312***	-0.641***	-0.195**
L5.st_foreignliab	0.0763	0.00263	0.101	0.235*	-0.0276
L5.st_residcapform	-0.0208	-0.00820	-0.0363	-0.121	0.0935
L5.st_houseprices	-0.333***	-0.258**	-0.462***	-0.356***	-0.306***
L5.st_aggassetprices	-0.347***	-0.337***	-0.400***	-0.276*	-0.385***
L6.st_wfdiinflow	0.178**	0.143	0.00826	-0.0150	0.202*
L7.st_termspread	-0.111***	-0.0872	-0.178**	0.0513	-0.249***
L8.st_wcreditpriv	-0.343***	-0.400***	-0.429***	-0.489***	-0.358***
L9.st_domprivcredit	0.0996*	0.102*	0.125	-0.101	0.155**

[8] Note that the selection of variables is performed taking into account the whole sample. A proper out-of-sample forecast would require both the selection and the estimation to be performed only on the pre-2007Q1 part of the sample.

L10.st_comprice	0.0986	-0.00652	0.0887	-0.124	0.193*
L10.st_trade	0.154*	-0.0211	0.291**	-0.0604	0.153
L12.st_termsoftrade	0.274***	0.225***	0.325***	0.596***	0.192***
L12.st_neer	0.134***	0.134**	0.0931	-0.0450	0.158***
L13.st_mmrate	0.124**	0.100	0.231**	0.189**	0.171**
L14.st_winf	0.262***	0.262**	0.223**	0.145*	0.264***
s1	-0.0800	-0.0738	-0.133	-0.306*	0.0527
s2	0.188*	0.191***	0.136	0.0989	0.248*
s3	0.0903	0.0712	0.0459	-0.0657	0.182
_cons	-0.201**	-0.248***	-0.133	0.0447	-0.351***
Observations	3015	3015	3015	1086	1929
Countries	38	38		19	19
R-squared	0.318			0.305	0.343

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Response variable: hp_cii. We select lag length using PVAR and only include variables with inclusion probability from BMA higher than 50%.

Figure 7. *Pseudo-out-of-sample prediction of the recent crisis, United States*

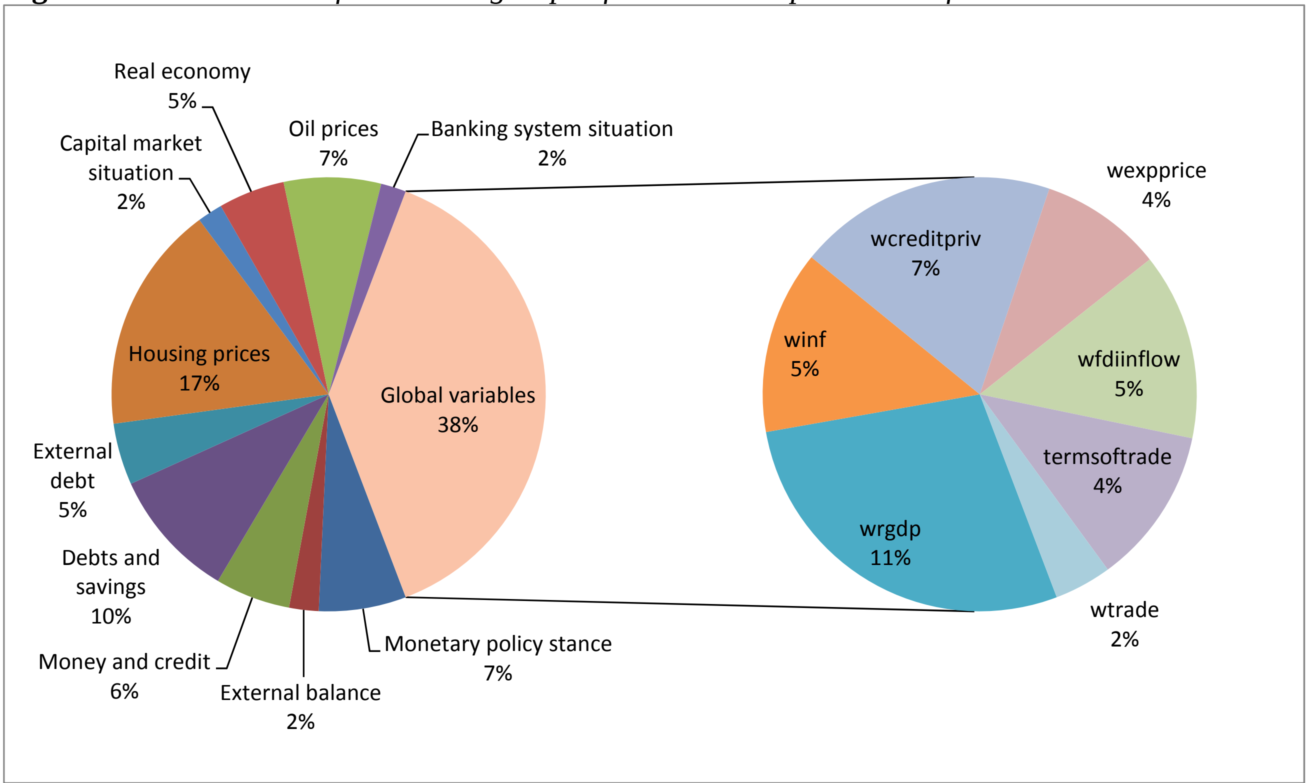


5. Tentative Inputs into the Macroprudential Policy Debate

In this section, we outline how the continuous EWM can be used in the macroprudential policy debate. First and the most importantly, the EWM can be used to identify the main sources of risk. As a result, policy makers could incorporate the useful early warning indicators identified by the EWM into their risk dashboards (Trichet et al., 2011). Second, one could look at the out-of-sample forecasts of CII as we presented above. According to our definition of the early warning indicator, the minimum time lag considered is four quarters. Therefore, the CII cannot be predicted for more than one year ahead. Third, potential policy responses to early warnings could be assessed in PVAR framework. However, since due to data limitations this implies limiting the country coverage, we do not pursue this strategy either (see Babecký et al., 2011 for some preliminary results).

In order to identify the major sources of risk, we look closely at the explanatory power of the useful leading indicators selected by BMA. To make the analysis easier to follow, we use the division of the indicators into groups, which are meant to represent distinct areas from which a risk or a signal of potential crisis could originate, such as the banking system, capital markets, and global variables. We use the baseline specification (fixed effects) and in Figure 8 we report the results for each group of variables. In addition, in the right pie chart we provide the percentages for the individual variables within the most important group, global variables.

Figure 8. *Contributions of individual groups of indicators to prediction of CII*



Note: Shares in the model's R-squared (0.37); based on fixed effects regression reported in Table 1.

The percentages in Figure 8 denote the groups' shares in the model's R-squared, which is equal to 0.37. The most important groups of potential indicators are global variables (38%), domestic housing prices (17%) and domestic debts and savings (10%). Taken together, these groups comprise about 2/3 of the model's R-squared, which means about 30% of the total variance in the CII. On the other hand, indicators related to capital market situation or external balance, seem to be of little importance.

It follows that regarding the sources of risk, it pays off for macroprudential policy to watch global variables and housing prices, since they represent economic segments that are important sources of risk.

6. Conclusions

We provided a critical review of the early warning literature and proposed a model reflecting some common problems of the previous contributions. In particular, we created a continuous EWM for crisis incidence, which characterizes the real costs of crises for the economy. As the basis for our analysis, we collected a dataset for 40 developed countries, including the EU-27 group, over 1970–2010 at quarterly frequency. This approach fills a gap in the early warning literature, which has so far mainly focused on either panel data sets comprising developing economies or large heterogeneous cross-sections.

We tracked the economic crises by the means of the continuous crisis incidence index that measures the real cost of crises to the economy in terms of output and employment loss and fiscal deficit. Using the set of 50 potential leading indicators we identified the determinants of crisis incidence using estimation techniques which are novel in the empirical literature on early warning. First, we relaxed the typical assumption of a fixed horizon at which the early warning signals come. We tested for the optimal lag length employing a panel VAR framework and examine the impulse responses of crisis incidence and its potential leading indicators. Second, we applied Bayesian model averaging in order to identify useful leading indicators out of the total of 50 collected potential indicators. Third, we used panel estimation techniques (including dynamic estimations and system GMM) to assess the determinants of crisis incidence. We dealt with sample heterogeneity by employing the random coefficient model and illustrate the stability of coefficients among endogenously determined clusters. Finally, we assessed the models' performance in terms of in-sample and out-of-sample fit.

Our key results can be summarized as follows. First, we find that crisis incidence warning signals come at various horizons. We classify those horizons into early warning (one to three years), late warning (less than one year), and ultra early warning (more than three years). We argue that it is important to account for the time lags of potential leading indicators when building an early warning model. The way economic indicators develop prior to the crisis depends on the horizon chosen. For example, we find that a strengthening of the domestic currency increases crisis incidence in four years (hence currency appreciation could issue an 'ultra early warning' signal), while the domestic currency depreciates just several quarters prior to an observed increase in crisis incidence (a 'too late warning'). Thus, timely policy reactions could mitigate crisis incidence. Next, we find that historical decomposition provides useful information on the sources of crisis incidence, in particular national versus global factors. Regarding national factors, we find in particular that decreasing housing prices signal an important risk for macroeconomic stability five quarters ahead. Global variables signal another substantial risk 1.5 to 3.5 years ahead depending on the specific variable. In the presence of global risks, national policies are unlikely to be an efficient tool to cope with crises. In what follows, more attention should be paid to international policy coordination.

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ANNEX I. Data

I.1. List of countries

No.	Country	EU	OECD
1	Australia		OECD
2	Austria	EU	OECD
3	Belgium	EU	OECD
4	Bulgaria	EU	
5	Canada		OECD
6	Cyprus	EU	
7	Czech Republic	EU	OECD
8	Denmark	EU	OECD
9	Estonia	EU	OECD
10	Finland	EU	OECD
11	France	EU	OECD
12	Germany	EU	OECD
13	Greece	EU	OECD
14	Hungary	EU	OECD
15	Chile		OECD
16	Iceland		OECD
17	Ireland	EU	OECD
18	Israel		OECD
19	Italy	EU	OECD
20	Japan		OECD
21	Korea		OECD
22	Latvia	EU	
23	Lithuania	EU	
24	Luxembourg	EU	OECD
25	Malta	EU	
26	Mexico		OECD
27	Netherlands	EU	OECD
28	New Zealand		OECD
29	Norway		OECD
30	Poland	EU	OECD
31	Portugal	EU	OECD
32	Romania	EU	
33	Slovakia	EU	OECD
34	Slovenia	EU	OECD
35	Spain	EU	OECD
36	Sweden	EU	OECD
37	Switzerland		OECD
38	Turkey		OECD
39	United Kingdom	EU	OECD
40	United States		OECD

I.2. Groups of variables

No.	Groups
CII	Crises Incidence Index
G1	Monetary policy stance
G2	Interest rates
G3	Banking system situation
G4	Capital market situation
G5	Money and credit
G6	Debts and savings
G7	External debt
G8	Housing prices
G9	Real economy
G10	Fiscal stance
G11	External balance
G12	Global variables

I.3. Variables, transformations, and data sources

No.	Group	Sign in the group average: 1 for +, 0 for -	Transformation: growth (g) or level (l)	Code	Variable	Source
1	CII	0	g	rgdp	GDP, real, seasonally adjusted, HP-filtered gap	IMF IFS
2	CII	0	l	govtbalance	Government balance, per cent of GDP, HP-filtered gap	NIGEM
3	CII	1	l	unemployment	Unemployment rate (% of labor force), seasonally adjusted, HP-filtered gap	IMF IFS
4	G1	0	g	neer	Nominal effective exchange rate	IMF IFS
5	G1	1	g	m1	M1	IMF IFS
6	G1	0	l	mmrate	Money market interest rate	IMF IFS
7	G2	0	l	lenrate	Interest rate on credit	IMF IFS
8	G2	0	l	deprate	Deposit interest rate	IMF IFS
9	G2	0	l	govtbond	Long-term bond yield, nominal	IMF IFS
10	G3	0	l	termspread	Spread (long-term bond yield minus short-term interest rate)	IMF IFS
11	G3	0	l	debtcreditspread	Deposit-credit spread	IMF IFS
12	G3	0	l	bankcapratio	Banking sector capital ratio	WDI
13	G3	0	l	bankliqratio	Bank liquid reserves to bank assets ratio (%)	WDI
14	G3	1	l	nonperfloans	Bank non-performing loans (% of loans, 2006)	WDI
15	G4	1	l	mktcap	Stock market capitalization	NIGEM
16	G4	1	g	shareprice	Stock market index	IMF IFS
17	G4	1	l	equityreturns	Equity market returns	IMF IFS
18	G5	1	g	m2	M2	IMF IFS
19	G5	1	g	m3	M3	IMF IFS
20	G5	1	l	domprivcredit	Domestic private sector credit (% of GDP, 2006)	WDI
21	G6	1	l	govtdebt	Government debt (% of GDP)	NIGEM
22	G6	1	g	hhdebt	Gross liabilities of personal sector	NIGEM
23	G6	0	l	netsavings	Net national savings (% of GNI)	WDI
24	G6	0	l	grosssavings	Gross national savings (% of GDP)	WDI
25	G7	1	g	foreignliab	Gross foreign liabilities	NIGEM
26	G7	0	l	nfa	Net external position (% of GDP, 2004)	IMF
27	G7	1	l	foreigndebt	Foreign debt/GDP (%)	WDI
28	G8	1	l	residcapform	Private residential fixed capital formation	OECD
29	G8	1	g	houseprices	House price index	[a]
30	G8	1	g	aggassetprices	Nominal aggregate asset price index	[a]
31	G9	**1**	**l**	indprodch	Percentage change in industrial production	IMF IFS
32	G9	1	g	hhcons	Private final consumption expenditure	IMF IFS

33	G9	1	g	capform	Gross total fixed capital formation	IMF IFS
34	G9	1	l	indshare	Industry share	WDI
35	G9	1	l	servshare	Services share	WDI
36	G9	1	l	trade	Trade (% of GDP)	WDI
37	G10	1	g	govtcons	Government consumption	IMF IFS
38	G10	0	l	taxburden	Total tax burden	OECD
39	G11	0	g	curaccount_ifs	Current account	IMF IFS
40	G11	0	g	trbalance	Trade balance	IMF IFS
41	G11	0	g	reer	Real effective exchange rate index	IMF IFS
42	G11	1	l	fdiinflow	FDI net inflows (% of GDP)	WDI
43	G11	1	l	fdioutflow	FDI net outflows (% of GDP)	WDI
44	G12	1	l	termsoftrade	Terms of trade	IMF IFS
45	G12	1	g	wrgdp	Global GDP[b]	NIGEM
46	G12	1	g	wtrade	Global trade	NIGEM
47	G12	1	l	winf	Global inflation	IMF IFS
48	G12	1	l	wbankcredit	Global credit (% of GDP)	IMF IFS
49	G12	1	l	wcreditpriv	Global domestic credit to private sector (% of GDP)	WDI
50	G12	1	l	wfdiinflow	Global FDI inflow (% of GDP)	UNCTAD
51	G12	1	g	wexpprice	Global export prices	IMF IFS
52	v1	1	l	inflation	Consumer price inflation (%)	IMF IFS
53	v2	0	g	comprice	Commodity prices (we take crude oil petroleum, high correlation)	IMF IFS

Note: [a] Global Property Guide (www.globalpropertyguide.com) and BIS calculations based on national data.
[b] Although country-specific GDP enters the composition of the CII, the use of global GDP among the explanatory variables should not cause significant endogeneity bias since each country's weight in global GDP can be considered marginal to very low.

ANNEX II. Bayesian model averaging

II.1. Detailed results for each potential predictor

Table A1. *Dynamic BMA with lags set upon PVAR*

	PIP	Post Mean	Post SD	Pos. Sign
Crisis Incidence Index				
hp_cii_L4	**1.000**	**0.315**	**0.017**	**1.000**
Monetary policy stance				
st_neer_L12	**0.927**	**0.184**	**0.065**	**1.000**
st_m1_L12	0.009	0.000	0.006	0.994
st_mmrate_L13	**0.989**	**0.224**	**0.057**	**1.000**
Interest rates				
st_lenrate_L13	0.023	0.003	0.025	1.000
st_deprate_L14	0.010	0.001	0.009	1.000
st_govtbond_L15	0.065	-0.008	0.034	0.000
Banking system situation				
st_termspread_L7	**0.951**	**-0.142**	**0.051**	**0.000**
st_debtcreditspread_L13	0.145	-0.015	0.039	0.000
st_bankcapratio_L13	0.005	0.000	0.002	0.173
st_bankliqratio_L13	0.017	0.001	0.009	1.000
st_nonperfloans_L8	0.006	0.000	0.003	0.000
Capital market situation				
st_mktcap_L5	0.078	-0.010	0.040	0.000
st_shareprice_L5	0.154	-0.023	0.059	0.000
st_equityreturns_L4	**1.000**	**-0.354**	**0.052**	**0.000**
Money and credit				
st_m2_L8	0.344	0.044	0.066	1.000
st_m3_L4	**0.880**	**-0.133**	**0.065**	**0.000**
st_domprivcredit_L9	**0.967**	**0.137**	**0.045**	**1.000**
Debts and savings				
st_govtdebt_L4	**0.569**	**-0.093**	**0.091**	**0.000**
st_hhdebt_L11	0.010	0.001	0.007	1.000
st_netsavings_L5	0.013	0.001	0.012	0.938
st_grosssavings_L4	**0.942**	**-0.171**	**0.064**	**0.000**
External debt				
st_foreignliab_L5	**1.000**	**-0.215**	**0.040**	**0.000**
st_nfa_L8	0.161	-0.015	0.038	0.000
st_foreigndebt_L4	0.005	0.000	0.003	0.993
Housing prices				
st_residcapform_L5	**1.000**	**-0.253**	**0.043**	**0.000**
st_houseprices_L5	**1.000**	**-0.377**	**0.045**	**0.000**
st_aggassetprices_L5	**0.935**	**-0.209**	**0.076**	**0.000**
Real economy				
st_indprodch_L4	0.016	-0.001	0.008	0.000
st_hhcons_L4	0.012	-0.001	0.007	0.000
st_capform_L4	0.086	-0.007	0.027	0.000
st_indshare_L15	0.006	0.000	0.005	0.363
st_servshare_L15	0.006	0.000	0.006	0.651

st_trade_L10	**0.996**	**0.245**	**0.061**	**1.000**
Fiscal stance				
st_govtcons_L4	0.172	0.015	0.037	1.000
st_taxburden_L6	0.005	0.000	0.002	0.975
External balance				
st_curaccount_ifs_L4	0.117	0.011	0.033	1.000
st_trbalance_L4	**0.811**	**0.098**	**0.057**	**1.000**
st_reer_L12	0.085	0.014	0.049	1.000
st_fdiinflow_L5	0.011	-0.001	0.007	0.000
st_fdioutflow_L6	0.157	-0.016	0.041	0.000
Global variables				
st_termsoftrade_L12	**0.998**	**0.209**	**0.050**	**1.000**
st_wrgdp_L4	**1.000**	**-0.653**	**0.081**	**0.000**
st_wtrade_L4	**0.599**	**0.102**	**0.094**	**1.000**
st_winf_L14	**1.000**	**0.270**	**0.057**	**1.000**
st_wcreditpriv_L8	**1.000**	**-0.433**	**0.067**	**0.000**
st_wfdiinflow_L6	**0.998**	**0.251**	**0.060**	**1.000**
st_wexpprice_L4	**1.000**	**0.191**	**0.042**	**1.000**
Inflation				
st_inflation_L16	0.006	0.000	0.004	0.279
Commodity prices				
st_comprice_L10	**1.000**	**-0.388**	**0.065**	**0.000**

Note: Coefficients in bold type have posterior inclusion probability higher than 0.5

ANNEX III. Contents of online appendix available at http://ies.fsv.cuni.cz/en/node/372

Detailed results for 40 countries:

CII_model_fit	*- plots of in-sample and out-of-sample model fit*
CII_plots	*- plots of the CII*
COI_model_fit	*- plots of in-sample and out-of-sample model fit*
COI_plots	*- plots of the COI*

Panel VAR impulse responses for the whole panel of 40 countries:

Optimal_lags_PVAR	*- plots of bivariate (CII, each predictor) PVAR impulse responses for lag selection (note: hp_cii_neg is the CII, st_XX is leading indicator XX)*
Policy_simulations_PVAR	*- plots of bivariate (CII/EWI, each policy variable) PVAR impulse responses for assessment of CII/EWI response to each policy variable (note: hp_cii_neg is the CII, EWI is the EWI, st_YY is policy variable YY)*

Anonymized database of crises (Crisis Occurrence Index, COI), details provided in Babecký et al. (2011):

CDEC40_40_AT_LEAST_TWO.xls	*Crisis occurrence = 1 if at least two of the sources agree on the occurrence of a crisis (e.g. a country expert and at least one research paper, or at least two research papers); 0 otherwise*

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