Early warning indicators of economic crises

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Evidence from a Panel of 40 Developed Countries

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Early Warning Indicators of Economic Crises: Evidence from a Panel of 40 Developed Countries

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Kateřina Šmídková, and Bořek Vašíček*

Abstract

Using a panel of 40 EU and OECD countries for the period 1970–2010 we construct an early warning system. The system consists of a discrete and a continuous model. In the discrete model, we collect an extensive database of various types of economic crises called CDEC 40-40 and examine potential leading indicators. In the continuous model, we construct an index of real crisis incidence as the response variable. We determine the optimal lead employing panel vector autoregression for each potential indicator, and then select useful indicators employing Bayesian model averaging. We re-estimate the resulting specification by system GMM and, to allow for country heterogeneity, additionally evaluate the random coefficients estimator and divide countries into clusters. Our results suggest that global variables are among the most useful early warning indicators. In addition, housing prices emerge consistently as an important source of risk. Finally, we simulate the past effectiveness of several policy instruments and conclude that some central bank tools (for example, reserves) could be useful in mitigating crisis incidence.

JEL Codes: C25, C33, E44, E58, G01.

Keywords: Bayesian model averaging, dynamic panel, early warning indicators, macroprudential policies, panel VAR.

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Nontechnical Summary

The 2008/2009 economic crisis brought the early warning literature back into the spotlight. In the several past rounds of debate, this literature stream developed the concept of an early warning system (EWS) that should be able to identify various costly events, such as imbalances or financial crises, early enough for policy makers to reduce the costs. Despite noticeable progress in the theoretical and empirical literature on this subject in previous decades, the 2008/2009 crisis demonstrated that there is still ample room for improving the EWS. First, while initial early warning studies tried to offer tools to warn against currency and balance-of-payment crises in emerging economies, nowadays the research interest has shifted toward financial crises in developed economies. Second, the credibility of the initial EWS was not always sufficient for policy makers to act on warnings, 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 interconnections between market segments and countries.

We contribute to the early warning literature in several ways. First, we focus solely on the developed economies. For this purpose, we build an extensive database of various types of economic crises (e.g. banking, currency, and fiscal) for a set of 40 EU and OECD countries over the past forty years at quarterly frequency. We point out that determining the exact dates of the crises (and in particular the exact timing of when the crisis is over) is a subject of substantial disagreement among the surveyed sources. We therefore construct a robust indicator by aggregating the sources, which include previous academic studies and our own survey of expert opinions from national central banks.

Second, we try to build an EWS that consists of a more traditional 'discrete' model where crises are 'yes/no' events as well as a 'continuous' model designed to capture the real costs to the economy, where the key indicator is the incidence of crises in the economy measured in terms of output and employment loss and fiscal deficit (the latter is used to characterize countries' propensity to opt for debt-driven growth). Both models have advantages and disadvantages. The continuous one does not require expert judgment of crisis occurrence and instead focuses on the real economic costs measured by data. Nevertheless, real costs are not necessarily immediate indicators of crises, but rather characterize the ultimate 'measurable' outcome in the economy. The discrete model is able to send a more straightforward signal to policy makers on when to act. On the other hand, the practical application of the discrete model is challenged by the need to find an optimal trade-off between false alarms (a warning was issued but no crisis occurred) and missed crises (no warning was issued and a crisis occurred). Therefore, to explore the best of both approaches, our EWS is represented by the two complementary models, which share a common set of potential leading indicators for the same group of countries.

Third, we employ a number of advanced estimation techniques to build the continuous model. 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 study the dynamic linkages between crisis incidence and leading indicators within the panel VAR framework. 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 early warning system. Furthermore, we contribute to the methodological aspects of model and variable selection for the EWS. While it is 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 using Bayesian model averaging (BMA). BMA is a procedure that selects a subset of the most likely empirical models, and consequently a subset of the most useful leading indicators of crisis, as the dependent variable from the extensive number of model specifications for crisis incidence. Unlike in the previous literature, where all insignificant indicators remain inside the EWS, we re-estimate the continuous model after removing indicators that have not been found useful by the BMA procedure. Finally, we use dynamic panel estimation techniques that allow cross-country heterogeneity to reveal the marginal impact of each selected leading indicator on crisis incidence. Moreover, cluster analysis is used to check the implications of country heterogeneity for our results.

Our results show that the choice of model (continuous or discrete) as well as the choice of early warning indicators examined (all potential indicators or only the useful ones) matters for which factors are detected as the major sources of risk by the early warning exercise. Nevertheless, the importance of certain factors seems to be robust across different specifications. We find that rising housing prices and external debt are important national risk factors for both crisis occurrence and crisis incidence. The warning power of housing prices gains in prominence when we estimate the model without the indicators identified as unimportant by BMA. 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.

Another substantial source of risk is represented by global factors, such as world credit growth and world output growth. These factors are important in both the discrete and the continuous model, although they seem to matter especially for the continuous model, describing crisis incidence. Again, their role in the EWS gains in prominence when the continuous model is re-estimated with only the useful indicators (as per BMA) included on the right-hand side.

Our paper concludes with an assessment of the efficiency of various policy tools that could be used to mitigate the impact of crises on the economy. The results show that certain policy variables may be significantly related to risk factors. However, major data limitations prevent us from making strong inferences from this part of the analysis.

1. Introduction

In this paper, we construct an early warning system comprising two complementary models—a discrete one and a continuous one—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. While the discrete model serves to explain the occurrence of economic crises (binary 'yes/no' events), the continuous model captures the incidence of crises in the economy (in terms of output and employment loss and of fiscal deficits that are run to mitigate real costs).

There are several contributions to the early warning literature. First, we estimate our discrete model for a broad panel of developed countries, including the EU-27, for which we build a comprehensive database called CDEC 40-40 that contains various types of economic crises, such as banking crises and currency and debt crises, for 40 countries over 40 years. The evidence of crises, collected both from the literature and from country experts, is aggregated into indicators robust to potential biases in individual sources. To our knowledge, the early warning literature focuses mainly on emerging markets or several selected developed countries and so the CDEC 40-40 database is quite unique.

Second, in the case of the continuous model, we determine the optimal lead in the panel-vector-autoregression framework by examining the impulse responses of crisis incidence and potential leading indicators instead of following the early warning literature by assuming a fixed horizon for all early warning signals.

Furthermore, we employ Bayesian model averaging in order to retain only those leading indicators that are useful for early warning. To our knowledge this is the first application of Bayesian model averaging to variable and model selection in the early warning literature. Next, we employ panel estimation techniques (including system GMM) to investigate the determinants of crisis incidence. As a sensitivity check, we relax another typical assumption used in studies dealing with cross-section or panel early warning models, namely, the hypothesis of common parameters. To allow for country heterogeneity, we employ two methods: the random coefficient estimator and clustering, which divides countries into subgroups. 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.

Finally, using model simulations on historical data, we examine how efficient the selected policy instruments (among others, central bank reserves and the policy interest rate) were in mitigating crisis incidence in the economy.

The paper is organized as follows. Section 2 motivates our design of the discrete and continuous model by identifying key lessons and challenges from the stock of early warning literature. Section 3 describes our approach to the construction of the data set and shows some stylized facts. Section 4 presents the discrete early warning model, followed by multinomial logit estimates of the determinants of crisis occurrence, and an assessment of model performance in terms of in-sample and out-of-sample fit, loss function, and usefulness for policy. Section 5 is devoted to the continuous early warning model and presents the optimal lag selection upon panel VAR, the selection of variables employing Bayesian model averaging, dynamic panel estimations, assessment of model performance upon in-sample and out-of-sample fit, and sensitivity checks, including clustering. Section 6 outlines the main sources of macroeconomic risks and discusses possible policy reactions based on model simulations. Section 7 concludes. There are six annexes attached to the paper, containing data and methodological descriptions and selected empirical results. More detailed data descriptions and results are available from the online appendix (http://ies.fsv.cuni.cz/en/node/372). The content of the online appendix is listed in the last annex 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 is trying to build an early warning system for financial crises. Despite the extensiveness of the literature in the 1990s, the current research still needs to tackle four considerable tasks if this second generation of early warning models is going to help policy makers reduce the likelihood of future financial crises.

First, in the 1990s, policy makers were mostly concerned with currency and twin crises, while the recent policy agenda also includes costly imbalances and global financial crises. The current research reflects the fact that policy makers would like to be warned about various events (IMF, 2010) and proposes alternative dependent variables. For example, the signaling approach initially employed in the 1990s (Kaminsky, Lizondo, and Reinhart, 1998) has been used to predict costly asset price cycles (Alessi and Detken, 2009).

Second, while the early warning literature of the 1990s was concerned primarily with developing economies that had suffered from currency or twin crises (Kaminsky, 1999), the current research looks typically at a large sample of developed as well as developing countries (Rose and Spiegel, 2009) to reflect the international scale of the recent financial crisis. However, lessons for developed economies are rare.

Third, the 1990s debate focused on currency and twin crises, which might have had different causes compared to the recent financial crisis. The current literature therefore searches for new leading indicators, which are also referred to as early warning indicators. Early warning indicators are typically selected from comprehensive databases that result from systematic reviews of available studies (Frankel and Saravelos, 2010) instead of narrower datasets matching selected stylized facts of currency crises in the 1990s.

Fourth, the 1990s methodology did not gain enough credibility to be transferable to the second generation of early warning models without significant modifications. Specifically, many studies reported too high noise-to-signal ratios to predict future crises credibly in the eyes of policy makers (Berg and Pattillo, 1998). The current research tries to improve credibility by using new techniques such as Markov switching (Peria, 2002; Abiad, 2003) and multinomial logit models (Bussiere and Fratzscher, 2006). In addition, it offers policy makers an explicit choice to pre-select their preferences regarding missed crises and false alarms (Alessi and Detken, 2009).

These four tasks to some extent correspond to the components of the early warning models (EWMs) that are being put forward as parts of the early warning system (EWS). The EWS refers to the class of empirical and theoretical works aimed at the early identification of various costly events, such as imbalances or crashes, in the economy. These works propose various EWMs that are built of several components. First, they specify which costly events they intend to warn against. Second, they select which countries should be incorporated into the EWMs, some EWMs being built for national economies and others for large samples of more than 100 economies. Third, they identify which indicators could potentially provide a useful early warning about these costly events. Fourth, they define time lags for these leading indicators in order to give policy makers some time to respond to the warnings issued by the EWMs. Fifth, they apply an empirical methodology—which may also include a specification of sufficient predictive power—to decide which potential leading indicators exhibit sufficient predictive power to be useful in the early warning exercise. Last, they include an either implicit or explicit methodology for dealing with policy variables, which has implications for the policy relevance of the EWMs.

The early warning literature offers many useful lessons on how to approach these six components when building an EWM. However, important challenges still prevail. Some of them, such as the issues of a too heterogeneous sample and ad hoc time lag and indicator selection, we attempt to tackle in this paper. The literature survey presented below is organized around these components and challenges.

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 some (or all) of these costly events, there is no consensual approach in the literature on how to define them. Some 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. Alternatively, systemic events are 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). 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 continuous or a discrete way. The latter way, according to which crises are yes/no events, is 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) 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 sufficiently high values 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.

It follows that defining the dependent variable for an EWM involves a lot of judgment. One must select which type of costly events to include, whether to focus on their nominal or real manifestations, and—in the case of the discrete definition—where on the scale the threshold value is. It is therefore important to check that the choices made are appropriate. In some papers this is done by direct comparison with the dates of actual crises obtained from surveys (Louzis and Vouldis, 2011). Some of these surveys are available for large samples of countries (Laeven and Valencia, 2010).

In our paper, we try to build an EWS consisting of a traditional EWM that relies on a discrete measure of costly events and a continuous EWM that departs from the stock of available literature in several aspects described in the following sections. The discrete EWM uses a crisis occurrence index that aggregates indices obtained from a survey of the literature and expert opinions as the left-hand side variable. This aggregated index takes the value 'yes' if at least two surveyed sources agreed on the occurrence of a costly event, such as a currency, banking, or fiscal crisis. The discrete EWM is used to exploit the possibilities of the traditional early warning literature in the current EWS, mainly the possibility to send straightforward signals regarding crisis probability.

The main focus of our paper is on the continuous EWM, which follows a more novel approach. For the purposes of this EWM, 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 try to build both a discrete and a continuous EWM for a sample consisting of EU-27 and OECD countries only. Our panel consists of 40 developed countries taken from the

EU-27 and OECD groups, 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 too complex a 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 time-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. 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). 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, information about interactions 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.

In our discrete EWM, we work with an early warning index (EWI), as described above. The performance of this EWI is then tested using the noise-to-signal ratios and minimized policy loss functions (in the spirit of Alessi and Detken, 2009). Second, in 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 both of our EWMs, we employ the pseudo-out-of-sample evaluation technique. In both cases, 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).

2.6 Policy Variables

The last component of the EWM relates to variables representing (or closely related to) policy tools such as two-week repo rates, foreign exchange reserves, structural fiscal deficits, and capital adequacy ratios. It is often the case in the literature that the approach to these variables is not explicitly explained. The implicit treatment of policy variables relates perhaps to the concept of the EWM itself. The function of the EWM is to issue warnings to policy makers that there is a risk of a costly event. Such warnings are often viewed as a yes/no type of information. It is not the aim of the EWM to propose preemptive policy actions that could eliminate this risk. Therefore, there is no need to pay closer attention to the transmission from the variables representing policy tools to the risk of occurrence of costly events.

Most studies include policy variables among the potential leading indicators and test their early warning power in exactly the same way as they test other variables. In our EWM, we excluded variables that directly represent policy tools (such as 2W repo rates). Both the inclusion and the exclusion of policy variables pose certain problems for the EWM. On the one hand, the exclusion of policy variables reduces the information content of the data set, since in some cases policy errors might have been among the factors contributing to the occurrence of costly events. On the other hand, the inclusion of policy variables reduces the potential for subsequent analyses. However, such analyses should be exploited as much as possible, given the ongoing debate about the usefulness of alternative macroprudential policy tools (as illustrated, for example, in Frait and Komárková, 2011). Specifically, by excluding policy variables from our EWM, we can test the responsiveness of the EWI to changes in policy tools. To eliminate the problem of reduced information content, we work with indicators that are closely related to policy tools due to fast transmission (such as 3M interest rates).

It follows that we proceed in two steps with our analysis. First, we exclude variables representing policy tools from the potential indicators. Second, we explicitly model the impulse responses of the EWI to shocks in policy variables. This two-step approach gives us more options for further analysis. For example, we use the EWM to see which sources of risk (such as global variables or housing prices) are behind the anticipated costly event. We can then relate them to a certain category of policy tools and see how much they can affect the probability of the costly event. This type of information can be useful for policy makers, for whom the probability of a forthcoming crisis may not be sufficient information to prompt an adequate policy action. The recent crisis revealed that a lack of signals strong enough to prompt policy action could be a serious problem.

Due to the Lucas critique, we do not propose that the EWM should be used to calibrate policy actions since their implementation could change the underlying relationships, thus making it inappropriate to infer from the past in order to assess the effects of the policy on the economy in the future. Nevertheless, we do propose that the EWM could be used to give more detailed information about the factors behind crises and potential policy solutions. Also, the Lucas critique could be mitigated if we consider ‘small’ (i.e., marginal) policy changes that are unlikely to affect the underlying relationships significantly. That is why we prefer continuous measures of costly events. Discrete indicators might lead to less frequent but more abrupt policy actions since they change value (between yes and no) less often than continuous indicators.

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 four categories of variables, namely, the discrete indicator of crisis occurrence, the continuous indicator of crisis incidence, potential leading indicators, and policy variables. Most of the data come from commonly available sources.

3.1 Crisis Occurrence Index

For the purposes of this study, we put together a Comprehensive Database of Economic Crises in 40 developed countries over 1970:Q1–2010:Q4 (CDEC 40-40 henceforth). The CDEC 40-40 captures several types of crises, including banking crises, currency crises, and debt crises, as reflected in the literature (Caprio and Klingebiel, 2003; Reinhart and Rogoff, 2008; Laeven and Valencia, 2008 and 2010; Kaminsky and Reinhart, 1999; Kaminsky, 2006). We cross-check the crisis episodes identified by these papers using a comprehensive survey among experts mostly from central banks in all countries in the sample. The EU-27 survey was conducted as part of the ESCB MARS work.

When collecting the data, we faced the following difficulties. First, while some studies identify crisis episodes if a certain variable or indicator exceeds its threshold value (e.g. Kaminsky and Reinhart, 1999; Kaminsky, 2006), other studies (e.g. Caprio and Klingebiel, 2003; Laeven and Valencia, 2008) employ expert judgment or use systematic reviews. Second, it is easier in general to find information on the exact timing of the start rather than the end of a crisis, since the underlying crisis indicators typically return to their 'normal' levels only gradually. Third, in a number of studies the crisis episodes are recorded at yearly frequency, while our data set is built on a quarterly basis. Thus, some measurement error could occur during the transformation from yearly to quarterly frequency. Besides, for a number of countries—e.g. those which experienced economic transition from a planned to a market economy—the data only start at the beginning of the 1990s.

Given these issues, we verified our data using a survey among country experts, mostly from national central banks. To limit various biases in the individual studies and survey responses we construct our discrete dependent variable—the Crisis Occurrence Index (COI)—by aggregating the sources in the following way. We record a positive event 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).

Due to the relatively low occurrence of the individual types of crises over the sample period, we code the COI equal to one if at least one of the four types of the crises occurred, and zero otherwise. Apart from the statistical argument for this approach, evidence from the literature suggests that crises are related; for example, it is well documented that currency crises often go hand-in-hand both with debt crises (Dreher et al., 2006; Herz and Tong, 2008) and with banking crises—so-called 'twin crises' (Kaminsky, 1999; Glick and Hutchinson, 1999). For illustration, the COI for the United Kingdom[1] is shown in Figure 1. A complete set of indices for the 40 countries is provided in the online appendix.

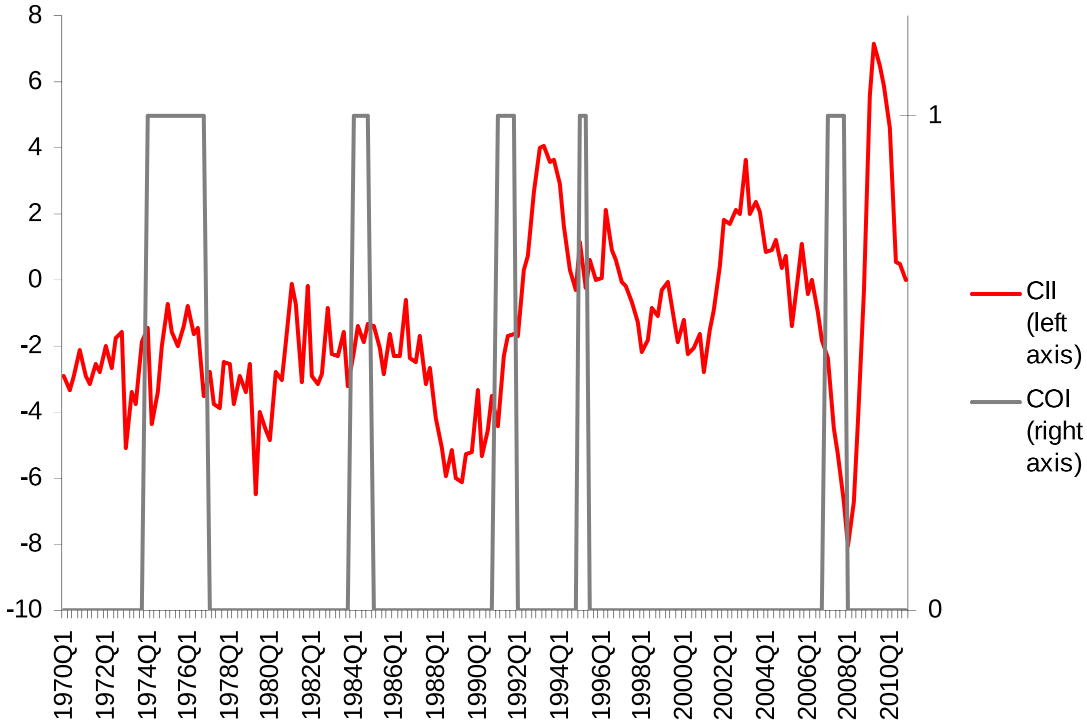
[1] In what follows, we use the United Kingdom to illustrate our results. We do so for a number of reasons: the developments in the UK are relatively well known, there are long time series available (and, importantly, crises occur along that time span), and the UK can be considered a representative country in terms of the size of its economy. Besides, due to space limitations, there is no way of reporting the results for all 40 countries of our sample. All these results are available in the online appendix at http://ies.fsv.cuni.cz/en/node/372.

3.2 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. The CII for the United Kingdom is shown in Figure 1, along with the COI. The CIIs 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 Occurrence Index and Crisis Incidence Index, United Kingdom



As can be seen on the example of the United Kingdom, there are relatively few episodes of (any type of) crises captured by the COI, while the CII exhibits much more variation over time. Visual inspection of Figure 1 suggests that there are episodes when the COI precedes the CII in time, but the link between the COI and the CII is not straightforward. Some surveyed sources defined banking and currency crises by looking at nominal variables only. It is likely that not every sharp movement in the nominal exchange rate was followed by a significant drop in economic growth. For example, there might have been a policy response from the national authorities preventing such a drop. Therefore, not every change in the COI is followed by a change in the CII. At the same time, not every increase in the CII is preceded by a crisis captured by the binary COI, since the economic downturn may have been, for example, imported from abroad as a result of weakening external demand.

3.3 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 data set 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, for example *Reserves* versus *Reserves excluding gold*. In such cases we kept only one variable (the one for which more data was available). As a result, our data set consists of 50 potential leading indicators listed on rows 9 through 58 in Annex I.3. 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 the Global Property Guide. We standardized all variables[2] 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.

3.4 Policy Variables

In addition to the twelve groups, we keep a separate group of **policy variables**. Policy variables were not included among the explanatory variables of our empirical specifications linking crisis occurrence and/or crisis incidence to the set of 50 potential indicators. In fact, policy variables are assumed to influence the observed crisis incidence only indirectly, via the leading indicators discussed above. We will use the policy variables in the sixth section of the paper (policy simulations).

4. Early Warning Indicators: A Discrete Model

We begin our empirical analysis by assessing the determinants of the 'traditional' discrete indicator, the Crisis Occurrence Index, but on our new CDEC 40-40 database. This approach serves two objectives. First, such an analysis will allow us to extend the existing evidence from the early warning literature to a sample of 40 developed countries over the past 40 years. Second, evaluation of the COI will serve as a complementary EWM to the continuous CII-based EWM, conditional on the same common set of information (50 explanatory macroeconomic and financial variables listed in rows 9 to 58 in Annex I.3).

4.1 Methodology: Dynamic Panel Logit Model

Since the dependent variable—the COI—is binary, taking the value of 1 if at least two of the sources agree on the occurrence of a crisis, and 0 otherwise, we use the panel logit estimation

[2] 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.

technique to be able to interpret the predicted values as the respective probabilities of crisis occurrence. The specification takes the following form:

$$COI_t = f(\beta X_{t-k} + \varepsilon_t),$$

where X is the vector of 50 explanatory variables augmented with the lagged value of the COI to address the dynamics (we set the lag to 4; see more on the continuous case below), k is the lag length, ε_t is the white noise disturbance, and *f(.)* is the logistic function:

$$f(z) = \frac{e^z}{e^z + 1}.$$

Following the common approach from the early warning literature, we choose a fixed lag length for this exercise. According to this approach, the probability of a crisis is assessed over the policy horizon, which typically equals two to three years ahead. Therefore, we set the lag length equal to 8 and 12 quarters.

The equation is estimated using maximum likelihood. The country fixed effects are used to avoid time-invariant country-specific endogeneity bias arising from omitted variables. The estimation results for the two lag lengths—8 and 12 quarters—are reported in Annex II.

4.2 Results: Predicted Probabilities of Crises

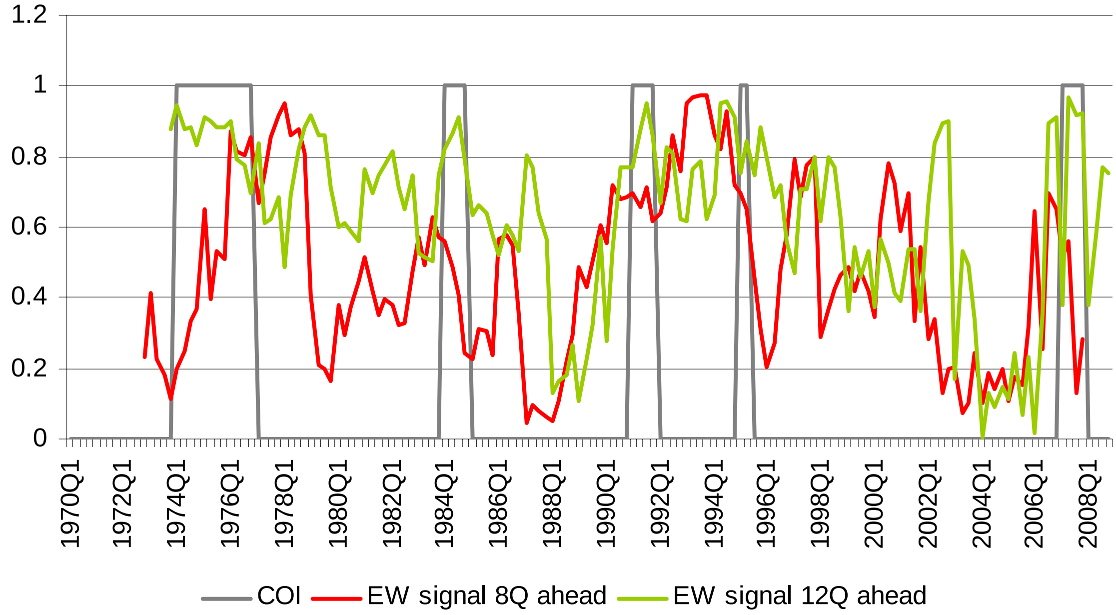
The dynamic logit model allows us to interpret the fitted values from the estimated equation as the probabilities of crisis occurrence at the horizons of 8 and 12 quarters. Among the variables significantly affecting the probability of a crisis, a low interest rate on credit and a rise in the amount of credit to the private sector increase the probability of crises at both the 8- and 12-quarter-ahead horizons, suggesting a major role for the credit boom-bust cycle fuelled by low interest rates. The long-term government bond yield also turns out to be positively associated with the probability of a future crisis.

Trade openness is found to consistently reduce the crisis probability. A solid external position of the economy contributes to stability as well. Somewhat surprisingly, the size of the tax burden does not reduce the probability of crises, possibly because there is not much space left for potential tax increases needed to mitigate a fiscal crisis. Strong global FDI flows signal confidence in the world economy and a low probability of crises occurring in the next 2–3 years.

4.3 Assessment of Model Performance

Next, we evaluate the model's ability to predict a crisis—or, in other words, the quality of the early warning signals—at the horizons of 8 and 12 quarters ahead. The assessment is done in-sample as well as out-of-sample. Given space limitations, here we present the results for the United Kingdom; the results for the full set of 40 countries are reported in the previously mentioned online appendix.

Figure 2: In-Sample Fit of Predicted Crisis Occurrence, United Kingdom



Note: Actual values of the COI versus in-sample predicted values at the horizons of 8 and 12 quarters ahead. Crisis occurrence probability is on the vertical axis.

The in-sample fit of the binary EWM can be seen in Figure 2. The COI denotes the actual episodes of crisis occurrence, while the other two lines show the predicted probabilities, which can be interpreted as early warning signals of crisis occurrence. The in-sample fit is quite high at both horizons; in fact, early warning signals sent 12 quarters ahead are somewhat more pessimistic compared to the 8-quarter horizon, as reflected in higher predicted probabilities of a crisis (including episodes when no crisis was recorded according to the actual COI). However, as is known from the literature, most of the early warning models have good ex-post explanatory power, while it is a common challenge to provide satisfactory out-of-sample early warning signals.

To illustrate the out-of-sample predictive performance, we estimated the model on a sample up to the last quarter of 2006 and let the model perform an out-of-sample forecast for the period of the recent crisis. Figure 3 depicts the real-time early warning signals for the United Kingdom. For both the 8- and 12-quarters-ahead specifications the model was able to warn against the coming turbulence and the credit crunch of late 2007, signaling the probability of crisis occurrence as being 60% two years in advance and 95% three years in advance, respectively. In the case of the United Kingdom, the three-year-ahead early warning signal is more pessimistic overall, as can be seen from the figures showing the in-sample and out-of-sample fit. There is also an obvious trade-off between missed crises and false alarm, to which we turn in the next subsection.

Figure 3: Out-of-Sample Fit of Predicted Crisis Occurrence in 2007–2008, United Kingdom

Note: Actual values of the COI versus out-of-sample predicted values at the horizons of 8 and 12 quarters ahead. Crisis occurrence probability is on the vertical axis.

4.4 Noise-to-Signal Ratio and Loss Function

We follow the early warning literature and evaluate the overall performance of the binary EWM on the sample of 40 countries over 40 years by employing the noise-to-signal ratio (Kaminsky and Reinhart, 1999; Alessi and Detken, 2009; and van der End, 2010, among others). Along with Alessi and Detken (2009), we believe that such a purely statistical criterion may not be sufficient for the evaluation of early warning models from the policy maker's viewpoint, since it does not take into account the policy makers' preferences regarding type I (missed crises) versus type II (false alarms) errors of crisis warning indicators. While Alessi and Detken (2009) assess the quality of individual variables as early warning indicators, we evaluate a single early warning index composed of 50 variables (a linear combination thereof), with weights taken from the linear probability model estimation.

The four possible combinations of warnings issued and crisis occurrence—denoted by letters A to D—can be illustrated using the following table:

	Crisis occurred	No crisis occurred
Warning issued	A (477)	B (268)
No warning issued	C (100)	D (2,556)

where the numbers in parentheses are our counts of the respective events in the whole sample, optimized for an equal policy makers' preference weight between false alarms and missed crises (θ=0.5; details on the policy makers' loss function will be given below).

Then the noise-to-signal ratio is defined as $aNtS = \frac{B}{B+D} \Big/ \frac{A}{A+C}$, capturing the ratio of the share of false alarms (noise) to the share of correctly predicted crises (signal). Further, the Type I prediction error (missed crises) is defined as $\frac{C}{A+C}$ and the Type II error (false alarms) is defined as $\frac{B}{B+D}$. Alessi and Detken (2009) propose minimization of the policy makers' loss function in the form of

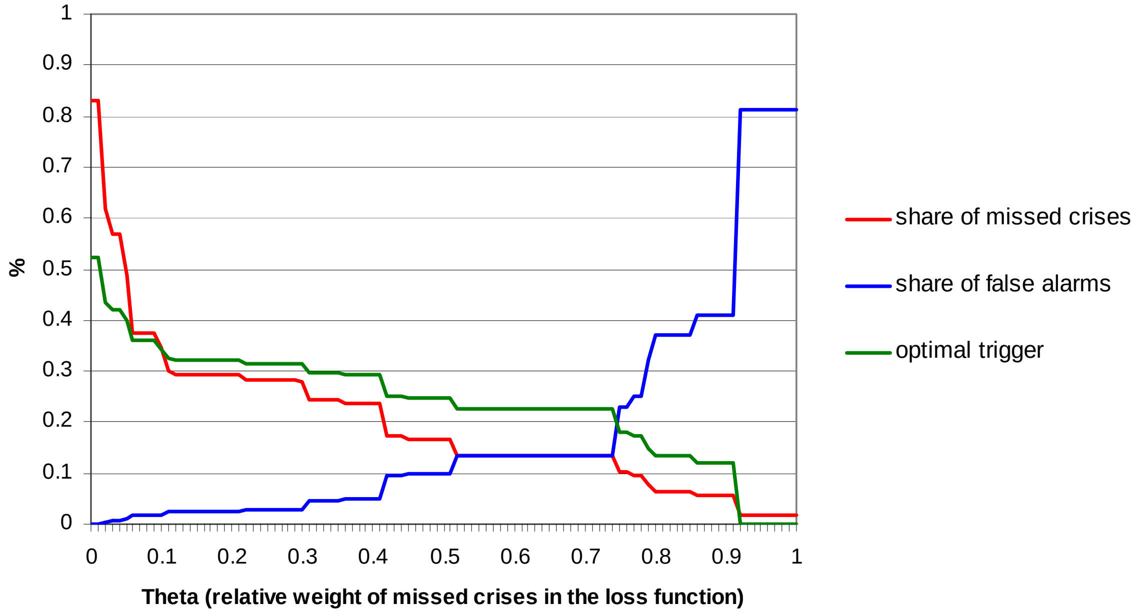
$$L = \theta \frac{C}{A+C} + (1-\theta) \frac{B}{B+D} \,,$$

where θ is the parameter of relative importance of Type I errors. Realizing that the policy maker can always achieve a loss of min{(1- θ); θ } without using the early warning indicator (for θ>0.5 the policy maker always reacts, while for θ<0.5 he does not react at all), we can define the usefulness of the indicator as

$$\min\{(1-\theta); \theta\} - \mathrm{L}(\theta) \,.$$

If the usefulness is positive, there is a positive benefit of using the proposed early warning mechanism. Figure 4 shows the share of Type I (missed crises) versus Type II (false alarms) errors for the whole sample of 40 countries over 40 years, along with the optimal trigger value of the early warning indicator from the 8-quarter-ahead linear probability model.

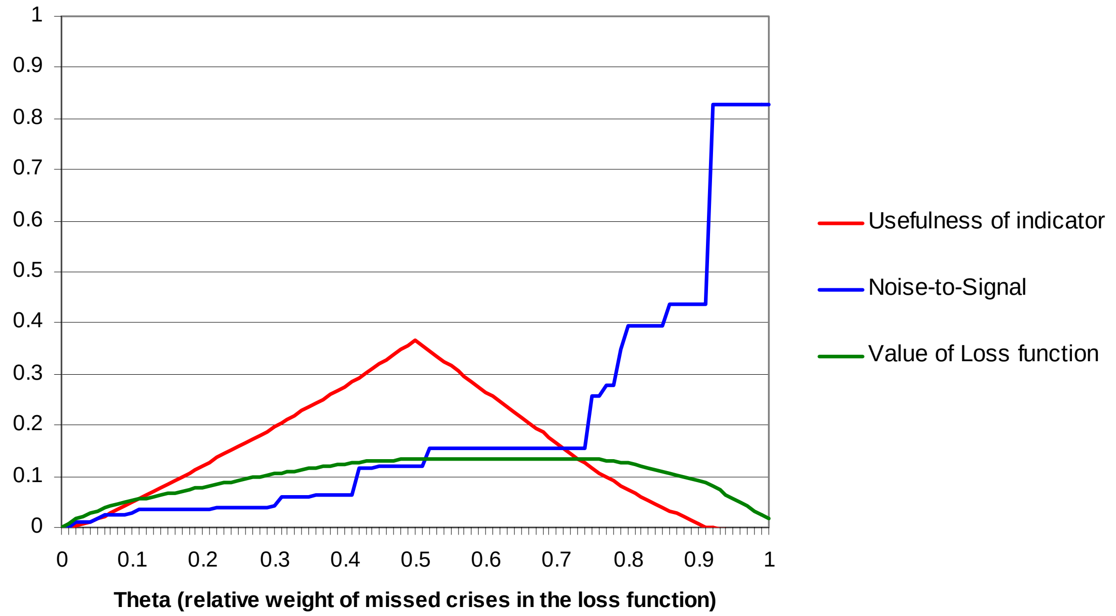
Figure 4: Policy Makers' Trade-off between Missed Crises and False Alarms



For every value of the preference weight, we find the optimal trigger value of the early warning indicator by minimizing the loss function. If the indicator exceeds the trigger value, the signal should be issued (and the policy response executed). When the policy maker has a weak preference against missed crises, the trigger is high, as is the share of missed crises. With increasing *preference weight*, the trigger falls and the initially low share of false alarms is traded off against the share of missed crises.

Finally, Figure 5 shows the trade-off between the noise-to-signal ratio and the loss function in terms of the so-called usefulness indicator established in the early warning literature (Alessi and Detken, 2009). In our EWM, estimated on the whole sample of 40 countries, usefulness achieves its maximum when false alarms and missed crises are viewed as equally harmful. The usefulness of the discrete EWM takes a value of just above 0.35, meaning that it is possible to avoid over 35% of the loss coming from missed crises and false alarms by using the EWM. For comparison, Alessi and Detken (2009) report a usefulness of single-variable indicators of around 0.2–0.25 for the same preference schedule. We conclude that using the composite early warning index reduces the loss by around 10% in comparison to single-variable indicators.

Figure 5: Trade-off between Noise-to-Signal Ratio and Loss Function



Note: Calculated for the 8-quarter-ahead early warning indicator.

5. Early Warning Indicators in the Continuous Model

5.1 Optimal Lag Selection upon Panel VAR

Expert judgment is commonly applied in the early warning literature in order to set the horizon at which leading indicators send a warning of a potential crisis. 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 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.[3] 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 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 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, 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 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. The exact selected lag length for each variable is shown in Table A1 in Annex IV.2. To illustrate the lead selection logic, three examples of impulse responses are reported in Figures 6 to 8 below. Each figure corresponds to the bivariate PVAR consisting of the CII and one selected leading indicator, specifically, the nominal effective exchange rate (NEER), world inflation (WINF), and house prices (HOUSPRIC). A full set of impulse responses for all leading indicators is available in the online appendix.

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 6). 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.

A similar logic applies to the lag selection for world inflation (WINF, Figure 7) and we set the lag equal to 14, where the response function takes on a maximum value behind our minimum threshold of 4 quarters. In this case, a shock to world inflation increases the incidence of crises (see also Section 6 on policy simulations). Given that world inflation potentially predicts the CII with a lead of more than 12 quarters, it can be considered a candidate as an ultra-early warning indicator.

[3] 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.

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

Last, the maximum response of the CII to a shock to housing prices appears within 5 quarters and is negative, indicating that an increase (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 6: Impulse Responses for Bivariate Panel VAR (NEER, CII)

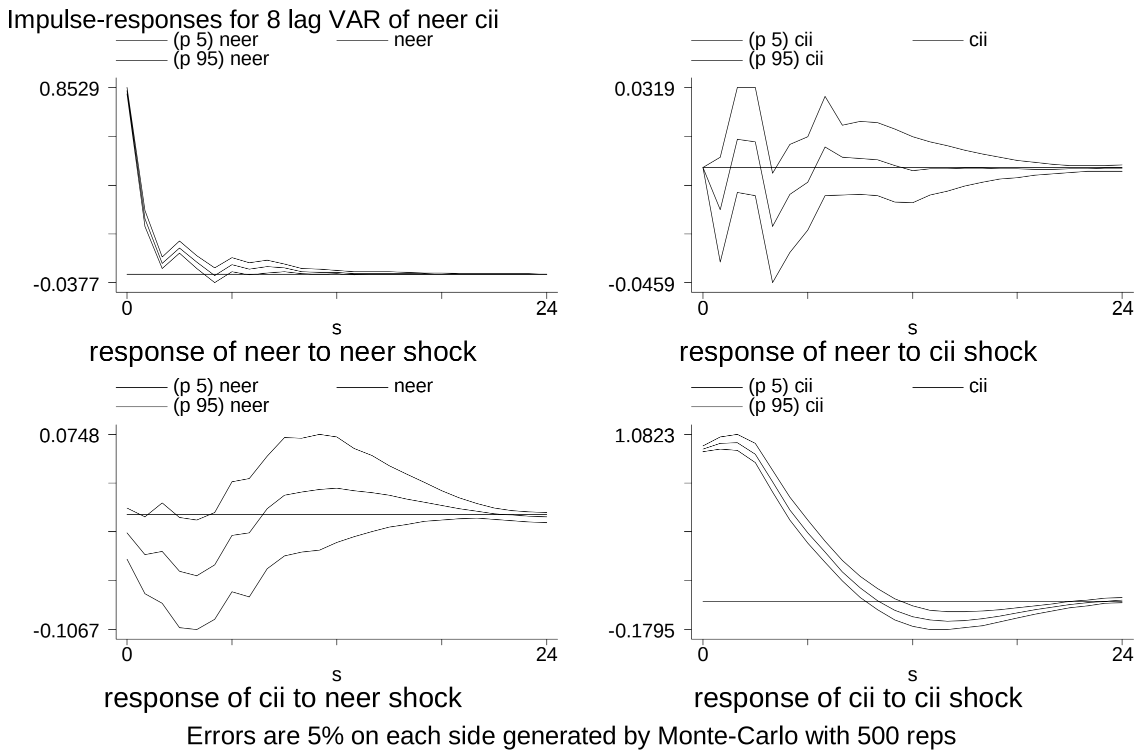


Figure 7: Impulse Responses for Bivariate Panel VAR (WINF, CII)

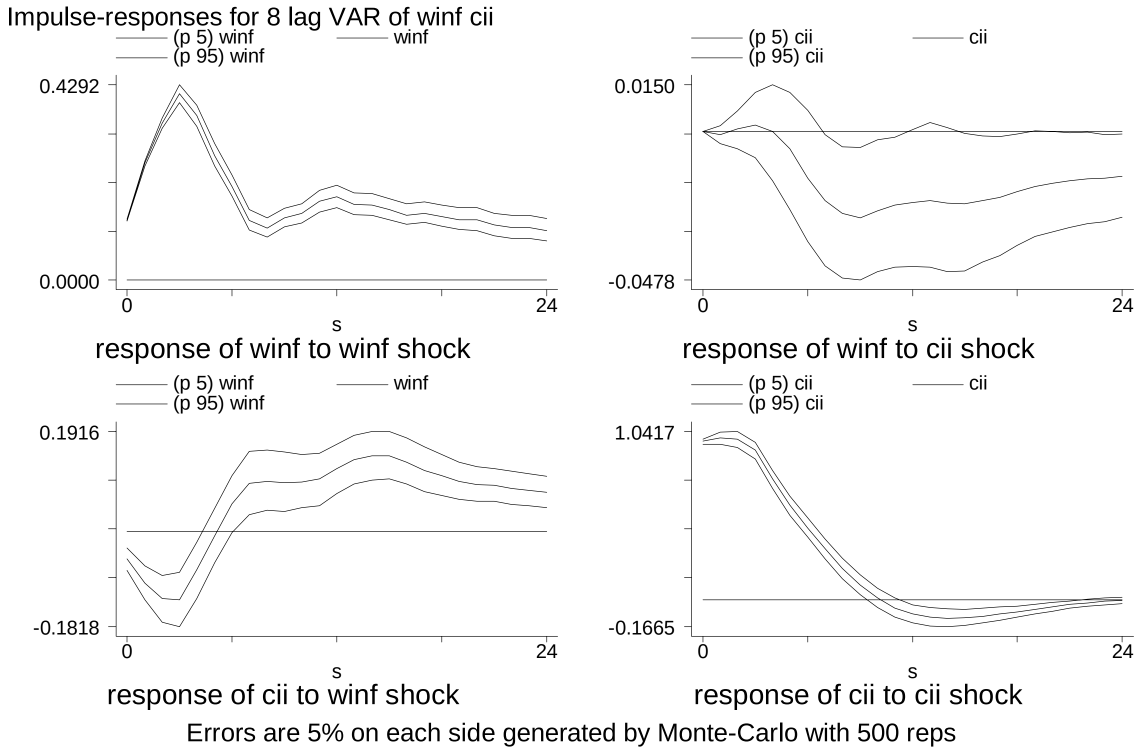
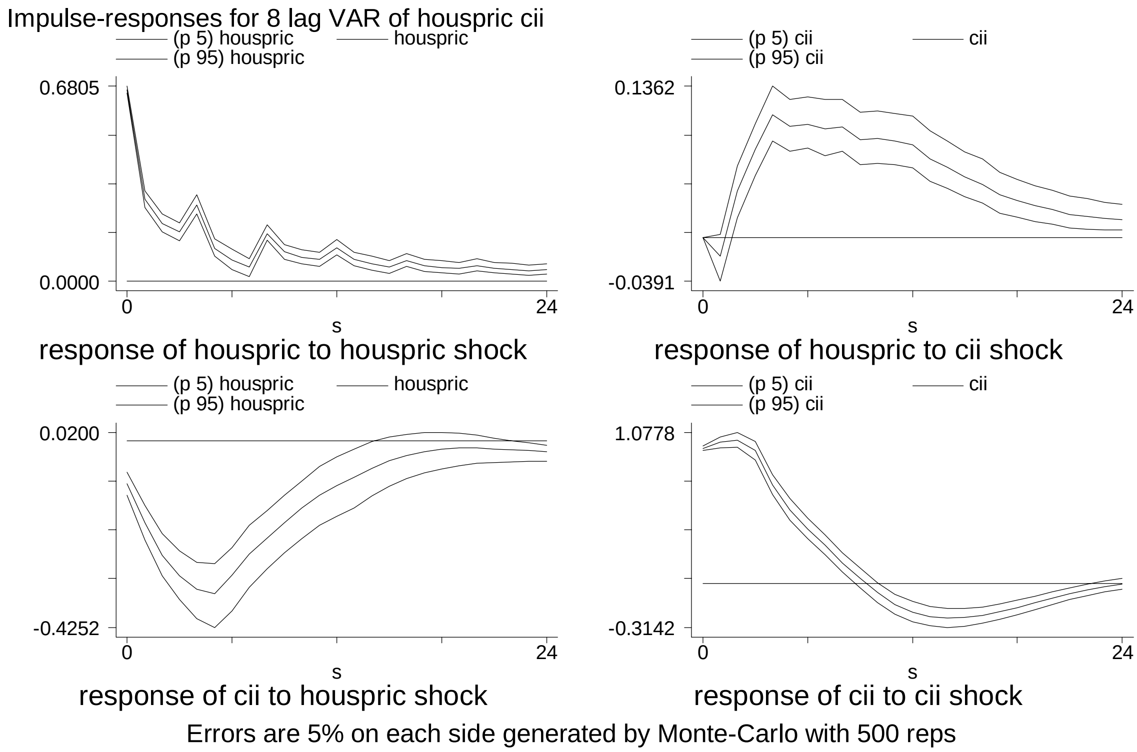


Figure 8: Impulse Responses for Bivariate Panel VAR (HOUSPRIC, CII)



5.2 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 (Fernandez et al., 2001b; Sala-i-Martin et al., 2004; Durlauf et al., 2008; 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. Further details are provided in Annex IV.

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. In principle, we could skip the first step and choose the appropriate lags within the BMA model. However, a number of issues would arise. 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. This might be less of an issue for a pure forecasting exercise; however, it hinders any structural interpretation.[5] 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 2^{800} possible models). Third, we 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. For all these reasons we decided to use the two-step strategy. In addition, as a 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.

[5] Cuaresma and Slacik (2009) consider different lags in their currency crisis forecasting BMA exercise. However, the variables included are not associated with any structural interpretation.

Figure 9: Inclusion of Variables in 1,000 Best Models in Exact Lag Dynamic Specification

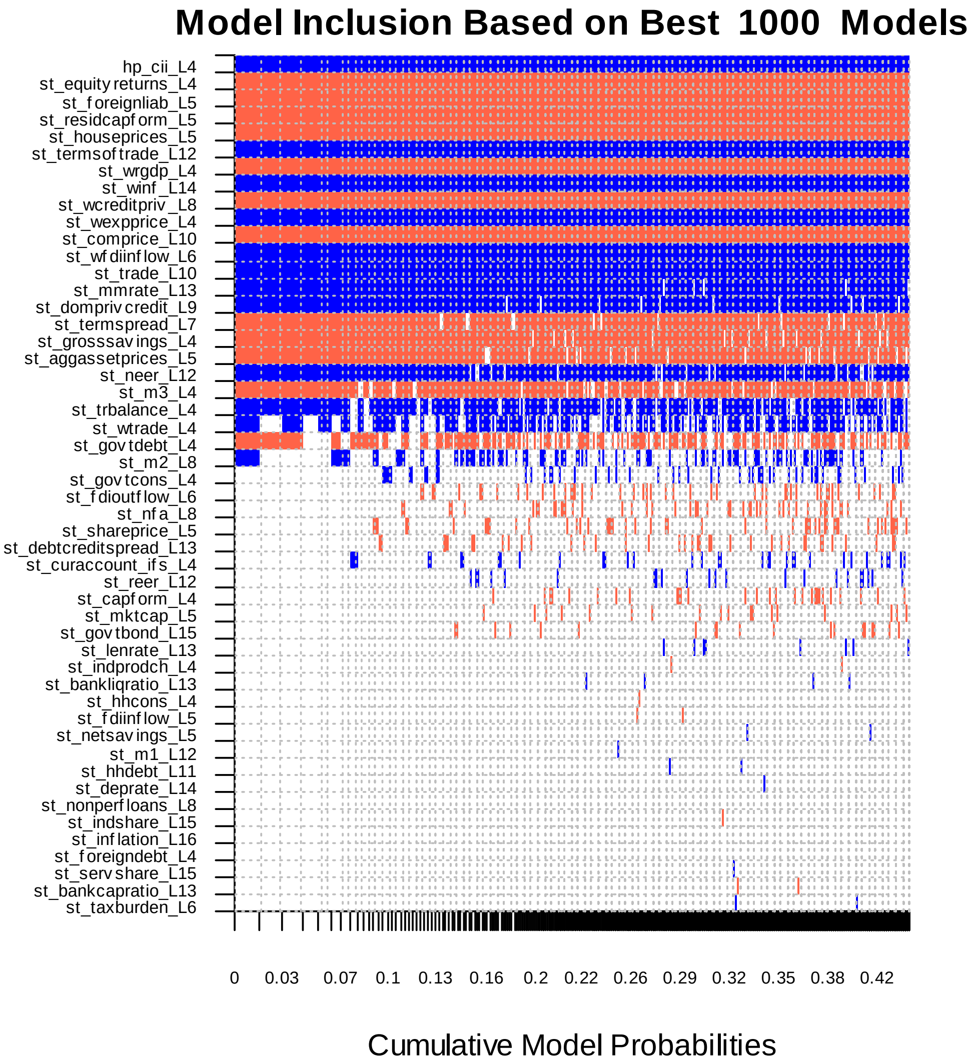


Table A1 in Annex IV.2 presents the results for the first exercise. For each variable, we report its posterior inclusion probability, posterior mean, posterior standard deviation, and conditional posterior sign (the posterior probability of a positive coefficient conditional on its inclusion). The correlation 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 partly capture the contagion of crises.

Figure 9 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 9 shows that most of the model mass includes variables that have a posterior inclusion probability (PIP) higher than 0.5.

Tables A2 and A3 in Annex IV.2 present the results for the 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 MC3 PMPs is higher than 0.99 for both exercises. Note that the results relative to the exact lag specification are different to a large extent. The number of variables that have a PIP higher than 0.5 is 12 if we use the variables lagged by 3 years. Interestingly, variables belonging to the group of housing prices experience a drop in PIPs. When using the variables lagged by 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.

5.3 Dynamic Panel Estimations

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 dependent variable 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.

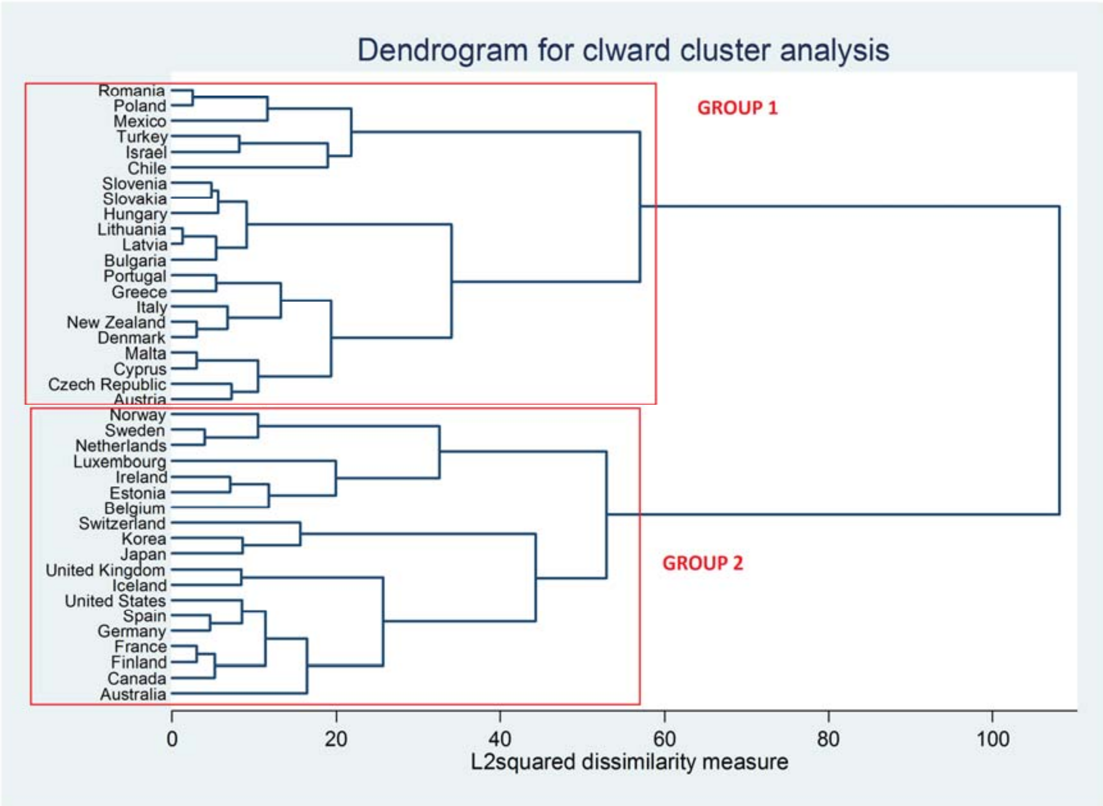
As another sensitivity check, we allow for cross-country heterogeneity in the estimated parameters. Although our database only includes OECD and EU countries, and is thus substantially more homogeneous than the data set used, for example, by Rose and Spiegel (2009) and Frankel and Saravelos (2010) to 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:

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

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 10: Clusters of Countries in our Sample



The results of the clustering exercise are depicted in Figure 10, 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 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, 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.

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
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%.

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 (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.

Table 2: Early Warning Indicators for Crisis Incidence (3 years)

	Fixed Effects	System GMM	Random Coefficients	Cluster 1 Fixed Effects	Cluster 2 Fixed Effects
L4.hp_cii	0.197^{***}	0.276^{***}	0.110^{*}	0.183^{***}	0.194^{***}
L12.st_nonperfloans	-0.310^{***}	-0.402^{***}	-0.217^{***}	-0.253^{***}	-0.248^{**}
L12.st_govtdebt	-0.398^{***}	-0.385^{***}	-0.300^{***}	-0.492^{***}	-0.358^{***}
L12.st_foreignliab	0.540^{***}	0.515^{***}	0.696^{***}	0.773^{***}	0.418^{***}
L12.st_winf	0.423^{***}	0.383^{***}	0.627^{***}	0.265^{***}	0.552^{***}
L12.st_wcreditpriv	0.584^{***}	0.676^{***}	0.359^{***}	0.591^{***}	0.531^{***}
L12.st_wfdiinflow	1.373^{***}	1.356^{***}	1.329^{***}	1.247^{***}	1.436^{***}
L12.st_comprice	-0.558^{***}	-0.636^{***}	-0.643^{***}	-0.718^{***}	-0.431^{***}
L12.st_mmrate	0.250^{***}	0.152	0.314^{***}	0.269^{**}	0.254^{*}
L12.st_shareprice	-0.231^{***}	-0.210^{***}	-0.251^{***}	-0.206^{**}	-0.221^{***}
L12.st_lenrate	0.291^{***}	0.393^{**}	0.302^{**}	0.352^{***}	0.241^{*}
L12.st_taxburden	0.0598	0.153	0.0780	-0.118^{*}	0.182^{**}
s1	0.222^{*}	0.217^{***}	0.260^{*}	0.272	0.201
s2	0.239^{*}	0.248^{***}	0.273^{*}	0.352^{*}	0.182
s3	0.230^{*}	0.241^{***}	0.319^{**}	0.431^{**}	0.124
_cons	-0.202^{*}	-0.0766	-0.403^{***}	-0.342^{**}	-0.177
Observations	3488	3488	2834	1393	2095
Countries	38	38		19	19
R-squared	0.301			0.319	0.303

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Response variable: hp_cii. We only include variables with inclusion probability from BMA higher than 50%.

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 (Table 3).

Table 3: Ultra Early Warning Indicators for Crisis Incidence (6 years)

	Fixed Effects	System GMM	Random Coefficients	Cluster 1 Fixed Effects	Cluster 2 Fixed Effects
L4.hp_cii	0.299^{***}	0.389^{***}	0.283^{***}	0.276^{***}	0.304^{***}
L24.st_foreignliab	0.880^{***}	0.931^{***}	0.979^{***}	0.893^{***}	0.869^{***}
L24.st_winf	-0.445^{***}	-0.427^{***}	-0.471^{***}	-0.394^{***}	-0.482^{***}
L24.st_wcreditpriv	0.531^{***}	0.488^{***}	0.558^{***}	0.550^{***}	0.499^{***}
L24.st_wfdiinflow	-0.570^{***}	-0.600^{***}	-0.514^{***}	-0.525^{***}	-0.609^{***}
L24.st_servshare	0.255^{***}	0.368^{**}	0.248^{***}	0.0263	0.351^{***}
L24.st_wrgdp	0.178^{**}	0.189^{***}	0.216^{***}	0.308^{**}	0.142^{*}
L24.st_wexpprice	0.140^{**}	0.108	0.129^{*}	0.0489	0.202^{**}
L24.st_wtrade	0.404^{***}	0.364^{***}	0.405^{***}	0.578^{***}	0.193
L24.st_termspread	-0.0466	-0.0560	-0.0753	0.0530	-0.121^{*}
L24.st_aggassetprices	0.464^{***}	0.477^{***}	0.490^{***}	0.385^{*}	0.525^{***}
s1	0.0929	0.0899	0.109	0.284	-0.00321
s2	0.0927	0.0900	0.0753	0.164	0.0327
s3	0.200	0.196^{***}	0.203	0.308	0.139
_cons	-0.0215	-0.00829	-0.00151	0.0848	-0.0316
Observations	3337	3337	3337	1210	2127
Countries	40	40		21	19
R-squared	0.269			0.279	0.274

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

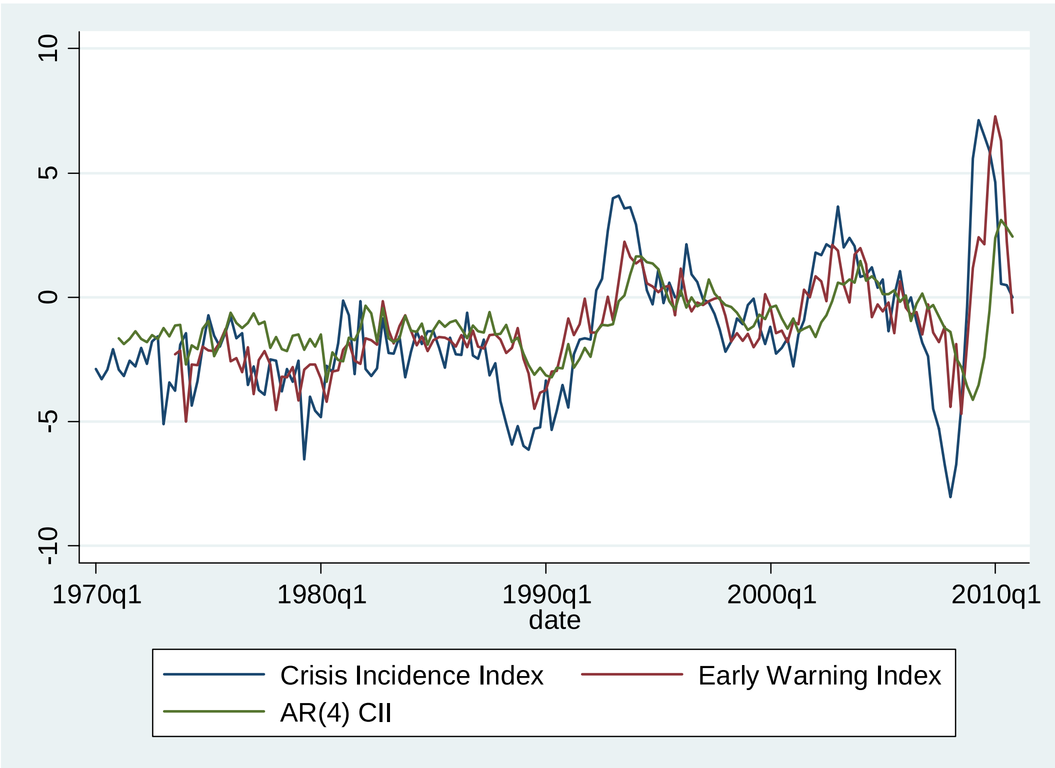
Response variable: hp_cii. We only include variables with inclusion probability from BMA higher than 50%.

5.4 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.

Figure 11 illustrates the in-sample fit of the EWI for the United Kingdom. It compares the EWI with 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 Annex V (the four biggest European economies and the four Visegrad countries), allow for similar inference. The EWI was able to predict quite precisely the incidence of the last two recessions (the early 2000s recession and the one related to the recent crisis), while it failed, for example, to predict the magnitude of the 1973–75 recession. A possible explanation is that the causes of this crisis (an oil shock and the Vietnam War, among others) were too different from the rest of the sample.

Figure 11: In-Sample Fit of Crisis Incidence, United Kingdom



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 4; 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 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 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 Kingdom is depicted in Figure 12.[6] 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 Annex V. In all cases the EWI seems to perform better than the simple autoregressive function.

Table 4: Warning Indicators for Crisis Incidence (Exact Lags, Data till 2007Q1)

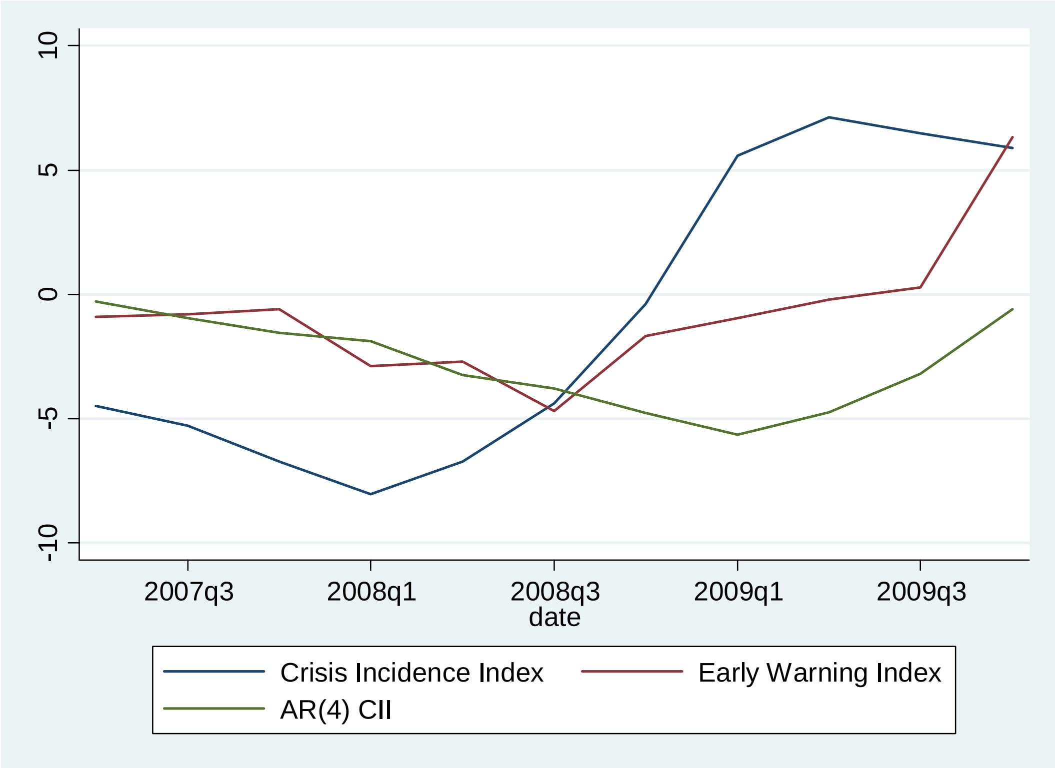
	Fixed Effects	System GMM	Random Coefficients	Cluster 1 Fixed Effects	Cluster 2 Fixed Effects
L4.hp_cii	0.360^{***}	0.421^{***}	0.267^{***}	0.269^{***}	0.384^{***}
L4.st_equityreturns	-0.297^{***}	-0.288^{***}	-0.240^{***}	-0.154^{*}	-0.378^{***}
L4.st_wrgdp	-0.178^{***}	-0.232^{***}	-0.192^{**}	-0.308^{***}	-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^{**}
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%.

[6] 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.

Figure 12: Pseudo-out-of-Sample Prediction of the Recent Crisis, United Kingdom



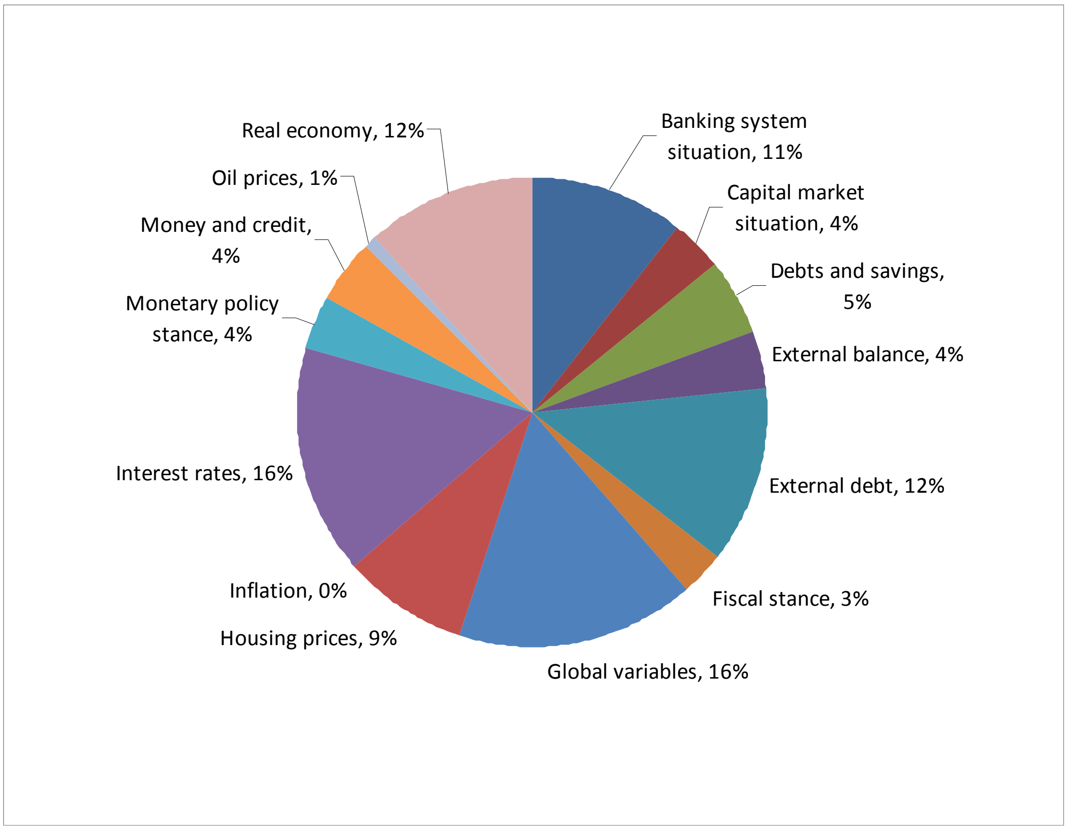
6. Tentative Inputs into the Macroprudential Policy Debate

In this section, we outline how the early warning system (EWS) consisting of our two EWMs can input into the macroprudential policy debate. We can see two possible inputs. First, the EWS 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 two EWMs into their risk dashboards (Trichet et al., 2011). Should the risk dashboard warn against large nominal volatilities as well as costly events, indicators from both EWMs could be considered. Second, potential policy responses to early warnings can be assessed. This assessment can only be done very broadly due to data limitations. However, it can provide guidance as far as the effectiveness of macroeconomic policies is concerned. In addition to these two policy inputs, one could look at the out-of-sample forecasts for both the COI and the CII. In the paper, the out-of-sample forecasts have been employed in order to evaluate the EWMs. However, the methodology used allows predicting the COI two years ahead and the CII one year ahead of the last data update period. Given the large time requirements of data updates, we do not feel confident to put forward these predictions as another practical input into policy debates.

6.1 Sources of Risks

In order to identify the major sources of risk, we look closely at the explanatory power of the useful leading indicators; to make the analysis easier to follow, we use the division of the indicators into groups introduced in Section 3. The groups 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. The contributions of individual groups of indicators to the prediction of the COI, as follows from the dynamic panel logit regression reported in Annex III, are summarized in Figure 13a.

Figure 13a: Contributions of Individual Groups of Indicators to Prediction of COI

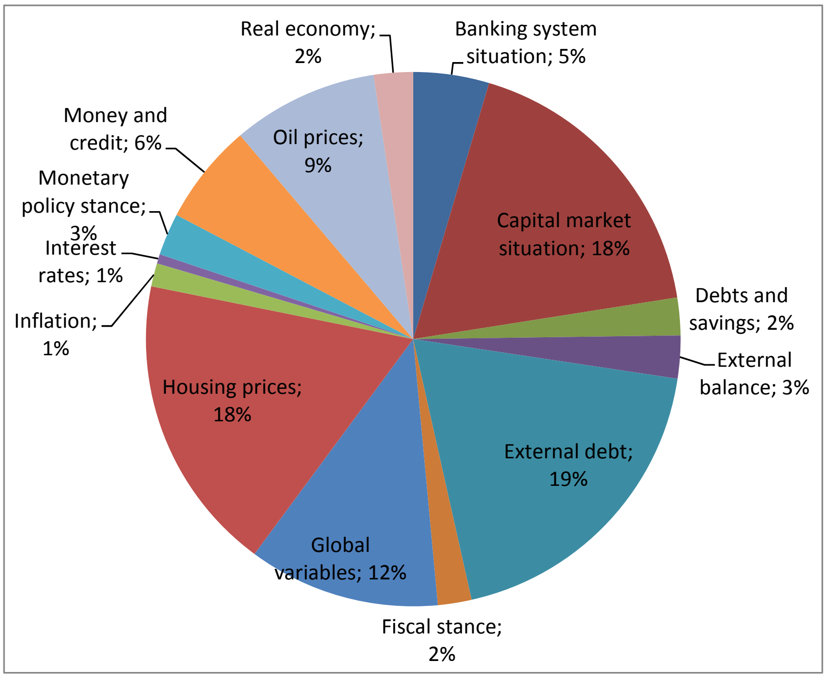


Note: Shares in the model's R-squared (0.21); based on regression with 8 lags reported in Annex II.

The chart illustrates the main determinants of the COI eight quarters ahead, aggregated into the above-described groups; the associated percentages correspond to the groups' shares in the model's R-squared, which is equal to 0.21. Among the main sources of risk, global variables play a prominent role (16%), along with interest rates (16%), external indebtedness (12%), and developments in the real economy (12%). These four groups of variables together account for more than 56% of the model R-squared, which is equivalent to explaining around 12% of the total variation in the COI itself.

We conduct a similar analysis for the CII, based on the results reported in Annex III. We assess the partial coefficients of determination and sum them for all the lags of each group. The results are depicted in Figure 13b.

Figure 13b: Contributions of Individual Groups of Indicators to Prediction of CII



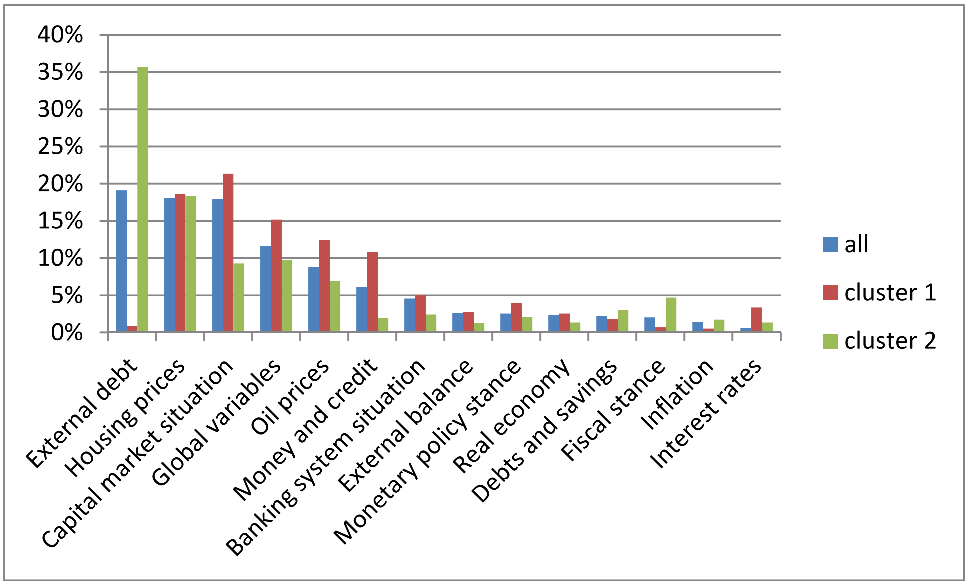
Note: Shares in the model's R-squared (0.45); based on fixed effects regression reported in Annex III.

The percentages shown in Figure 13b correspond to the groups' shares in the model R-squared, which is equal to 0.45. The most important groups of potential indicators are external debt (19%), housing prices (18%), the capital market situation (18%), and global variables (12%). 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. Oil prices are important as well, accounting for about 9% of the model's R-squared. On the other hand, the fiscal stance and the banking system situation, among others, seem to be of little importance.

A comparison of the determinants of crisis occurrence (Figure 13a) and crisis incidence (Figure 13b) reveals one interesting finding: groups of indicators such as global variables, external debt, and housing prices are common important factors. On the other hand, some variables which account for a significant share of the variation of the COI make only a marginal contribution to the CII (e.g. interest rates) and vice versa (e.g. oil prices). The fact that the COI and the CII have different structures of their determinants is inherently related to the different aspects of a crisis captured by those two indicators: while the COI focuses on crisis occurrence, typically defined as large nominal volatility, the CII characterizes the *real* costs to the economy.

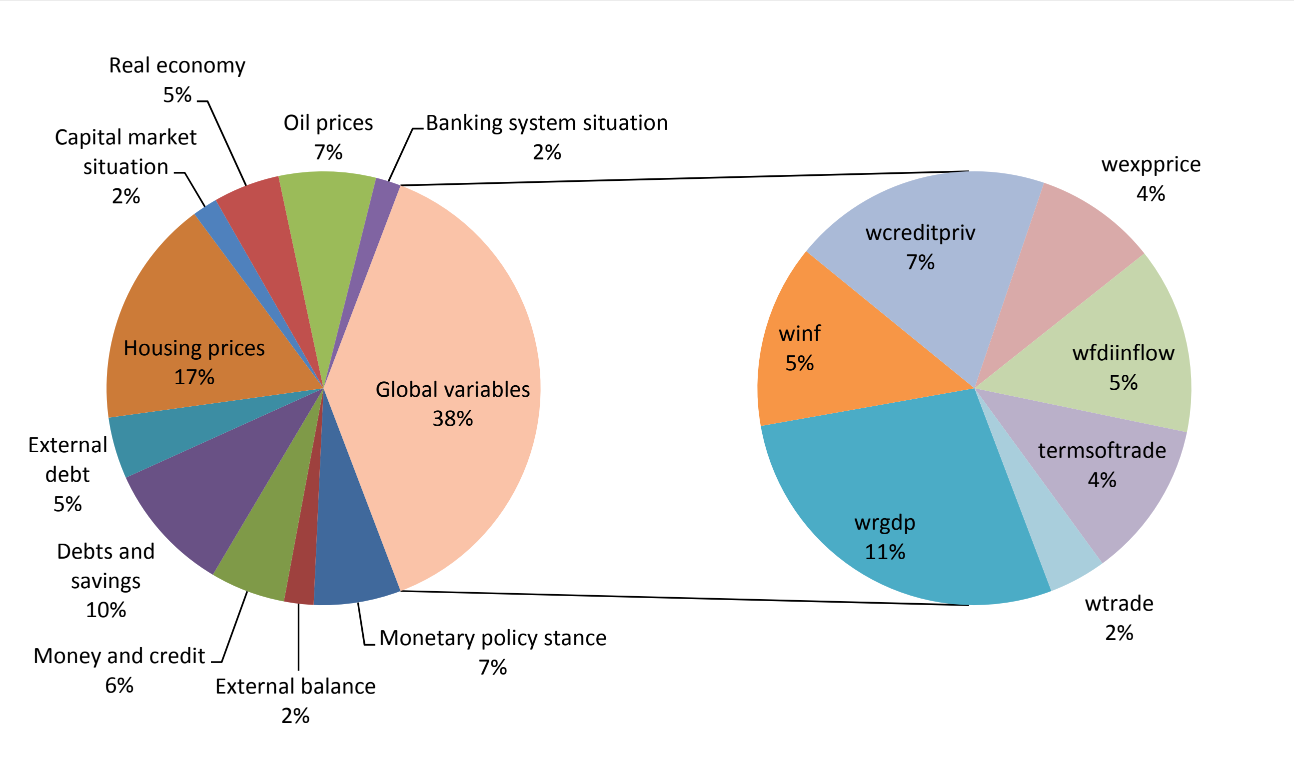
In the next step, we conduct the same analysis for the two clusters of countries separately and present the results in Figure 14. While housing prices seem to be consistently important in both clusters and account for about 18% of the model's R-squared, the importance of other groups differs greatly across clusters. External debt is highly important for the 'core' countries (Cluster 2), accounting for 35% of the model's R-squared, but is negligible for the countries included in Cluster 1. On the other hand, the capital market situation, global variables, oil prices, and money and credit indicators are much less important for the 'core' countries.

Figure 14: Contributions of Individual Groups of Indicators to Prediction of CII, by Clusters of Countries



Last, we conduct a similar exercise using the results from our preferred EWM from Table 1, where the optimal leads were selected employing PVAR and the set of useful leading indicators was chosen by Bayesian model averaging. We use the baseline specification (fixed effects) and in Figure 15 report the results for each group of variables. The percentages in Figure 15 denote the groups' shares in the model's R-squared, which is equal to 0.37. In addition, in the right pie chart of Figure 15 we provide the percentages for the individual variables within the most important group, global variables.

Figure 15: Most Important Early Warning Indicators



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

Compared to the previous results, several differences deserve attention. First, when our preferred EWM is used to examine the importance of potential leading indicators, variables reflecting the capital market situation are much less important (2% of the explanatory power, compared with 18% in the previous case). The same finding applies to variables reflecting external debt (5%, compared with 19% in the previous case). On the other hand, global leading variables (such as world GDP, world inflation, and world credit) are much more important in our preferred EWM. The importance of oil prices remains similar (7%, compared with 9%). Finally, our results suggest that housing prices retain high explanatory power in all the models.

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.

6.2 Possible Policy Reactions

Following the discussion in Subsection 5.4, we employ our early warning index (EWI) and assess whether the available policy instruments are able to affect the predicted values of the CII for an 'average country' in our panel. We also check whether the responses are similar for both the EWI and the CII; in other words, whether policy makers with the information provided by our EWM in real time would be able to alter the future course of crisis incidence.

The panels of Figure 16 report the response function of the CII and the EWI (from bivariate PVAR consisting of the CII or the EWI and each policy variable) to a one-standard-deviation shock to selected policy variables. These policy variables cover monetary policy (central bank reserves, policy interest rate), fiscal policy (government consumption, tax burden), and financial supervision (banking sector capital ratio, banking sector liquidity ratio). These variables are meant to represent the policy tools that the national authorities have used during past decades to keep their economies stable.

Three important caveats must be kept in mind. First, data limitations are a serious problem in many policy areas. For example, data on various financial sector bail-outs are not incorporated into fiscal budget data consistently across countries. Second, given the size of the country sample as well as the time span we cannot include all the variables we would like to. It can be argued that each macroeconomic policy area can be represented by numerous policy variables when it comes to crisis prevention. Tax incentives affecting the housing market are a good example of such measures. For the sake of simplicity and due to data limitations, we select a few variables only to represent each policy, mostly according to data availability. Third, we lack variables to represent macroprudential policy, for example the extent of leverage among institutions and investors, and supervisory and regulatory instruments (see Table 2 in Frait and Komárková, 2011, for a comparison of monetary versus macroprudential indicators and instruments). The last caveat is the least serious. It can be argued that these tools were not consistently used in the past and so, given our data sample, omitting them is not a problem. However, for future research, missing data on macroprudential policy tools may seriously affect this type of analysis.

The illustrative results can be summarized as follows. First, the response functions are consistent for the EWI and the CII, corroborating the previous checks (measures of fit and forecasting performance), which indicated that the EWI predicts the CII reasonably well. Second, there is substantial heterogeneity in the efficiency of different policy tools.

The actions of central banks seem to be the most efficient in altering the risk of crises. In particular, an increase in central bank reserves and an increase in the policy rate reduce crisis incidence in one year. While the downward effect of a rising policy rate on crisis incidence seems rather counterintuitive should it occur over the longer term, in the short run an increase in the policy rate may serve as a stabilizing tool, helping to anchor market expectations.

The evidence on the efficiency of other policies is mixed. Government consumption does not seem to have any effect on crisis incidence.[7] Also, variables related to financial supervision do not affect the CII or EWI substantially. This finding should be interpreted with caution, however. There are a lot of serious data limitations in this area that prevent us from representing supervisory policies adequately and on a sufficient data sample.

Figure 17 reports the same response functions when the data of only one country, the Czech Republic, are considered. The general impression is that the patterns found in the panel setting for the 'average country' hold also for the Czech Republic. Monetary policy seems to be efficient in

[7] Since the three variables which enter the CII are expressed in deviations from the HP trend and are then combined, we believe that endogeneity between the CII and fiscal policy is not an issue. In fact, the correlation between the CII and fiscal policy variables is quite small.

smoothing crises: both increasing reserves and an increasing policy rate reduce the incidence of crisis. However, there are some important differences. First, due to a substantially smaller sample size the confidence intervals are rather wide and the estimates imprecise, especially in the longer term (4–12 quarters). This illustrates the usefulness of the panel approach. Second, an increase of the banking capital ratio seems to reduce crisis incidence (traced by both the CII and the EWI) in the Czech case.

In addition, we consider the possibility of international policy spillover. Given that the previous results pointed to the importance of monetary policy, we test whether the Fed's actions induce actions in other central banks as well as directly affecting crisis incidence in other countries. We run a trivariate VAR with the US policy rate (a global policy variable, which is common to all countries), the national policy rate, and the CII/EWI, and report the response functions of the national policy rate and the CII/EWI to a one-standard-deviation shock to the US policy rate. The results, reported in Figure 18, confirm that an increase of the US policy rate not only induces an increase in national policy rates (with a peak at 6 to 9 quarters), but also directly reduces both the CII and the EWI (with a peak at 4 to 8 quarters). Though this should be considered as only preliminary evidence on global policy spillovers, it seems that US monetary policy can alter crisis incidence abroad.

Finally, it should also be noted that shocks to the EWI and the CII also produce some policy variable responses, suggesting that policy actions might also come as a result of crisis materialization (these figures are not reported here but are available in the online appendix). For robustness checks, we (i) tested an alternative ordering with policy instruments coming after the EWI/CII, (ii) ran the PVAR including different combinations of policy instruments at the same time, and (iii) tested the consistency of the results for the two clusters of countries. The benchmark results, reported in Figures 16, 17, and 18, were confirmed in all cases.

Figure 16: Response of CII/EWI to Policy Instruments (RESERVES, POLRATE, GOVTCONS, TAXBURDEN, BANKCAPRATIO, BANKLIQRATIO) in Bivariate 4-Lag Panel VAR

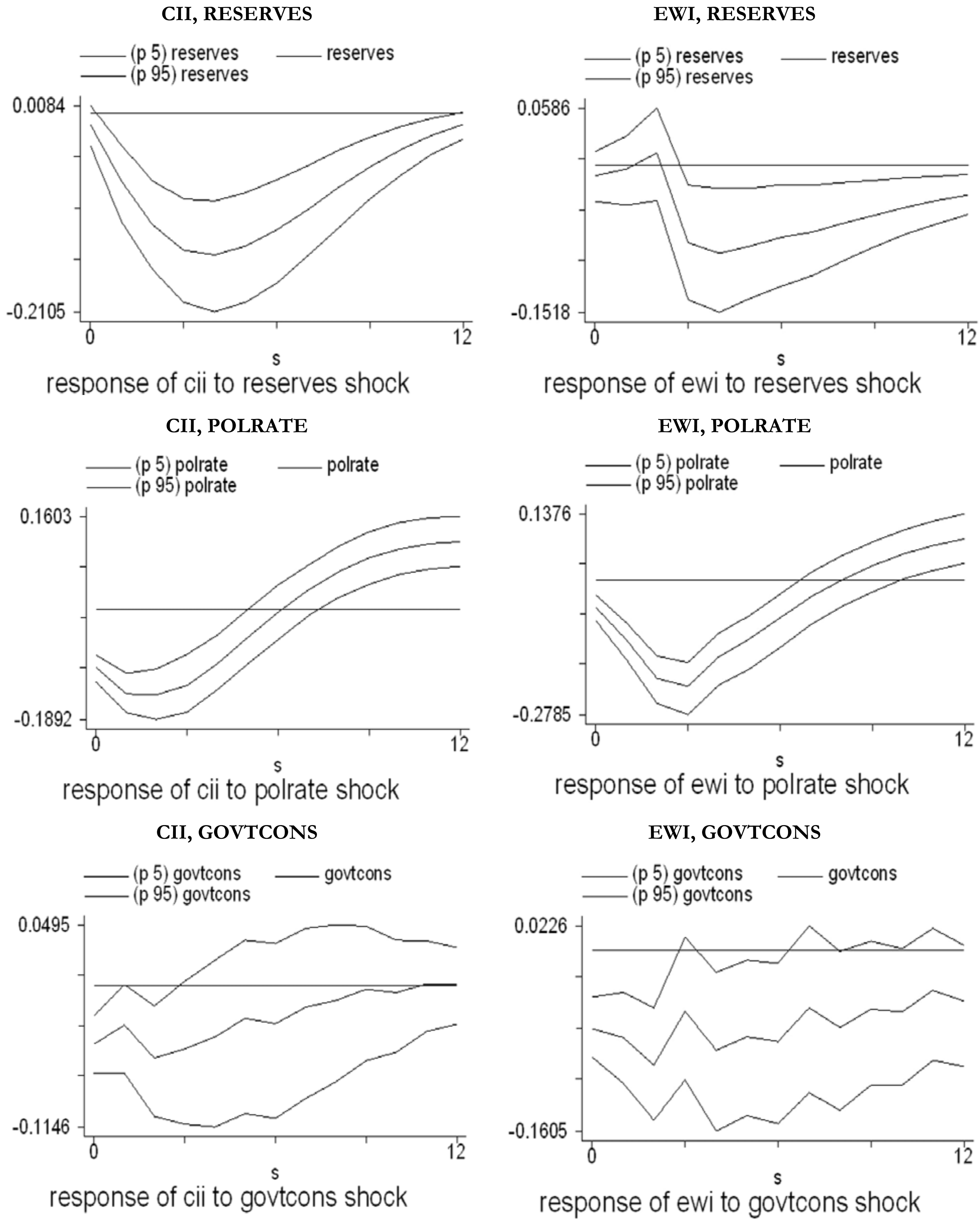
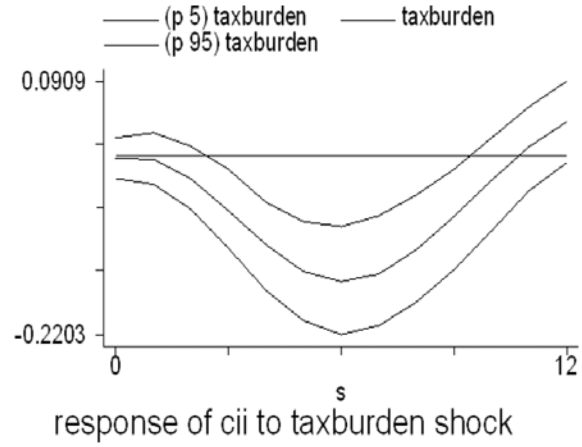
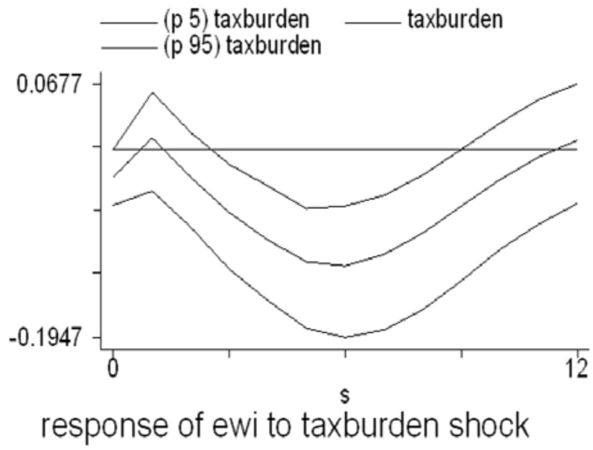


Figure 16: (cont.) Response of CII/EWI to Policy Instruments (RESERVES, POLRATE, GOVTCONS, TAXBURDEN, BANKCAPRATIO, BANKLIQRATIO) in Bivariate 4-Lag Panel VAR

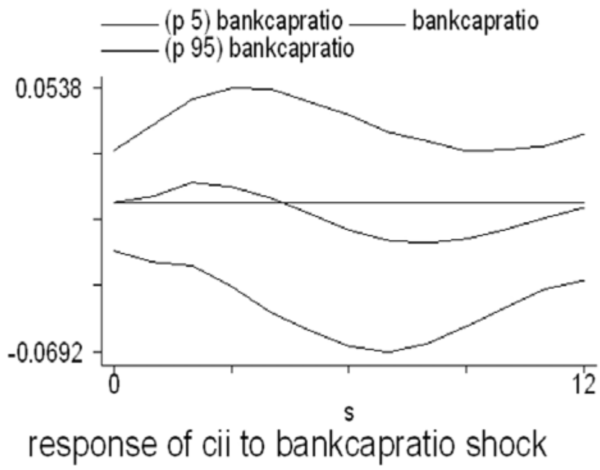
CII, TAXBURDEN



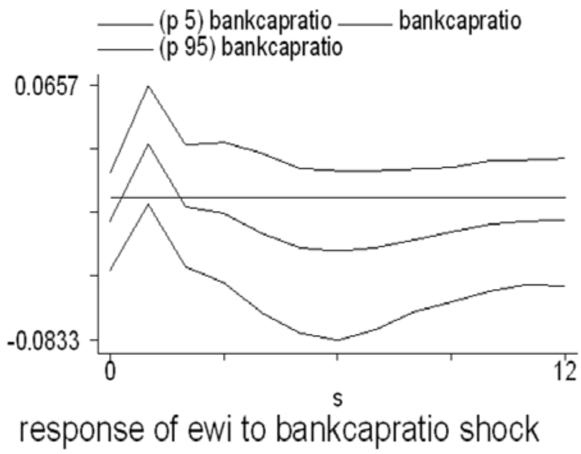
EWI, TAXBURDEN



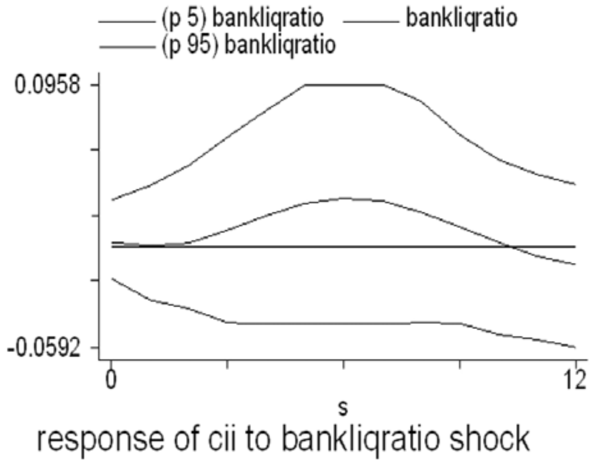
CII, BANKCAPRATIO



EWI, BANKCAPRATIO



CII, BANKLIQRATIO



EWI, BANKLIQRATIO

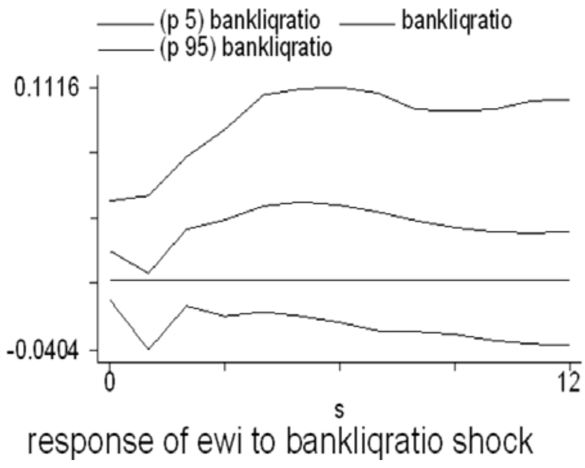


Figure 17: Response of CII/EWI to Policy Instruments for Czech Republic (RESERVES, POLRATE, GOVTCONS, TAXBURDEN, BANKCAPRATIO, BANKLIQRATIO) in Bivariate 4-Lag Panel VAR

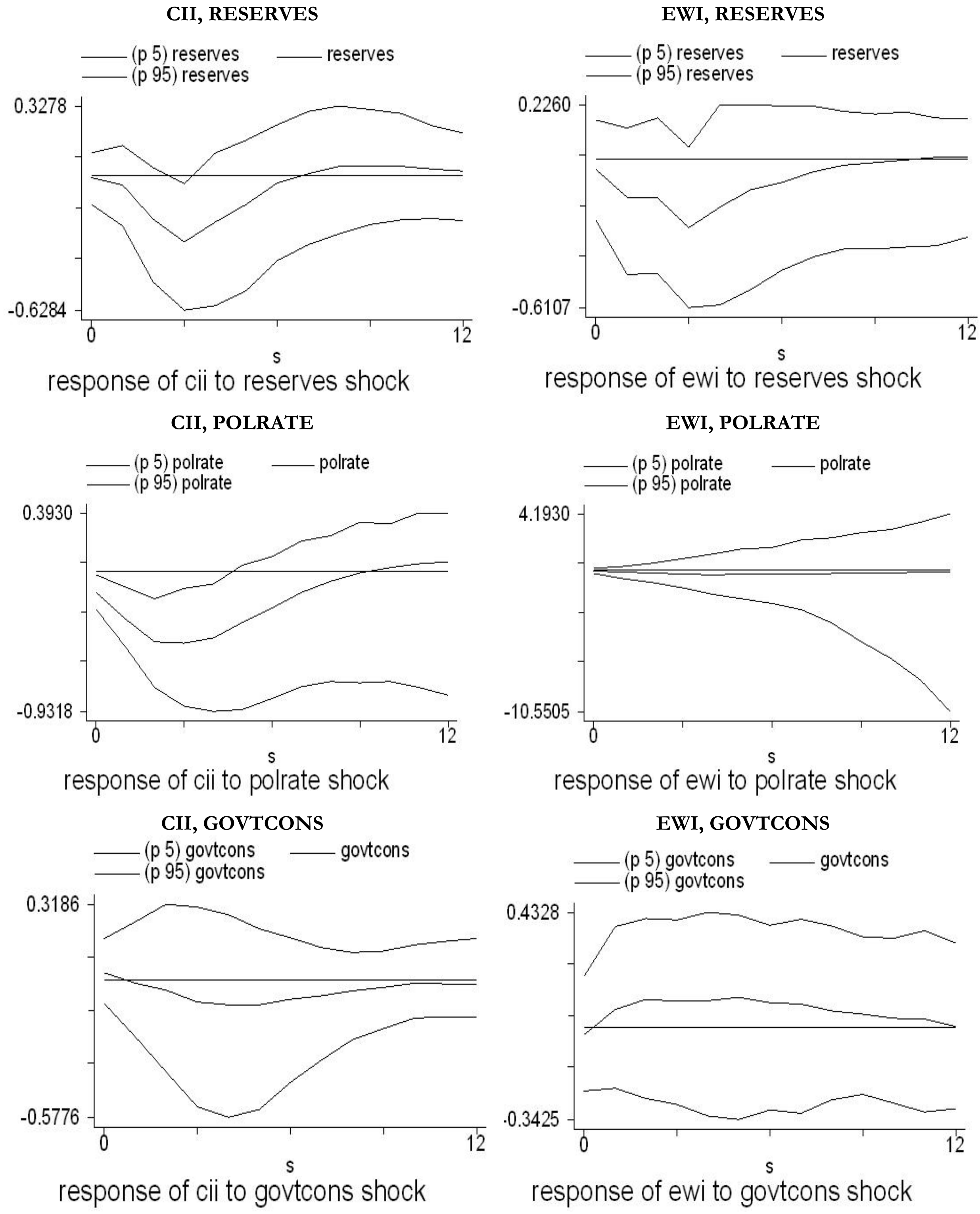
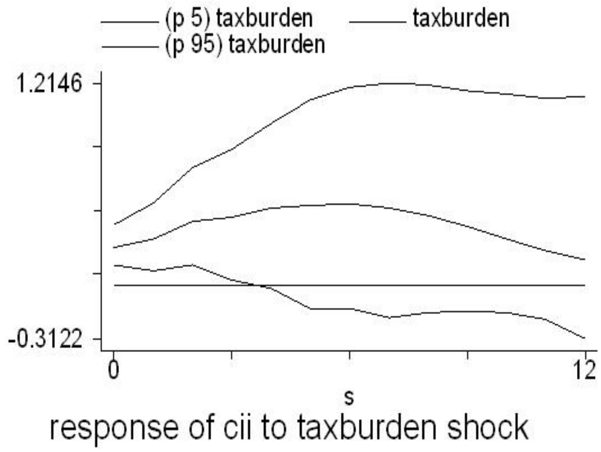
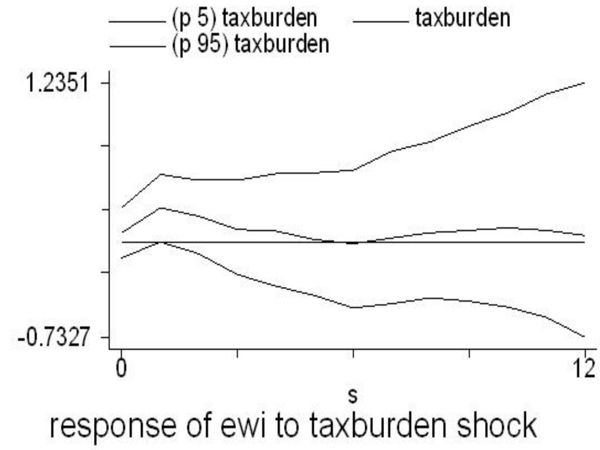


Figure 17: (cont.) Response of CII/EWI to Policy Instruments for Czech Republic (RESERVES, POLRATE, GOVTCONS, TAXBURDEN, BANKCAPRATIO, BANKLIQRATIO) in Bivariate 4-Lag Panel VAR

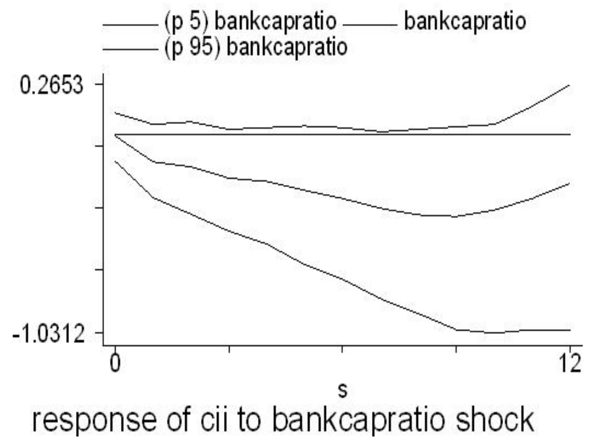
CII, TAXBURDEN



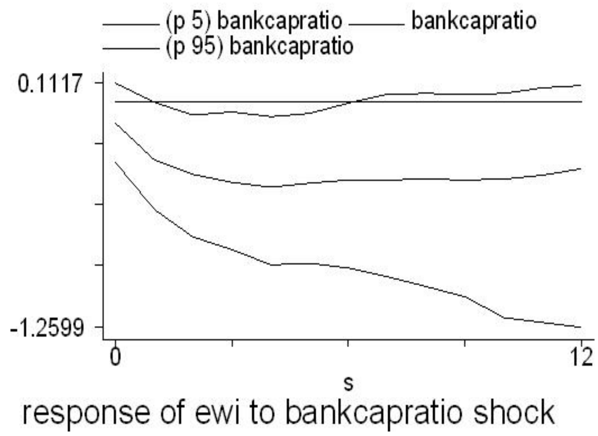
EWI, TAXBURDEN



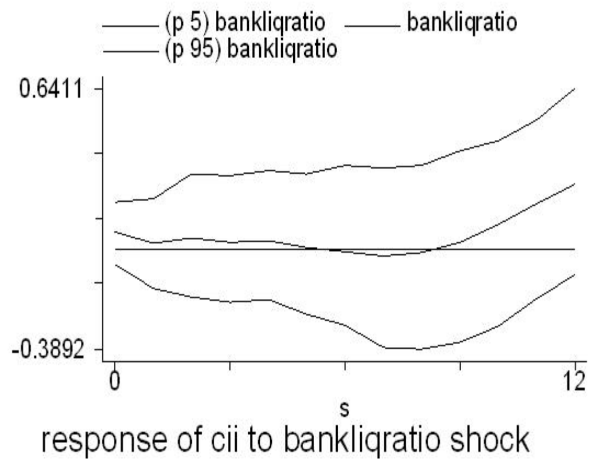
CII, BANKCAPRATIO



EWI, BANKCAPRATIO



CII, BANKLIQRATIO



EWI, BANKLIQRATIO

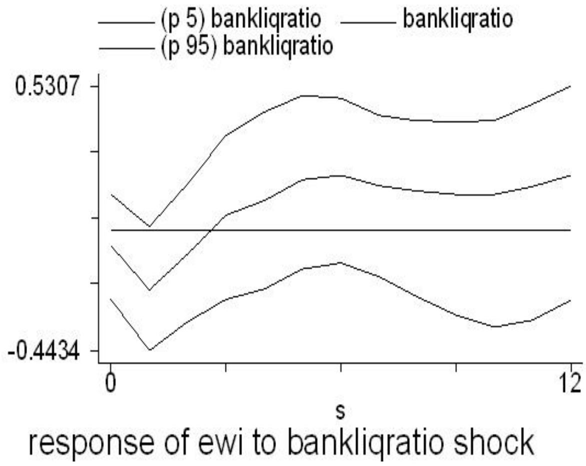
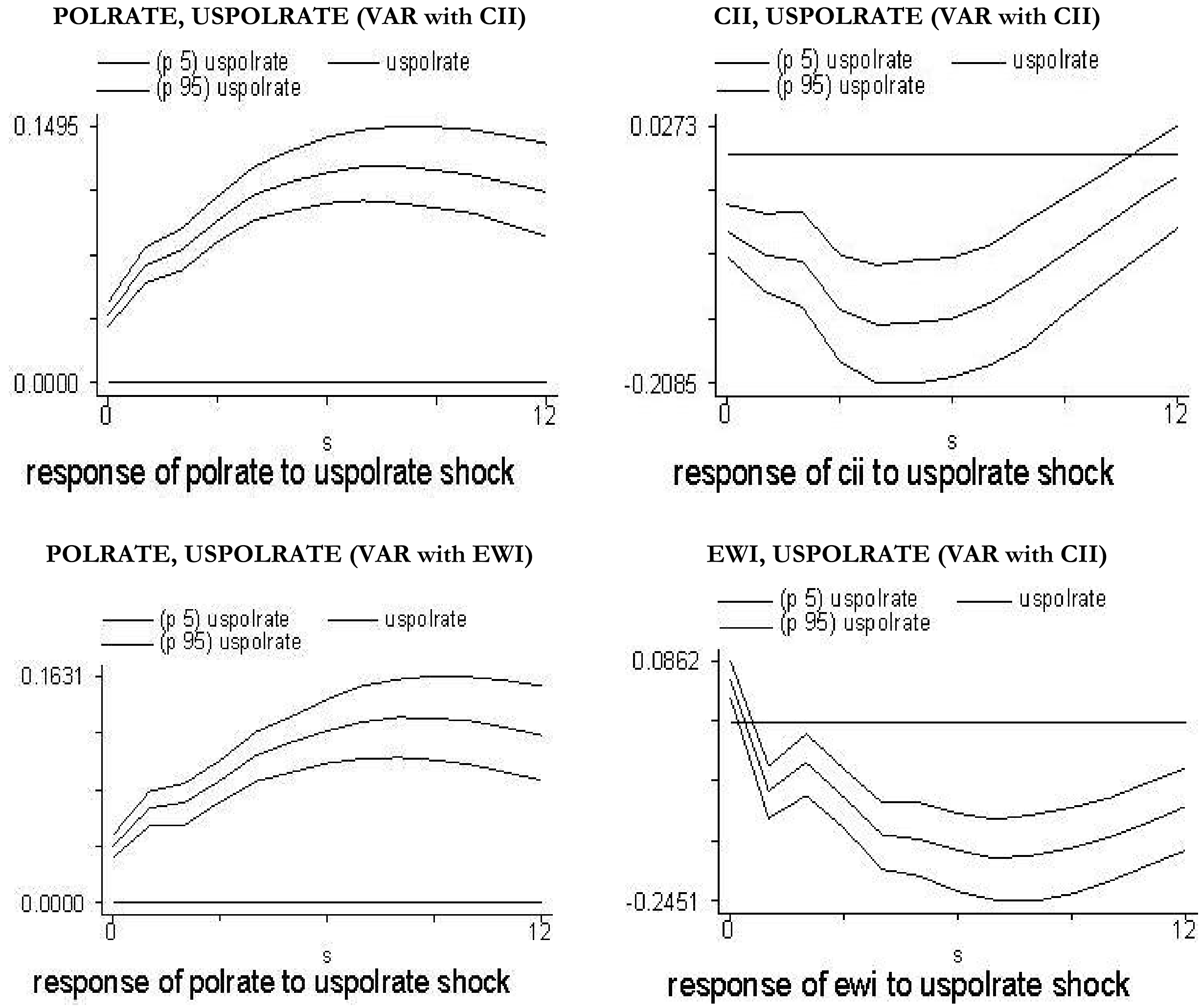


Figure 18: Effect of Global Policy Instruments: Response of POLRATE and CII/EWI to USPOLRATE in Trivariate 4-Lag Panel VAR

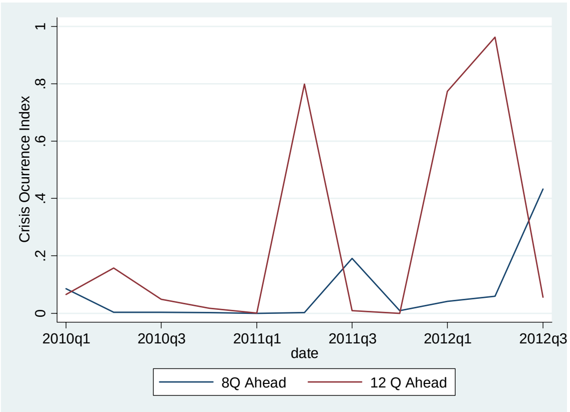


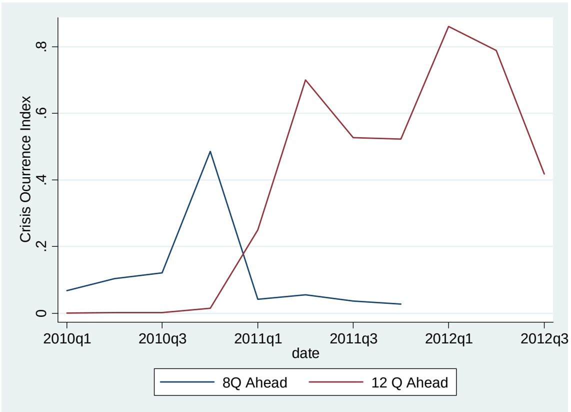
6.3 Predicting the Crisis Occurrence Index and the Crisis Incidence Index

The out-of-sample predictions of both indexes can potentially yield interesting information for policy makers. In the case of the COI, the time horizon is fixed to two years (three years alternatively) due to the construction of the COI. It follows that for our data sample, which does not go further than 2010, we can predict the COI for the 2012 horizon. The time horizon is shorter for the CII since the CII utilizes the optimal time lags. 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. (Moreover, for some individual variables comprising the EWI we have data only till 2009q4, so we can only predict up to 2010q4.) This trade-off between searching for the best possible combination of early warning indicators (as represented by the COI) and the ability to predict crisis incidence with a sufficient lead (as done by the CII) illustrates well why it is useful to work with an EWS consisting of several EWMs.

Figure 19 shows the predicted COI values for the UK and Czech Republic, our two benchmark countries. 2010 comes out as a period of relatively low probability of crisis, while from the beginning of 2011 the probability of crisis starts to rise in both the United Kingdom and the Czech Republic, falling first toward late 2012. This might be caused by the worsening global outlook, while the effects of the need for fiscal restriction may play a role as well. Some similarity in the predicted crisis occurrence between the UK and the Czech Republic suggests the presence of common (global) factors. Next, the three-year-ahead predictions show a higher probability of crisis compared to the two-year-ahead case. Predictions with a longer horizon use a longer history (three years versus two years of data) to infer about the future and thus they are potentially more informative, at the same time being more volatile due to an increase in uncertainty along with a longer forecast horizon.

Figure 19: Predicted Crisis Occurrence, United Kingdom (left) and Czech Republic (right)

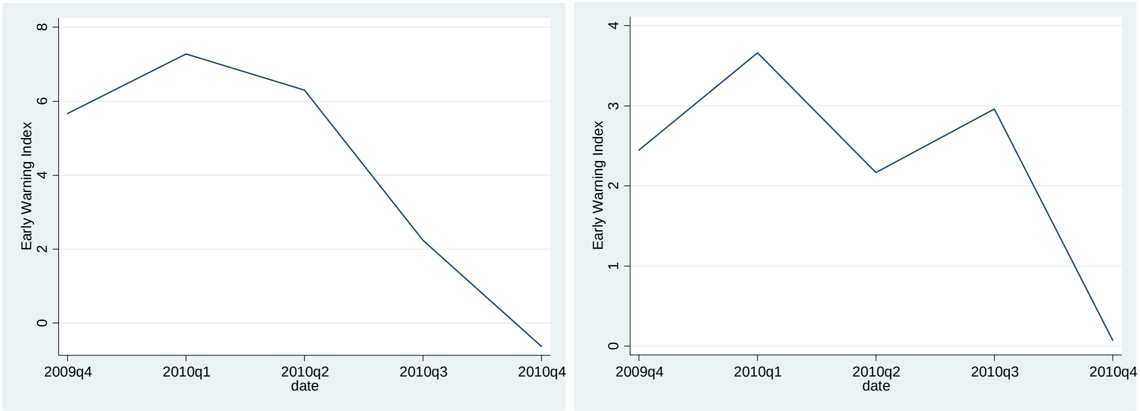




Note: Out-of-sample predicted values of crisis occurrence, 2010q1–2012q3. The forecast horizon for 8Q-ahead crisis occurrence in the Czech Republic case ends in 2011 due to data availability.

Figure 20 illustrates the more limited predictive capacity of the CII for the same two countries, the prediction horizon being limited to 2010q4. Following an upward trend as from the end of 2009 through a moderation during 2010, the crisis incidence shows a decline by the end of 2010 for both the United Kingdom and the Czech Republic, largely reflecting improving global factors in the aftermath of the 2008/2009 crisis.

Figure 20: Predicted Crisis Incidence, United Kingdom and Czech Republic



United Kingdom Czech Republic

Note: Out-of-sample predicted values of crisis incidence, 2009q4–2010q4.

7. Conclusions

In this study we create an early warning system represented by two complementary models: a discrete model exploring crisis occurrence and a continuous model dealing with crisis incidence, which characterizes the real costs of a crisis for the economy. As the basis for our analysis, we collect a unique CDEC 40-40 data set of crisis occurrence and compute crisis incidence for a sample of 40 developed countries, including the EU-27 group, over 1970–2010 at quarterly frequency, thus filling a gap in the early warning literature, which has so far mainly focused on either panel data sets comprising developing economies or large cross-sections. We explicitly differentiate between policy variables and leading indicators; leading indicators, in turn, are divided into country-specific variables and global factors.

Using a set of 50 potential leading indicators we identify the determinants of crisis occurrence and crisis incidence employing our discrete and continuous models. We then assess the models' performance in terms of in-sample and out-of-sample fit. In addition, the discrete model is complemented with an indicator of usefulness, illustrating the trade-off between the noise-to-signal ratio and the loss function. The continuous model in turn allows us to simulate the past effectiveness of selected policy measures in mitigating crisis incidence for the economy.

In constructing our continuous model, we relax the typical assumption of a fixed horizon at which the early warning signals come. We test for the optimal lag length employing a panel VAR framework and examine the impulse responses of crisis incidence and its potential leading indicators. Next, we apply Bayesian model averaging in order to identify useful leading indicators out of the 50 potential indicators we collected. We then use panel estimation techniques (including dynamic estimations and system GMM) to assess the determinants of crisis incidence. Finally, we check for sample homogeneity by employing the random coefficient model and clustering.

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 that housing prices are an important source of risks to macroeconomic stability. Global variables are another influential risk factor. 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.

References

ABIAD, A. (2003): "Early-Warning Systems: A Survey and a Regime-Switching Approach." IMF Working Paper No. 03/32.

ALESSI, L. AND C. DETKEN (2009): "'Real Time' Early Warning Indicators for Costly Asset Price Boom/Bust Cycles: A Role for Global Liquidity." ECB Working Paper No. 1039.

ANDERSON, T. W. AND C. HSIAO (1982): "Formulation and Estimation of Dynamic Models Using Panel Data." *Journal of Econometrics* 18, pp. 47–82.

ARELLANO, M. AND S. BOND (1991): "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *Review of Economic Studies* 58(2), pp. 277–297.

ARELLANO, M. AND O. BOVER (1995): "Another Look at the Instrumental Variable Estimation of Error-Components Models." *Journal of Econometrics* 68(1), pp. 29–51.

BARRELL, R., E. P. DAVIS, D. KARIM, AND I. LIADZE (2009): "Bank Regulation, Property Prices and Early Warning Systems for Banking Crises in OECD Countries." Brunel University Working Paper No. 09-28.

BERG, A., E. BORENSZTEIN, AND C. PATTILLO (2004): "Assessing Early Warning Systems: How Have They Worked in Practice?" IMF Working Paper No. 04/52.

BERG, A. AND C. PATTILLO (1998): "Are Currency Crises Predictable? A Test." IMF Working Paper No. 98/154.

BILSON, J. F. O. (1979): "Leading Indicators of Currency Devaluations." *Columbia Journal of World Business* 14, pp. 62–76.

BLUNDELL, R. AND S. BOND (1998): "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87(1), pp. 115–143.

BORIO, C. AND P. LOWE (2002): "Assessing the Risk of Banking Crisis." BIS Quarterly Review, December 2002.

BURKART, O. AND V. COUDERT (2002): "Leading Indicators of Currency Crises for Emerging Countries." *Emerging Markets Review* 3, pp. 107–133.

BUSSIERE, M. AND FRATZSCHER, M. 2006. Towards a New Early Warning System of Financial Crises. Journal of International Money and Finance, 25, 953–973.

BUSSIERE, M. (2007): "Balance of Payment Crises in Emerging Markets: How Early Were the "Early" Warning Signals?" ECB Working Paper No. 713.

CAPRIO, G. AND D. KLINGEBIEL (2003): Episodes of Systemic and Borderline Financial Crises. World Bank, January 22. http://go.worldbank.org/5DYGICS7B0

CECCHETTI, S. G., I. FENDER, AND P. MCGUIRE (2010): "Toward a Global Risk Map." BIS Working Paper No. 309.

CUARESMA, J. C. AND T. SLACIK (2009): "On the Determinants of Currency Crises: The Role of Model Uncertainty." *Journal of Macroeconomics* 31(4), pp. 621–632.

DAVIS, E. P. AND D. KARIM (2008): "Comparing Early Warning Systems for Banking Crises." *Journal of Financial Stability* 4, pp. 89–120.

DREHER, A., B. HERZ AND V. KARB (2006): "Is There a Causal Link Between Currency and Debt Crises?" *International Journal of Finance & Economics* 11(4), pp. 305–325.

DURLAUF, S., A. KOURTELLOS, AND C. TAN (2008): "Are Any Growth Theories Robust?" *Economic Journal* 118, pp. 329–346.

FELDKIRCHER, M. AND S. ZEUGNER (2009): "Benchmark Priors Revisited: On Adaptive Shrinkage and the Supermodel Effect in Bayesian Model Averaging." IMF Working Paper 09-202.

FERNANDEZ, C., E. LEY, AND M. STEEL (2001A): "Benchmark Priors for Bayesian Model Averaging." *Journal of Econometrics* 100, pp. 381–427.

FERNANDEZ, C., E. LEY, AND M. STEEL (2001B): "Model Uncertainty in Cross-Country Growth Regressions." *Journal of Applied Econometrics* 16, pp. 563–576.

FRAIT, J. AND Z. KOMÁRKOVÁ (2011): "Financial Stability, Systemic Risk and Macroprudential Policy." Financial Stability Report 2010/2011, Czech National Bank, 96–109.

http://www.cnb.cz/en/financial_stability/fs_reports/fsr_2010-2011/fsr_2010-2011_article_1.pdf

FRANKEL, J. A. AND A. K. ROSE (1996): "Currency Crashes in Emerging Markets: An Empirical Treatment." *Journal of International Economics* 41(3–4), pp. 351–366.

FRANKEL, J. A. AND G. SARAVELOS (2010): "Are Leading Indicators of Financial Crisis Useful for Assessing Country Vulnerability? Evidence from the 2008–09 Global Crisis." NBER Working Paper No. 16047.

GALATI, G. AND R. MOESSNER (2010): "Macroprudential Policy—A Literature Review." DNB Working Papers 267, Netherlands Central Bank.

http://www.dnb.nl/en/binaries/267%20-%20Macroprudential_tcm47-243120.pdf

GLICK, R. AND M. HUTCHISON (1999): "Banking and Currency Crises: How Common are Twins?" Proceedings, Federal Reserve Bank of San Francisco, Sep issue.

GRAMMATIKOS, T. AND R. VERMEULEN (2010): "Transmission of the Financial and Sovereign Debt Crises to the EMU: Stock Prices, CDS Spreads and Exchange Rates." DNB Working Papers 287, Netherlands Central Bank.

http://www.dnb.nl/en/binaries/working%20paper%20287_tcm47-252981.pdf

HERZ, B. AND H. TONG (2008): "Debt and Currency Crises—Complements or Substitutes?" *Review of International Economics* 16, pp. 955–970.

HOLTZ-EAKIN, D., W. NEWEY AND H.S. ROSEN (1988): "Estimating Vector Autoregressions with Panel Data." *Econometrica* 56(6), pp. 1371–1395.

IMF (2010): *The IMF-FSB Early Warning Exercise: Design and Methodological Toolkit*. International Monetary Fund, September 2010.

http://www.imf.org/external/np/pp/eng/2010/090110.pdf

KAMINSKY, G. L. (1999): "Currency and Banking Crises: The Early Warnings of Distress." IMF Working Paper No. 99/178.

KAMINSKY, G. L. (2006): "Currency Crises: Are They All the Same?" *Journal of International Money and Finance* 25(3), pp. 503–527.

KAMINSKY, G. L., S. LIZONDO AND C.M. REINHART (1998): "The Leading Indicators of Currency Crises." *IMF Staff Papers* 45(1), pp. 1–48.

KAMINSKY, G. L. AND C. M. REINHART (1996): "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems." Board of Governors of the Federal Reserve System, International Finance Discussion Papers 544.

http://www.federalreserve.gov/pubs/ifdp/1996/544/ifdp544.pdf

KAMINSKY, G. L. AND C. M. REINHART (1999): "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems." *American Economic Review* 89(3), pp. 473–500.

KOOP, G. (2003): *Bayesian Econometrics*. John Wiley and Sons.

KRUGMAN, P. (1979): "A Model of Balance-of-Payments Crises." *Journal of Money, Credit and Banking* 11(3), pp. 311–325.

LAEVEN, L. AND F. VALENCIA (2008): *Systemic Banking Crises: A New Database*. International Monetary Fund. http://www.imf.org/external/pubs/ft/wp/2008/wp08224.pdf

LAEVEN, L. AND F. VALENCIA (2010): *Resolution of Banking Crises: The Good, the Bad and the Ugly*. International Monetary Fund.

http://www.imf.org/external/pubs/ft/wp/2010/wp10146.pdf

LEY, E. AND M. STEEL (2009): "On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regression." *Journal of Applied Econometrics* 24, pp. 651–674.

LOVE, I. AND L. ZICCHINO (2006): "Financial Development and Dynamic Investment Behavior: Evidence from Panel VAR." *The Quarterly Review of Economics and Finance* 46, pp. 190–210.

LOUZIS, D. P. AND A. T. VOULDIS (2011): *A Financial Systemic Stress Index for Greece*. Manuscript (January 7, 2011).

MADIGAN, D. AND J. YORK (1995): "Bayesian Graphical Models for Discrete Data." *International Statistical Review* 63, pp. 215–232.

MORAL-BENITO, E. (2010): Model Averaging in Economics. Mimeo.

NICKELL, S. J. (1981): "Biases in Dynamic Models with Fixed Effects." *Econometrica* 49(6), pp. 1417–1426.

PERIA, M. S. M. (2002): *A Regime-Switching Approach to the Study of Speculative Attacks: A Focus on EMS Crises.* In James D. Hamilton and Baldev Raj, editors, Advances in Markov-Switching Models. Heidelberg: Physica-Verlag.

RABE-HESKETH, S. AND A. SKRONDAL (2008): *Multilevel and Longitudinal Modeling Using Stata*, 2nd Edition. Stata Press Books. StataCorp LP, number mimus2, Autumn.

REINHART, C. M. AND K.S. ROGOFF (2008): *Banking Crises: An Equal Opportunity Menace*. http://www.nber.org/papers/w14587

ROODMAN, D. (2009): "How to Do xtabond2: An Introduction to Difference and System GMM" in Stata. *Stata Journal* 9(1), pp. 86–136.

ROSE, A. K. AND M. M. SPIEGEL (2009): "Cross-Country Causes and Consequences of the 2008 Crisis: Early Warning." NBER Working Paper No. 15357.

SALA-I-MARTIN, X., G. DOPPELHOFER, AND R. MILLER (2004): "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach." *American Economic Review* 94, pp. 813–835.

SLINGENBERG, J. W. AND J. DE HAAN (2011): "Forecasting Financial Stress." DNB Working Papers 292, Netherlands Central Bank.

http://www.dnb.nl/en/binaries/working%20paper%20292_tcm47-252477.pdf

TRICHET, J. C. (2010): "Macro-prudential Regulation as an Approach to Contain Systemic Risk: Economic Foundations, Diagnostic Tools and Policy Instruments." Speech at the 13th conference of the ECB-CFS Research Network, Frankfurt am Main, September 27, 2010. http://www.ecb.int/press/key/date/2010/html/sp100927.en.html

TRICHET, J. C., M. KING AND A. ENRIA (2011): Introductory Statement to the ESRB Press Conference. Frankfurt am Main, June 22, 2011.

VAN DEN END, J. W. (2010): "Trading off Monetary and Financial Stability: A Balance of Risk Framework." DNB Working Papers 249, Netherlands Central Bank.

http://www.dnb.nl/en/binaries/249%20Trading%20off%20monetary%20and%20financial%20stability_tcm47-233693.pdf

WARD, J. H. (1963): "Hierarchical Grouping to Optimize an Objective Function." *Journal of the American Statistical Association* 58(301), pp. 236–244.

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
G0	Policy tools
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	G0		l	m2toreserves	M2/foreign exchange reserves (%)	WDI
5	G0		g	cbreserves	Central bank reserves	IMF IFS
6	G0		g	reserves	Reserves	IMF IFS
7	G0		g	resimports	Reserves (in months of imports)	WDI
8	G0		l	polrate	Policy interest rate	IMF IFS
9	G1	0	g	neer	Nominal effective exchange rate	IMF IFS
10	G1	1	g	m1	M1	IMF IFS
11	G1	0	l	mmrate	Money market interest rate	IMF IFS
12	G2	0	l	lenrate	Interest rate on credit	IMF IFS
13	G2	0	l	deprate	Deposit interest rate	IMF IFS
14	G2	0	l	govtbond	Long-term bond yield, nominal	IMF IFS
15	G3	0	l	termspread	Spread (long-term bond yield minus short-term interest rate)	IMF IFS
16	G3	0	l	debtcreditspread	Deposit-credit spread	IMF IFS
17	G3	0	l	bankcapratio	Banking sector capital ratio	WDI
18	G3	0	l	bankliqratio	Bank liquid reserves to bank assets ratio (%)	WDI
19	G3	1	l	nonperfloans	Bank non-performing loans (% of loans, 2006)	WDI
20	G4	1	l	mktcap	Stock market capitalization	NIGEM
21	G4	1	g	shareprice	Stock market index	IMF IFS
22	G4	1	l	equityreturns	Equity market returns	IMF IFS
23	G5	1	g	m2	M2	IMF IFS
24	G5	1	g	m3	M3	IMF IFS
25	G5	1	l	domprivcredit	Domestic private sector credit (% of GDP, 2006)	WDI

26	G6	1	l	govtdebt	Government debt (% of GDP)	NIGEM
27	G6	1	g	hhdebt	Gross liabilities of personal sector	NIGEM
28	G6	0	l	netsavings	Net national savings (% of GNI)	WDI
29	G6	0	l	grosssavings	Gross national savings (% of GDP)	WDI
30	G7	1	g	foreignliab	Gross foreign liabilities	NIGEM
31	G7	0	l	nfa	Net external position (% of GDP, 2004)	IMF
32	G7	1	l	foreigndebt	Foreign debt/GDP (%)	WDI
33	G8	1	l	residcapform	Private residential fixed capital formation	OECD
34	G8	1	g	houseprices	House price index	[a]
35	G8	1	g	aggassetprices	Nominal aggregate asset price index	[a]
36	G9	**1**	**l**	indprodch	Percentage change in industrial production	IMF IFS
37	G9	1	g	hhcons	Private final consumption expenditure	IMF IFS
38	G9	1	g	capform	Gross total fixed capital formation	IMF IFS
39	G9	1	l	indshare	Industry share	WDI
40	G9	1	l	servshare	Services share	WDI
41	G9	1	l	trade	Trade (% of GDP)	WDI
42	G10	1	g	govtcons	Government consumption	IMF IFS
43	G10	0	l	taxburden	Total tax burden	OECD
44	G11	0	g	curaccount_ifs	Current account	IMF IFS
45	G11	0	g	trbalance	Trade balance	IMF IFS
46	G11	0	g	reer	Real effective exchange rate index	IMF IFS
47	G11	1	l	fdiinflow	FDI net inflows (% of GDP)	WDI
48	G11	1	l	fdioutflow	FDI net outflows (% of GDP)	WDI
49	G12	1	l	termsoftrade	Terms of trade	IMF IFS
50	G12	1	g	wrgdp	Global GDP[b]	NIGEM
51	G12	1	g	wtrade	Global trade	NIGEM
52	G12	1	l	winf	Global inflation	IMF IFS
53	G12	1	l	wbankcredit	Global credit (% of GDP)	IMF IFS
54	G12	1	l	wcreditpriv	Global domestic credit to private sector (% of GDP)	WDI
55	G12	1	l	wfdiinflow	Global FDI inflow (% of GDP)	UNCTAD
56	G12	1	g	wexpprice	Global export prices	IMF IFS
57	v1	1	l	inflation	Consumer price inflation (%)	IMF IFS
58	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: Determinants of Crisis Occurrence: Dynamic Panel Logit Estimations

	Lag length=8Q		Lag length=12Q	
Lagged COI	1.626***	(7.74)	0.797***	(3.42)
Nominal effective exchange rate	0.261*	(2.17)	0.0263	(0.23)
M1	0.129	(1.14)	0.400**	(3.09)
Money market interest rate	0.243	(0.93)	-0.543	(-1.56)
Interest rate on credit	-1.353***	(-4.02)	-1.551***	(-4.68)
Deposit interest rate	0.901**	(3.12)	0.642*	(2.28)
Long-term bond yield, nominal	1.042***	(5.09)	1.864***	(6.21)
Term spread	-0.254	(-1.84)	-0.529**	(-2.97)
Deposit-credit spread	0.558***	(4.18)	0.652***	(5.02)
Banking sector capital ratio	-0.117	(-1.05)	-0.426**	(-3.05)
st_creditinfoindex	-0.198	(-0.79)	-0.213	(-0.39)
Bank liquid reserves	-0.169	(-1.42)	-0.300*	(-2.27)
Bank non-performing loans	-0.565***	(-3.80)	-0.907***	(-4.59)
Stock market capitalization	0.284	(1.22)	1.027***	(3.42)
Stock market index	-0.00729	(-0.04)	0.0251	(0.12)
Equity market returns	-0.445*	(-2.36)	-0.369	(-1.92)
M2	0.135	(1.08)	0.116	(0.83)
M3	-0.0117	(-0.10)	0.0220	(0.17)
Domestic private sector credit	0.766***	(6.25)	0.833***	(6.39)
st_domcredit	-0.250	(-1.51)	-0.699***	(-3.36)
Government debt (% of GDP)	0.0642	(0.44)	-0.0686	(-0.47)
Gross liabilities of private sector	0.235*	(1.97)	0.593***	(4.73)
Gross national savings	0.608***	(4.07)	0.807***	(5.16)
Gross foreign liabilities	0.610***	(4.93)	-0.758***	(-5.22)
Net external position	-0.605***	(-4.96)	-0.577***	(-4.16)
Foreign debt/GDP	-0.337	(-1.54)	-0.00431	(-0.01)
Private residential fixed capital formation	1.433***	(7.52)	0.191	(0.94)
House price index	-0.0907	(-0.78)	-0.149	(-1.14)
Nominal aggregate asset price index	0.286	(1.82)	0.508**	(2.74)
Percentage change in industrial prod.	-0.0283	(-0.28)	0.0333	(0.32)
Private final consumption expenditure	-0.0500	(-0.46)	0.0492	(0.40)
Gross total fixed capital formation	0.0405	(0.37)	-0.100	(-0.78)
Industry share	0.501	(0.95)	0.348	(0.64)
Services share	0.578	(1.08)	0.204	(0.37)
Trade	-1.249***	(-6.74)	-1.587***	(-7.77)
Government consumption	-0.00288	(-0.03)	-0.0585	(-0.50)
Total tax burden	0.824***	(5.97)	0.660***	(4.11)
Current account	-0.0309	(-0.31)	-0.0970	(-0.87)
Trade balance	0.00648	(0.06)	-0.0758	(-0.63)
Real effective exchange rate index	-0.107	(-0.93)	0.0806	(0.70)
FDI inflows	-0.538***	(-4.07)	-0.188	(-1.35)
FDI outflows	0.256	(1.83)	0.902***	(5.20)
Terms of trade	-0.120	(-1.08)	0.274*	(2.31)
Global GDP	0.108	(0.79)	0.0457	(0.33)
Global trade	0.170	(0.87)	-0.0943	(-0.38)
Global inflation	0.0218	(0.18)	0.375**	(3.11)
Global credit	1.783	(1.90)	2.164*	(2.35)
Global domestic credit to private sector	-1.483	(-1.58)	-2.951**	(-3.16)
Global FDI, inflow	-0.656**	(-2.73)	-2.804***	(-7.86)
Global export prices	-0.198	(-1.82)	-0.250*	(-2.22)

Consumer price inflation	0.112	(0.94)	0.0455	(0.37)
Oil prices	-0.0865	(-0.65)	0.304	(1.85)
s1	-0.00723	(-0.03)	0.442	(1.48)
s2	0.0732	(0.31)	0.0929	(0.38)
s3	0.157	(0.55)	0.247	(0.82)
Observations	2611		2460	

Note: *t* statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *Dependent variable: binary, crisis incidence according to the literature; explanatory variables lagged by 8 and 12 quarters, respectively.*

ANNEX III: Early Warning Indicators for Crisis Incidence (groups, all lags)

	Fixed Effects		System GMM	
L4.Crisis Incidence Index	0.318***	(15.69)	0.389***	(9.88)
L8.Crisis Incidence Index	-0.231***	(-9.66)	-0.208***	(-5.91)
L12.Crisis Incidence Index	-0.107***	(-4.22)	-0.0705*	(-2.02)
L16.Crisis Incidence Index	-0.147***	(-6.53)	-0.0907**	(-2.88)
L4.Monetary policy stance	-0.122**	(-2.84)	-0.106	(-1.67)
L8.Monetary policy stance	0.00199	(0.04)	0.0253	(0.47)
L12.Monetary policy stance	0.0103	(0.21)	-0.00895	(-0.15)
L16.Monetary policy stance	0.132**	(2.81)	0.0980	(1.83)
L4.Interest rates	0.00355	(0.06)	-0.0546	(-0.52)
L8.Interest rates	0.0634	(0.80)	0.0568	(0.65)
L12.Interest rates	0.118	(1.49)	0.126	(1.15)
L16.Interest rates	0.0649	(1.02)	0.0109	(0.17)
L4.Banking system situation	0.0839	(1.66)	0.156*	(2.21)
L8.Banking system situation	-0.243***	(-3.61)	-0.271**	(-3.16)
L12.Banking system situation	0.115	(1.63)	0.107	(1.27)
L16.Banking system situation	0.0810	(1.33)	0.0973	(1.02)
L4.Capital market situation	-0.221***	(-7.41)	-0.255***	(-5.56)
L8.Capital market situation	-0.00321	(-0.10)	-0.0274	(-0.70)
L12.Capital market situation	-0.200***	(-6.03)	-0.221***	(-5.83)
L16.Capital market situation	-0.00291	(-0.09)	-0.000973	(-0.03)
L4.Money and credit	-0.137***	(-4.05)	-0.184***	(-3.87)
L8.Money and credit	0.0377	(0.94)	0.0307	(0.67)
L12.Money and credit	0.0421	(0.97)	0.0624	(1.10)
L16.Money and credit	0.153**	(3.28)	0.131*	(2.33)
L4.Debts and savings	-0.157*	(-2.51)	-0.167*	(-2.02)
L8.Debts and savings	0.158	(1.78)	0.154	(1.30)
L12.Debts and savings	-0.167	(-1.86)	-0.106	(-0.80)
L16.Debts and savings	0.0765	(1.17)	0.00920	(0.13)
L4.External debt	-0.349***	(-7.33)	-0.352***	(-3.31)
L8.External debt	0.344***	(6.38)	0.387**	(2.92)
L12.External debt	0.0824	(1.21)	0.0833	(0.60)
L16.External debt	0.0335	(0.44)	0.00996	(0.05)
L4.Housing prices	-0.346***	(-9.23)	-0.335***	(-4.62)
L8.Housing prices	0.00245	(0.06)	0.0693	(1.07)
L12.Housing prices	-0.0391	(-0.78)	0.0298	(0.32)
L16.Housing prices	-0.0258	(-0.53)	0.0206	(0.31)
L4.Real economy	-0.0410	(-0.64)	-0.114	(-1.12)
L8.Real economy	-0.0106	(-0.13)	-0.0435	(-0.51)
L12.Real economy	0.212*	(2.44)	0.177	(1.78)
L16.Real economy	0.139	(1.83)	0.140	(1.37)
L4.Fiscal stance	-0.0851	(-1.89)	-0.104*	(-2.04)
L8.Fiscal stance	-0.0171	(-0.32)	-0.00197	(-0.03)
L12.Fiscal stance	0.0112	(0.20)	0.0247	(0.35)
L16.Fiscal stance	0.105*	(2.00)	0.0912	(1.46)
L4.External balance	-0.0108	(-0.39)	-0.00633	(-0.13)
L8.External balance	-0.0370	(-1.13)	-0.0274	(-0.69)
L12.External balance	0.0718	(1.92)	0.0705	(1.57)
L16.External balance	0.114**	(2.97)	0.129*	(2.33)
L4.Global	0.137***	(3.77)	0.136*	(2.25)
L8.Global	-0.272***	(-6.06)	-0.288***	(-3.90)
L12.Global	0.0290	(0.55)	0.0328	(0.50)
L16.Global	0.114*	(2.56)	0.109*	(2.02)
L4.Inflation	-0.0886	(-1.25)	-0.0830	(-0.97)
L8.Inflation	0.115	(1.56)	0.156*	(2.09)
L12.Inflation	-0.0328	(-0.45)	-0.00387	(-0.05)

L16.Inflation	-0.0831	(-1.22)	-0.0689	(-0.98)
L4.Oil prices	0.109**	(3.14)	0.130***	(3.63)
L8.Oil prices	0.0703	(1.92)	0.0704	(1.61)
L12.Oil prices	-0.283***	(-3.85)	-0.294***	(-4.24)
L16.Oil prices	0.311***	(4.02)	0.267***	(4.31)
s1	0.555***	(4.82)		
s2	0.238*	(2.14)		
s3	0.139	(1.25)		
Constant	-0.367***	(-4.40)	-0.0680	(-0.59)
Observations	2916		2916	
Countries	37		37	
R-squared	0.447			

Note: *t* statistics in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Response variable: hp_cii. Groups are constructed as the first principal component of the underlying indicators.

ANNEX IV: Bayesian Model Averaging

IV.1 Methodology

Consider the following linear regression model:

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

where y is the dependent variable (the crisis incidence index in our case), 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:

$$p(M_\gamma \mid y, X) \propto p(y \mid M_\gamma, X) p(M_\gamma),$$

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:

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

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. (2001a), 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. Let m denote the model size, then

$m \sim Bin(K, \xi), \ \xi \sim \mathrm{Beta}(1, \frac{\mathrm{K - E(m)}}{\mathrm{E(m)}})$, where K is the number of regressors considered and ξ is the prior probability of including each variable. In order to get a completely flat model prior, we specify $E(m) = K/2$.

The robustness of the variable in explaining the dependent variables 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:

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

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 of interest for our sample of 50 explanatory variables in a quarterly panel of 40 countries over 1970–2010, 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.

Finally, to assess the quality of the BMA results, we perform the following frequentist check. As the baseline case, we select all variables with an inclusion probability that exceeds 50% based on the BMA exercise and run a regression model with fixed effects for the individual countries:

$$CII_{it} = \alpha_i + \beta CII_{it-4} + \gamma X_{ijt} + \delta S_{kt} + u_{it},$$

where CII denotes the crisis incidence index, CII_{it-4} denotes the value of the index observed four quarters ago, α_i denotes country dummies, S_k denotes seasonal dummies, u_{it} denotes normally distributed disturbances, *i* and *t* denote country and quarter subscripts, and X_j are potential warning indicators selected by BMA with lag length based on the panel VAR model discussed in Section 5.1. This specification can be thought of as a frequentist check of the BMA exercise: since we only select variables with an inclusion probability higher than 50%, all slope coefficients in the regression should be statistically significant. We also expect the signs of the estimated coefficients to be consistent with the posterior means reported by the BMA. The fixed-effects estimator is the obvious default choice for the panel data set at our disposal since the estimator takes into account unobserved individual country effects that do not change in time.

IV.2 Results

Table A1: Dynamic BMA with Exact Lags (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

Table A2: Dynamic BMA with Variables Lagged by 3 Years

	PIP	Post Mean	Post SD	Pos. Sign
Crisis Incidence Index				
hp_cii_L4	**1.000**	**0.209**	**0.017**	**1.000**
Monetary policy stance				
st_neer_L12	0.023	0.002	0.014	1.000
st_m1_L12	0.005	0.000	0.003	0.070
st_mmrate_L12	**0.995**	**0.326**	**0.085**	**1.000**
Interest rates				
st_lenrate_L12	**0.892**	**0.250**	**0.112**	**1.000**
st_deprate_L12	0.022	0.003	0.027	0.984
st_govtbond_L12	0.008	0.000	0.009	1.000
Banking system situation				
st_termspread_L12	0.007	0.000	0.007	0.047
st_debtcreditspread_L12	0.011	-0.001	0.008	0.017
st_bankcapratio_L12	0.055	0.003	0.015	1.000
st_bankliqratio_L12	0.007	0.000	0.005	1.000
st_nonperfloans_L12	**1.000**	**-0.246**	**0.042**	**0.000**
Capital market situation				
st_mktcap_L12	0.163	0.030	0.073	1.000
st_shareprice_L12	**0.959**	**-0.234**	**0.069**	**0.000**
st_equityreturns_L12	0.052	-0.011	0.052	0.000
Money and credit				
st_m2_L12	0.013	0.001	0.009	1.000
st_m3_L12	0.044	0.004	0.023	1.000
st_domprivcredit_L12	0.006	0.000	0.004	0.957
Debts and savings				
st_govtdebt_L12	**1.000**	**-0.304**	**0.053**	**0.000**
st_hhdebt_L12	0.005	0.000	0.004	0.000
st_netsavings_L12	0.014	0.003	0.028	0.942
st_grosssavings_L12	0.021	-0.003	0.031	0.000
External debt				
st_foreignliab_L12	**1.000**	**0.666**	**0.056**	**1.000**
st_nfa_L12	0.027	-0.002	0.013	0.000
st_foreigndebt_L12	0.011	0.001	0.008	1.000
Housing prices				
st_residcapform_L12	0.008	0.000	0.006	0.011
st_houseprices_L12	0.007	0.000	0.005	1.000
st_aggassetprices_L12	0.005	0.000	0.006	0.123
Real economy				
st_indprodch_L12	0.005	0.000	0.003	0.000
st_hhcons_L12	0.005	0.000	0.003	0.249
st_capform_L12	0.005	0.000	0.003	1.000
st_indshare_L12	0.005	0.000	0.004	0.612
st_servshare_L12	0.008	-0.001	0.009	0.000
st_trade_L12	0.006	0.000	0.005	0.064
Fiscal stance				

st_govtcons_L12	0.005	0.000	0.003	0.961
st_taxburden_L12	**0.624**	**0.064**	**0.055**	**1.000**
External balance				
st_curaccount_ifs_L12	0.006	0.000	0.004	1.000
st_trbalance_L12	0.006	0.000	0.004	1.000
st_reer_L12	0.033	0.003	0.017	1.000
st_fdiinflow_L12	0.454	0.064	0.076	1.000
st_fdioutflow_L12	0.013	0.001	0.010	0.989
Global variables				
st_termsoftrade_L12	0.106	0.012	0.039	1.000
st_wrgdp_L12	0.011	0.001	0.009	1.000
st_wtrade_L12	0.006	0.000	0.007	0.000
st_winf_L12	**1.000**	**0.584**	**0.059**	**1.000**
st_wcreditpriv_L12	**1.000**	**0.595**	**0.070**	**1.000**
st_wfdiinflow_L12	**1.000**	**1.440**	**0.081**	**1.000**
st_wexpprice_L12	0.284	0.048	0.082	1.000
Inflation				
st_inflation_L12	0.033	0.003	0.021	1.000
Commodity prices				
st_comprice_L12	**1.000**	**-0.408**	**0.079**	**0.000**

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

Figure A1: Inclusion of Variables in 1,000 Best Models in 3Year Lag Dynamic Specification

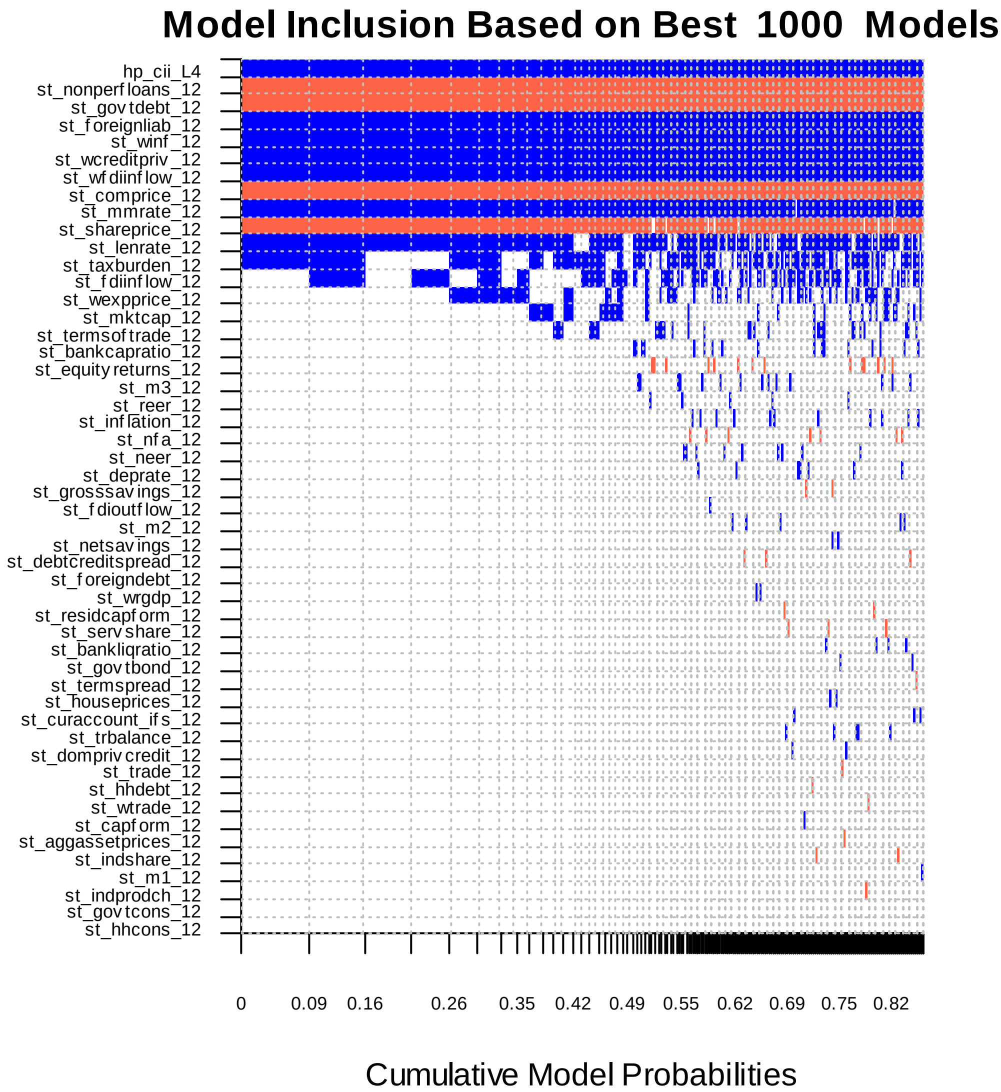


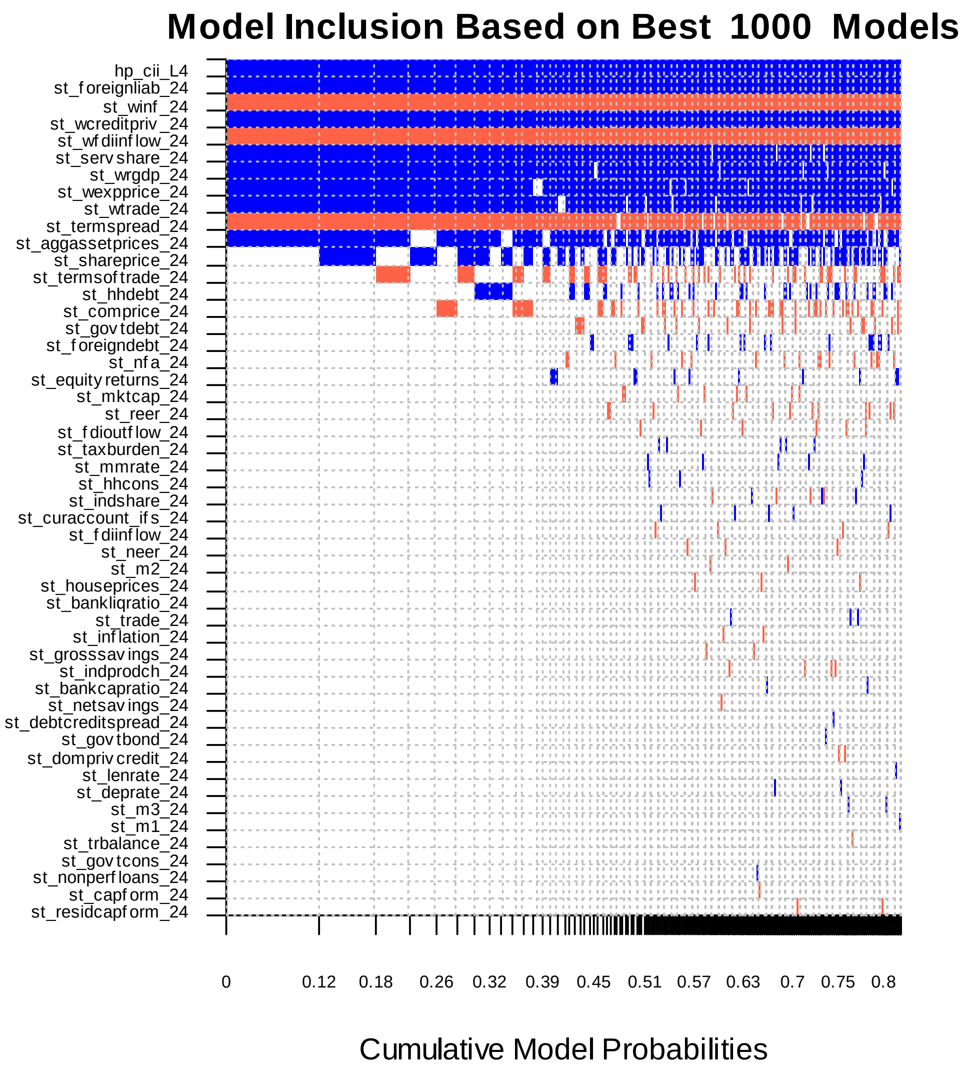
Table A3: Dynamic BMA with Variables Lagged by 6 Years

	PIP	Post Mean	Post SD	Pos. Sign
Crisis Incidence Index				
hp_cii_L4	**1.000**	**0.339**	**0.019**	**1.000**
Monetary policy stance				
st_neer_L24	0.011	-0.001	0.008	0.005
st_m1_L24	0.005	0.000	0.005	0.988
st_mmrate_L24	0.018	0.002	0.020	0.939
Interest rates				
st_lenrate_L24	0.006	0.000	0.007	0.983
st_deprate_L24	0.006	0.000	0.006	0.964
st_govtbond_L24	0.006	0.000	0.006	0.990
Banking system situation				
st_termspread_L24	**0.952**	**-0.176**	**0.059**	**0.000**
st_debtcreditspread_L24	0.007	0.000	0.005	1.000
st_bankcapratio_L24	0.007	0.000	0.003	1.000
st_bankliqratio_L24	0.009	-0.001	0.008	0.000
st_nonperfloans_L24	0.005	0.000	0.003	1.000
Capital market situation				
st_mktcap_L24	0.034	-0.006	0.038	0.000
st_shareprice_L24	0.462	0.127	0.154	1.000
st_equityreturns_L24	0.039	0.005	0.031	0.985
Money and credit				
st_m2_L24	0.010	-0.001	0.010	0.000
st_m3_L24	0.005	0.000	0.005	0.997
st_domprivcredit_L24	0.006	0.000	0.005	0.000
Debts and savings				
st_govtdebt_L24	0.063	-0.009	0.039	0.000
st_hhdebt_L24	0.184	0.033	0.076	1.000
st_netsavings_L24	0.007	0.000	0.008	0.026
st_grosssavings_L24	0.008	-0.001	0.009	0.001
External debt				
st_foreignliab_L24	**1.000**	**0.882**	**0.091**	**1.000**
st_nfa_L24	0.045	-0.005	0.025	0.000
st_foreigndebt_L24	0.050	0.006	0.028	1.000
Housing prices				
st_residcapform_L24	0.004	0.000	0.003	0.121
st_houseprices_L24	0.010	-0.001	0.010	0.001
st_aggassetprices_L24	**0.847**	**0.330**	**0.171**	**1.000**
Real economy				
st_indprodch_L24	0.008	0.000	0.006	0.000
st_hhcons_L24	0.018	0.001	0.013	1.000
st_capform_L24	0.004	0.000	0.004	0.109
st_indshare_L24	0.017	-0.003	0.028	0.306
st_servshare_L24	**0.986**	**0.357**	**0.087**	**1.000**

st_trade_L24	0.009	0.001	0.010	1.000
Fiscal stance				
st_govtcons_L24	0.005	0.000	0.003	0.830
st_taxburden_L24	0.020	0.001	0.009	1.000
External balance				
st_curaccount_ifs_L24	0.016	0.001	0.014	1.000
st_trbalance_L24	0.005	0.000	0.005	0.000
st_reer_L24	0.032	-0.003	0.018	0.000
st_fdiinflow_L24	0.014	-0.001	0.012	0.000
st_fdioutflow_L24	0.024	-0.003	0.019	0.000
Global variables				
st_termsoftrade_L24	0.251	-0.039	0.072	0.000
st_wrgdp_L24	**0.975**	**0.295**	**0.089**	**1.000**
st_wtrade_L24	**0.959**	**0.411**	**0.139**	**1.000**
st_winf_L24	**1.000**	**-0.594**	**0.059**	**0.000**
st_wcreditpriv_L24	**1.000**	**0.489**	**0.088**	**1.000**
st_wfdiinflow_L24	**1.000**	**-0.653**	**0.079**	**0.000**
st_wexpprice_L24	**0.968**	**0.259**	**0.082**	**1.000**
Inflation				
st_inflation_L24	0.009	-0.001	0.008	0.000
Commodity prices				
st_comprice_L24	0.175	-0.051	0.120	0.000

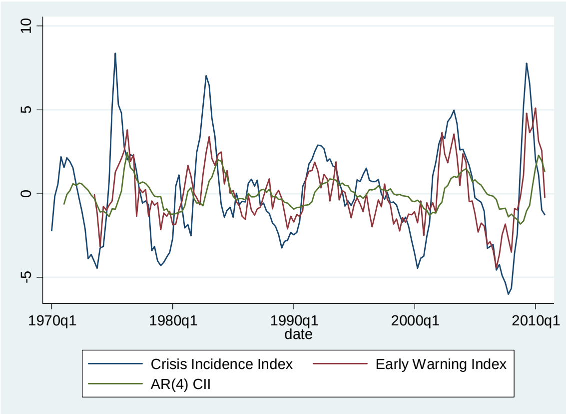
Note: Coefficients in bold type have posterior inclusion probability higher than 0.5

Figure A2: Inclusion of Variables in 1,000 Best Models in 6 Year Lag Dynamic Specification

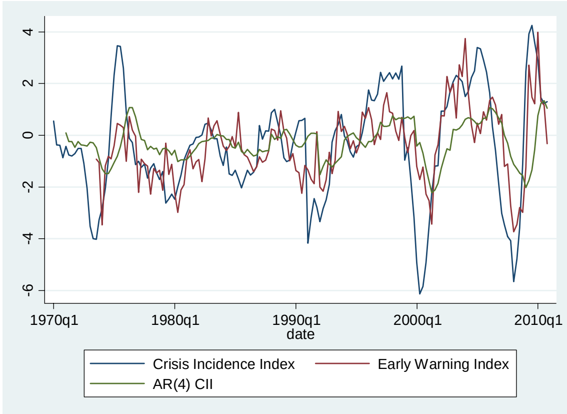


ANNEX V: Predicting Crisis Incidence: Model Performance

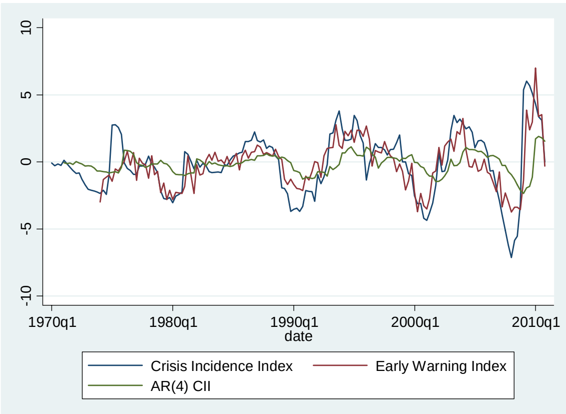
V.1 In-Sample Fit of Crisis Incidence Index, Selected Countries



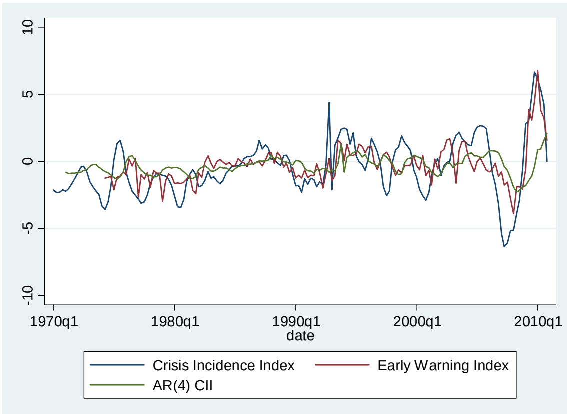
United States



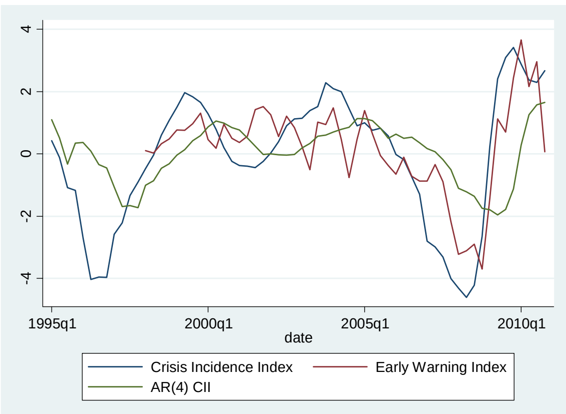
Germany



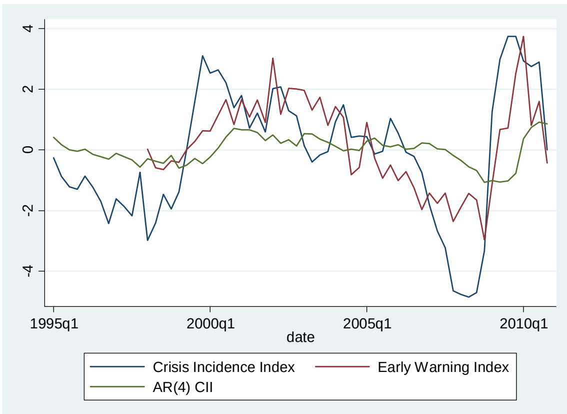
France



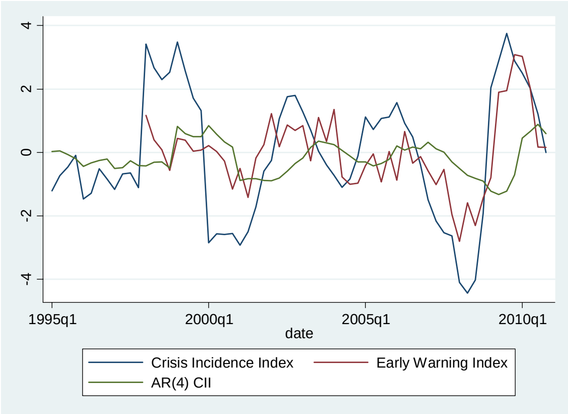
Italy



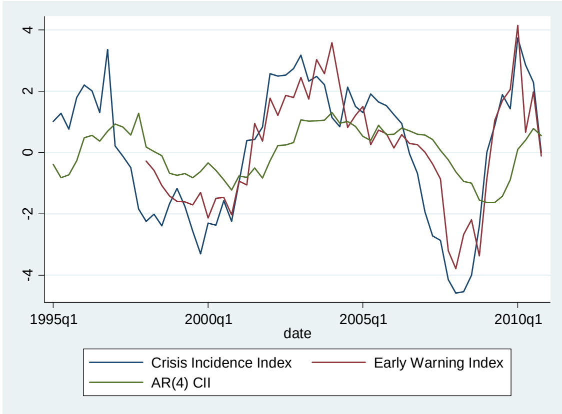
Czech Republic



Slovakia

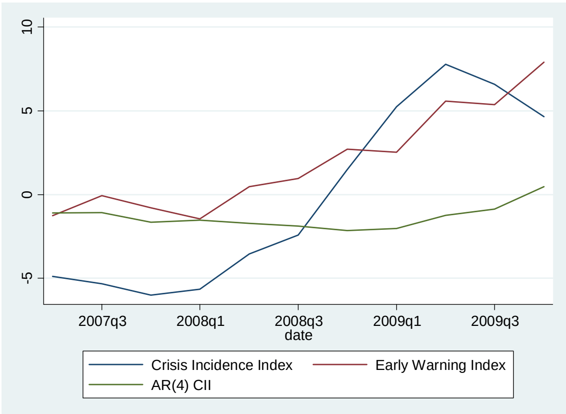


Hungary

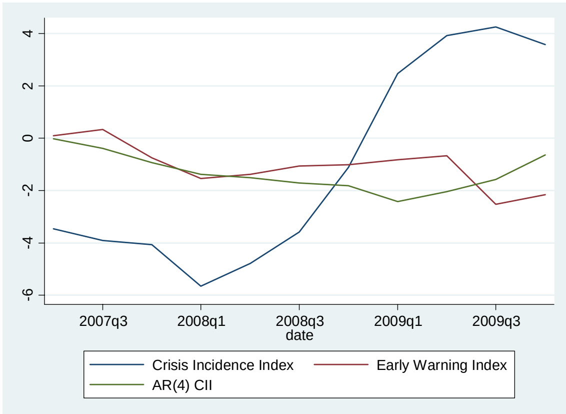


Poland

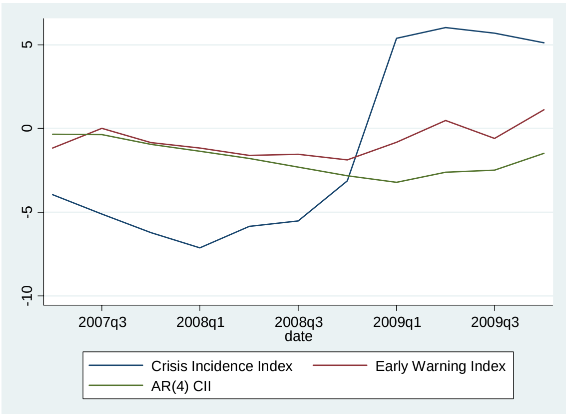
V.2 Out-of-Sample Fit of Recent Crisis, Selected Countries



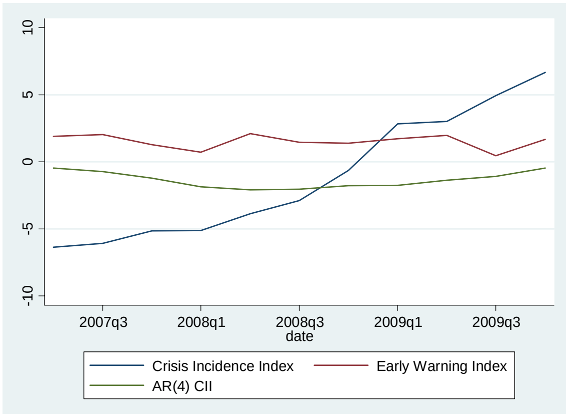
United States



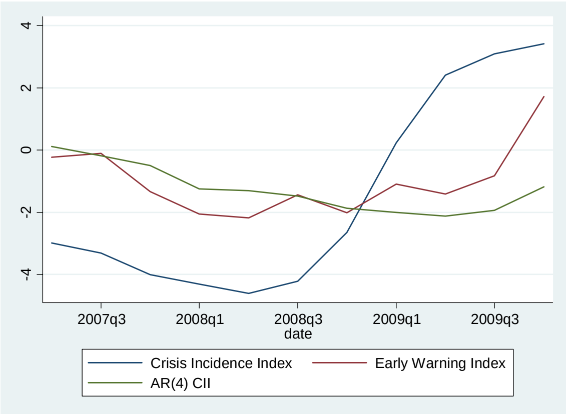
Germany



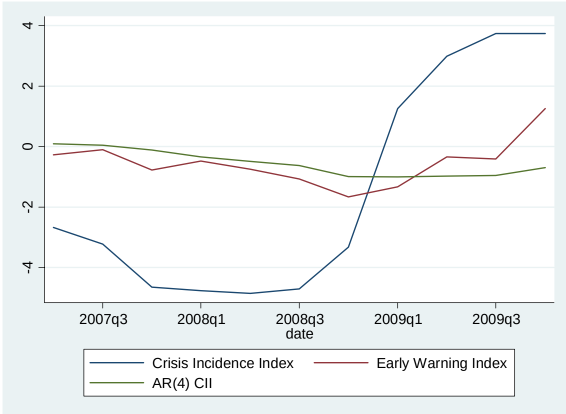
France



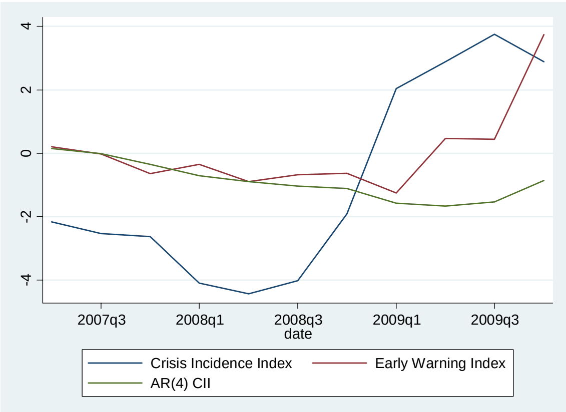
Italy



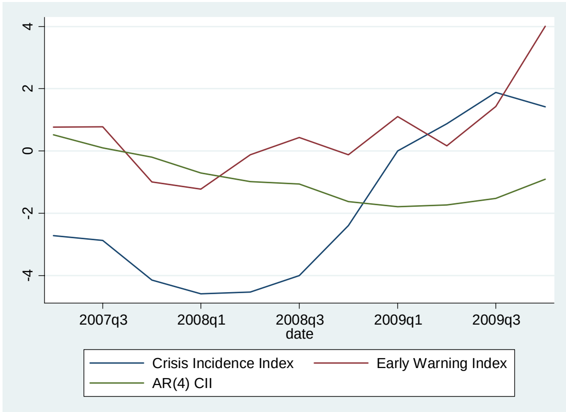
Czech Republic



Slovakia



Hungary



Poland

ANNEX VI: 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 (COI):

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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