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Did Established Early Warning Signals Predict the 2008 Crises?*

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Abstract

Over the past 60 years, a voluminous literature has painstakingly developed theories and associated candidate regressors to motivate Early Warning Signals of economic crises. The hallmark of this literature is the remarkable consistency with which selected Early Warning Signals are thought to predict different types of crises across countries and time. The diversity of theories motivating Early Warning Signals presents a challenge to empirical implementations. If the true model of Early Warning Signals is unknown, omitted variable bias contaminates estimates and *model uncertainty* inflates confidence levels since the uncertainty surrounding a particular theory has not been ignored. Addressing model uncertainty in Early Warning Signal regressions, we find no single Early Warning Signal that can successfully alert to all dimensions of the 2008 crisis. Instead, different types of crises are identified by economically meaningful but distinctly different sets of Early Warning Signals. The paper discusses the relevance of identified Early Warning Signals associated with four different types of crises (Banking, Balance of Payments, Exchange Rate Pressure, and Recessions).

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1. Introduction

Over the past 60 years, a voluminous literature established a set of Early Warning Signals to alert countries of impending economic crises. The hallmark of this literature is the remarkable robustness of select Early Warning Signals across time, countries, and types of crises.[1] Frankel and Saravelos (2011) provide a survey of 83 studies and report that currency reserves and exchange rate overvaluations are such useful Early Warning Signals that "the consistency of these results is impressive." The consistency is indeed remarkable as these Early Warning Signals are thought to be robust across different country subsamples (developed, emerging, and developing), time periods (1950s-2011s), and crises types (banking, currency, debt, equity, and inflation).

The remarkable robustness and consensus of the Early Warning Signals literature is surprising since dozens of alternative crisis theories have been proposed to motivate a vast number of potential signals. Statisticians refer to the uncertainty surrounding the validity of a particular theory as *model uncertainty.* Raftery (1995) shows that model uncertainty inflates confidence levels when the uncertainty surrounding a theory's validity has been ignored. Leamer (1978) and Raftery (1988) develop the appropriate statistical framework, Bayesian Model Averaging (BMA), to address model uncertainty as part of the statistical methodology. BMA can then be applied to simultaneously evaluate the validity of alternative theories and their associated candidate regressors.

In this paper we apply BMA to a prominent and comprehensive crisis dataset, which features the greatest coverage of countries and regressors to date. We employ the approach to examine the robustness of consensus Early Warning Signals, using the yardstick of the 2008 crisis. Aside from the interest for policy makers, there are a number of reasons why the 2008 crisis is particularly well suited to assess the validity of consensus Early Warning Signals. First, the magnitude of the crisis should evoke strong predictive power for any valid Early Warning Signal. Second, the crisis has been

[1] For comprehensive surveys, see Kaminsky, Lizondo and Reinhart (1998), Hawkins and Klau (2001), Abiad (2003), and Frankel and Saravelos (2011). Frankel and Saravalos (2010, Appendix 1) also highlight not only the diversity of previous theories and their empirical approaches, but also the staggering variety of criteria used to evaluate the importance of Early Warning Signals. For example, criteria used to identify "significant variables" range from out-of-sample prediction to statistical significance of a regressor in a researcher-specified fraction of regressions run.

uniquely broad and synchronized across the global economy. This provides a unique test whether Early Warning Signals exist that alert for different or all subsets of countries and crises.

Early studies do not produce evidence that conventional Early Warning Signals managed to predict the 2008 crisis. Obstfeld, Shambaugh, and Taylor (2009a,b) find that reserves/M2 predicted depreciations, but established Early Warning Signals were shown to be statistically insignificant. Rose and Spiegel (2009a,b), and also Blanchard et al. (2009) found that even reserves did not serve as Early Warning Signals for the 2008 crisis. In contrast, Frankel and Saravelos (2011) do uncover that reserves/debt and exchange rate appreciations are useful Early Warning Signals of the 2008 crisis. They surmise that their extended time series provided the necessary power. In sharp contrast to these early approaches, Frankel and Saravelos (2011) utilize only Early Warning Signals that had been suggested by the previous 60 years of crisis literature. The usefulness of Early Warning Signals can be questioned when they have been selected with hindsight.

The Frankel Saravelos methodology could be considered controversial, however, since it relies on bivariate regressions that are subject to substantial omitted variable bias. For robustness the authors also include per capita GDP in each, now trivariate, regression and their Table 3 features one set of multivariate regressions which consider a maximum of 5 (of their 57) candidate regressors. Another important feature of the Frankel and Saravelos dataset is the number of missing observations. Hence each bivariate regression actually identifies Early Warning Signals for different subsamples of countries.

BMA resolves omitted variable bias and eliminates the effects of model uncertainty that can inflate significance levels in bivariate and misspecified multivariate regressions. Using Frankel and Saravelos’ (2011) dataset that we updated and augmented for missing observations, we find no evidence that any one Early Warning Signal predicts the various dimensions of the 2008 crises. In contrast to previous studies of 2008 Early Warning Signals, however, we do indeed find that each dimension of the 2008 crisis is identified by a unique, parsimonious set of Early Warning Signals.

The paper is structured as follows. Section 2 reviews the BMA methodology and justifies its application, Section 3 motivates each Early Warning Signal employed in our analysis in terms of prior use and theory motivation, Section 4 provides the data sources, and Section 5 presents results and assessments that are relevant for policy makers in light of the past literature.

2. Uncovering Early Warning Signals Using Bayesian Model Averaging

Previous methodological approaches to assessing Early Warning Signals are dominated by researcher selected regression specifications that can be grouped into four categories (see Abiad, 2003; Hawkins and Klaw, 2000; Collins, 2003; and Frankel and Saravelos, 2011). One approach uses probit/logit techniques when crisis dedicators involve incidence thresholds (first popularized by Eichengreen, Rose and Wypslosz, 1995). Alternatively, non-parametric signaling approaches are used to identify crises via threshold values for sets of hand-picked Early Warning Signals (first popularized by Kaminski, Lizondo and Reinhart, 1998). A third approach is to split the sample into researcher-selected crisis and non-crisis countries (see Kamin, 1988).

Recent approaches use alternative statistical methods to identify thresholds for Early Warning Signals, via regression trees (Ghosh and Ghosh, 2002), artificial neural or genetic algorithms (Nag and Mitra, 1999), and Markov switching models (Cerra and Saxena, 2001). None of these approaches consider, however, that either the researchers-specified set of regressions or the researcher-selected regression trees examine only models that arise from theories whose validities are uncertain. The second limitation of previous statistical methodologies is the lack of a clear selection criterion to identify robust Early Warning Signals. Some studies identify valid Early Warning Signals as those regressors that are significant in at least one of their regressions (e.g., Kaminsky, Lizondo and Reinhart, 1998), while others identify valid Early Warning Signals as those that are significant in the majority of regressions (e.g., Frankel and Saravelos, 2011).

In this section we briefly sketch the basic ideas of Bayesian Model Averaging, BMA, following the exposition in Eicher, Papageorgiou and Raftery (2011). For a complete survey of BMA approaches, see Raftery, Madigan and Hoeting (1997). BMA bases prediction and inference not on one particular model, but on a weighted average over all the models and theories considered. The approach has the attractive feature that it directly addresses questions that are central to the researcher's interests, such as “what is the probability that a model is correct?” and “how likely is it that a regressor has an effect on the dependent variable?”

For linear regression models, the basic BMA setup is as follows. Given a dependent variable, *Y*, a number of observations, *n*, and a set of candidate regressors, $X_1,\ldots,X_p$, the variable selection problem is to find the “best” model, or subset of regressors. We denote by $M_1,\ldots,M_K$ the models considered, where each one represents a subset of the candidate regressors. Often all possible subsets are considered, in which case $K = 2^p$. Model M_k has the form

$$Y = \alpha + \sum_{j=1}^{p_k} \beta_j^{(k)} X_j^{(k)} + \varepsilon, \tag{1}$$

where $X_1^{(k)},\ldots,X_{p_k}^{(k)}$ is a subset of $X_1,\ldots,X_p$, $\beta^{(k)} = (\beta_1^{(k)},\ldots,\beta_{p_k}^{(k)})$ is a vector of regression coefficients to be estimated, and $\varepsilon \sim N(0,\sigma^2)$ is the error term. We denote by $\theta_k = (\alpha, \beta^{(k)}, \sigma)$ the vector of parameters in M_k.

The likelihood function of model M_k, $pr(D \mid \theta_k, M_k)$, summarizes all the information about θ_k that is provided by the data, D. The *integrated likelihood* (also commonly known as the marginal likelihood) is the probability density of the observable, conditional on the model M_k, which equals the likelihood times the prior density, $pr(\theta_k \mid M_k)$, integrated over the parameter space so that

$$pr(D \mid M_k) = \int pr(D \mid \theta_k, M_k)\, pr(\theta_k \mid M_k)\, d\theta_k. \tag{2}$$

The integrated likelihood is the crucial ingredient in deriving each model’s weight in the model averaging process. We denote by $pr(M_k)$ the prior probability that M_k is the correct model, given that one of the models considered is the true model. Then, by Bayes's theorem, the *posterior model probability* of M_k, $pr(M_k \mid D)$, is equal to the model's share in the total posterior mass,

$$pr(M_k \mid D) = \frac{pr(D \mid M_k)\, pr(M_k)}{\sum_{\ell=1}^{K} pr(D \mid M_\ell)\, pr(M_\ell)}. \tag{3}$$

The posterior mean and variance of a regression coefficient, β_j, are then given by

$$E[\beta_j \mid D] = \sum_{k=1}^{K} \hat{\beta}_j^{(k)}\, pr(M_k \mid D), \tag{4}$$

$$Var[\beta_j \mid D] = \sum_{k=1}^{K} \left(Var[\beta_j \mid D, M_k] + (\hat{\beta}_j^{(k)})^2 \right) pr(M_k \mid D) - E[\beta_j \mid D]^2, \tag{5}$$

where $\hat{\beta}_j^{(k)}$ is the posterior mean of β_j under model M_k, and is equal to zero if X_j is not included in M_k (Raftery, 1993). Hence the posterior mean is the weighted average of all model-specific posterior means, where the weights equal each model's posterior probabilities. The posterior variance reflects both the weighted average of the within-model posterior variances as well as the between-model variation of the posterior means.

The BMA posterior means and variances highlight that when inference is conditioned on a single model, the between-model variation is ignored. Thus a single model overestimates the certainty with which its results may actually reflect the true model's parameters. In a decision-making context, such an oversight leads to decisions that are riskier than the decision-maker thinks they are. BMA incorporates model uncertainty into the posterior distribution itself, and thus allows the uncertainty itself to be propagated through to final conclusions.

In addition to the posterior means and standard deviations, BMA provides the posterior inclusion probability of a candidate regressor, $pr(\beta_j \neq 0 \mid D)$, by summing the posterior model probabilities across those models that include the regressor. Posterior inclusion probabilities provide a probability statement regarding the importance of a regressor that directly addresses what is often the researcher's prime concern: "what is the probability that the regressor has an effect on the dependent variable?" The general rule developed by Jeffreys (1961) and refined by Kass and Raftery (1995) stipulates effect-thresholds for posterior inclusion probabilities. Posterior inclusion probabilities < 50% are seen as evidence against an effect, and the evidence for an effect is either weak, positive, strong, or decisive for posterior inclusion probabilities ranging from 50-75%, 75-95%, 95-99%, and > 99%, respectively. In our analysis, we refer to a regressor as "effective," if its posterior inclusion probability exceeds 50%.

Since BMA averages over all models considered, the model space may be a very large quantity. For example, in this paper we consider a crisis dataset with 57 regressors which implies 2^{57} candidate models. Such a vast model space poses a computational challenge such that direct evaluation is typically not feasible. The branch-and-bound algorithm of Furnival and Wilson (1974) is guaranteed to find the single best model contained in the data. The algorithm can be accelerated by employing Yeung, Bumgarner, Raftery's (2005) Iterative BMA (IBMA) refinement, as we do in this application. IBMA utilizes the Unit Information Prior for parameters and a uniform model prior assuming that, *ex ante*, each model is equally likely. In this application we consider a Unit Information Prior (UIP; Raftery, 1995) for parameters and a uniform prior for each model. Eicher et al. (2011) show that UIP provides excellent predictive performance. The uniform model prior is the most commonly used prior for applications where the true model size is unknown.

3. Dimensions of Crises and Early Warning Signal Candidate Regressors

3.1 The Early Warning Signal Dataset

The dataset used in our estimation is an updated and modified version of the Frankel and Saravelos' (2011) dataset, which includes 57 annual macroeconomic and financial independent variables and four dependent variables. It is crucial to note that all independent variables predate 2008 to minimize endogeneity issues. The main underlying data sources are the World Bank's *World Development Indicators* (World Bank, 2009), the IMF's *International Financial Statistics* (IMF, 2009), and the updated Klein and Shambaugh (2006) measure of exchange rate regimes, and the Chinn and Ito (2008) measure of financial openness updated to 2007. Data availability in Frankel and Saravelos (2011) differs dramatically, ranging from 217 countries with export data, to 72 countries with equity return data. The dataset is unbalanced, so that Frankel and

Saravelos' (2011) full model (with all possible regressors) would only feature 7 observations.

We updated the original Frankel and Saravelos dataset using the most recent 2011 World Development Indicators, International Financial Statistics, and IMF data to obtain a balanced panel of 93 countries. The data updates were important, for example, US GDP growth changes from -3.82% (in Frankel and Saravelos' dataset) to -5 % by November 2011, due to successive downward revisions of US GDP by the Bureau of Economic Analysis. Such revisions were common for many variables in several countries. This indicates the severe instability in forecasting and reporting by national statistics offices in the months preceding the global financial crises. All variables are normalized to a dimensionless *standard score* by subtracting the variable mean from each individual raw score and then dividing the difference by the variable's standard deviation.

3.2 Dimensions of the Crises

The Early Warning Signal literature commonly features a narrow set of dependent variables that are employed to identify the intensity, incidence, and economic dimension of a crisis. Balance of payment crises are usually proxied with a dummy that indicates whether an IMF facility was accessed. Alternatively, variations in nominal or real exchange rates against the US dollar or SDR are used,[2] and more general measures include exchange market pressure indices which combine exchange rates, reserves, and/or interest rates.[3] Banking crises have been identified using a range of regressors that reflect the health of the financial system, such as liquidity or leverage ratios.[4]

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[2] E.g., Edwards (1989); Frankel and Rose (1996); Bruggemann and Linne (1999); Osband and Rijckeghem (2000), Goldfajn and Valdes (1998); Esquivel and Larrain (1998); Apoteker and Barthelemy (2000), Rose and Spiegel (2009a, b).

[3] E.g., Sachs, Tornell and Velasco (1996a,b); Corsetti, et al. (1998); Fratzcher (1998); Kaminsky, Lizondo and Reinhart (1998); Berg and Pattillo (1999a, b); Tornell (1999); Bussiere and Mulder (1999, 2000); Collins (2003); and Frankel and Wei (2005), Eichengreen, Rose and Wyplosz (1995); Herrera and Garcia (1999); Hawkins and Klau (2000); Krkoska (2001); Frankel and Saravelos (2011).

[4] Demirguc-Kunt and Detragiache (2005), Davis and Karim (2008), Kaminsky and Reinhart (1999), Borio and Lowe (2002), Borio and Drehmann (2009), Duttagupta and Cashin (2008), Karim (2008), Davis and Karim (2008), and Barrell, Davis, Karim and Liadze (2009).

Equity and output contractions are straightforwardly proxied with changes in GDP or stock prices.[5] Below we examine which of the established Early Warning Signals identify countries that experienced larger output contractions, more severe balance of payments crises, banking crises, or required IMF support as lender of last resort. While some approaches use these Early Warning Signals in conjunction with thresholds,[6] we focus on continuous measures that produce results that are insensitive to particular researcher-specified crisis-threshold definitions.

3.3 Candidate Regressors for Early Warning Signals

The theoretical and empirical literature on economic crises has been succinctly summarized by Frankel and Saravelos (2011) in the most expansive survey to date. They survey 83 empirical approaches and motivate each potential Early Warning Signal in minute detail that we use below. Since we use the Frankel and Saravelos data, we provide only a short overview of the key areas that motivate the specific Early Warning Signals that are included in our dataset. The multitude of candidate theories and regressors highlight the associated model uncertainty. The regressors cover 3 broad categories: external imbalances; institutions; and size/size, income, and income/GDP growth.

Krugman's (1979) seminal paper on balance of payments crises provided the impetus for a voluminous literature that focuses on weak economic fundamentals, for example, unsustainable fiscal or monetary policies. Such policies then result in unsustainable losses in reserves accompanied by excessive growth in domestic credit. The credit growth could also result in the need to finance excessive fiscal deficits or debt imbalances. Extensions of Krugman's framework suggest that unsustainable fiscal and monetary policies can also lead to excessive demand for traded goods, causing deteriorations in the trade balance and real appreciations to foreshadow balance of payments crises.

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[5] E.g., Ghosh and Ghosh (2002), and Grier and Grier (2001).

[6] E.g., Frankel and Rose (1996) define "currency crashes" as a 20% nominal exchange rate depreciation that also exceeds the previous year's depreciation by least 10%; while Eichengreen, Rose and Wyplosz (1995), define "exchange market crises" as two standard deviation movements of a speculative pressure index.

To capture such factors, our dataset includes 20 detailed balance of payments measures, and two measures of Real Effective Exchange Rate changes (defined such that increases indicate appreciations) over five and ten years, as well as reserve movements (reserves as a percent of GDP, as well as the change and level of reserves in US$). In addition, the dataset features information on nine regressors that cover fiscal deficits, public debt, as well as monetary policy covering money supply, and interest rates (all variables and their sources are presented in Appendix 1).

Theories relating to domestic and international debt crises focus on a country's regulatory policies and on the determinants of fragility in the banking system (see De Gregorio, 2009). For banking crises, Cecchetti (2008) highlights the importance of the composition of banks' balance sheets when foreign or domestic funds dry up due to contagion, country risk, or global crisis. Demirguc-Kunt and Detragiache (1998) suggest banking crises may also be caused by macroeconomic variables such as slow real GDP growth, terms of trade deteriorations, and domestic real credit growth. All of these factors are thought to undermine economic fundamentals to negatively impact bank liquidity. To proxy for these effects we also include seven measures of credit growth, the quality of credit information, and banking fragility.

Acemoglu, et al. (2003) also document that weaknesses in countries' general institutional environments can increase macroeconomic volatility. To control for institutional differences, we include 3 indices that address the quality of countries' legal frameworks, their openness to capital flows, and their quality of disclosure in business and financial transactions. Montiel and Reinhart (1999) argue that openness to capital flows is especially important in liquidity crises. While openness can assist foreign borrowing necessary to finance domestic bottlenecks, it can also lead to excessive capital flow reversals when hot money exits a country due to, for example, contagion. For example, Diaz and Alejandro (1985) and Velasco (1987) model difficulties in the banking sector as giving rise to balance of payments crises. They argue that central banks' bail-outs of troubled financial institutions could be financed by printed money, causing a classical currency crash prompted by excessive money creation.

Several theories of economic crises suggest country size and income levels as important determinants. Smaller countries can experience exceptional growth, capital inflows, or credit expansion relative to the size of their financial sectors or GDPs. Size also correlates with openness, as smaller countries are usually more open (as suggested by optimal tariff arguments) and thus relatively more exposed to fluctuations in world trade. In addition, smaller countries lack the ability to provide extensive government assistance in times of crisis, see (e.g. Reinhart and Reinhart, 2009). Calomiris and Gorton (1991) point out those recessions can precede banking crises, especially when output contractions follow periods of high credit growth. Hence we include 5 different measures of GDP, per capita GDP, as well as credit growth to proxy for these theories.

4. Empirical Support for Early Warning Signals

We examine Early Warning Signals for 4 different dimensions of the 2008 crisis a) banking crises, b) balance of payments crises, c) ecessions, and d) exchange rate crises. As outlined in the previous section, all candidate Early Warning Signals employed have been motivated by past theoretical approaches and empirical implementations. Early Warning Signals have previously been identified as “robust” when they effectively alerted to all different crisis dimensions.

Our indicator for banking crises is the ratio of banks’ liquid reserves to assets from the World Development Indicators. Balance of payments crises are identified by IMF programs that are termed Stand By, Exogenous Shocks, and/or Poverty Reduction and Growth facilities. GDP contractions are proxied simply by the real 2008 growth rate. Exchange rate crises are given by the Frankel and Saravelos’ Foreign Exchange Market Pressure Index from August 2008 to March 2009, which measures combined changes in exchange rates and international reserves. Following Eichengreen, Rose and Wyplosz (1995), the index is a weighted average of exchange rate and reserve changes, where the weights are the inverse of the relative standard deviation of each series to compensate for differences in volatilities. Our BMA results are presented in Table 1.

4.1 Early Warning Signals for Balance of Payments Crises

The incidence of balance of payment crises is proxied by country access to IMF programs. This measure indicates not only the incidence of a crisis, but also whether a country requested access and received IMF approval. The advantage of this indicator is that it measures balance of payment crises narrowly, since IMF Articles of Agreement require justification only in terms of adverse developments in the balance of payments. Strictly speaking, a country facing a pure debt or banking crisis should not access IMF financing. Since there exist potentially significant time lags between crisis incidence and IMF program approval, we included all programs approved through 2011. Coverage of the global sample is important for this indicator, since the recent crisis produced programs for advanced countries that had not accessed IMF credit for decades.

BMA identifies three Early Warning Signals for balance of payments crisis: high inflation, low reserves, and trade deficits are shown to predict the incidence of IMF programs during the 2008 crisis. All of these are key variables of macroeconomic imbalances and external weakness that tend to be a focus of IMF programs, so their presence is not surprising. Surprising is perhaps how parsimonious the regressors are that predict balance of payment crises.

4.2 Early Warning Signals of Recessions

The regressions linking real GDP contractions to Early Warning Signals clearly highlight that the most dramatic output contractions occurred in high income countries. BMA indicates that high income countries were more likely to have more dramatic output contractions. Crucial in determining the magnitude of the recessions was also the size of the current account deficit in 2007, as well as the change in the current account surplus in the previous 5 years. The former is easier to interpret than the latter. Large trade deficits are difficult to finance in times of illiquid international credit, which could lead to recessions. BMA also indicates, however, that countries which experienced greater improvements in their current accounts in the previous 5 years were also more likely to experience larger recessions. The explanation here could be that the trade credit collapse exerted a greater impact on countries that had recently relied relatively more heavily on export growth in the recent past.

Along with the external balance, the rise in domestic credit in the 5 years preceding the crisis is also identified as a crucial determinant of the magnitude of recessions. The results suggest that a greater run up in credit generates more severe recessions. Marginally important regressors are inflation and reserves. Higher inflation (as measured by the GDP deflator) and a reduction in the level of reserves are shown to exert a weak effect on predicting recessions. Curiously, we also find that countries that increased reserves more dramatically during the crisis experienced sharper recessions. This may indicate that some countries' austerity measures, designed to protect or even increase FX reserves, may have led to larger recessions along the lines of Keynes paradox of thrift. Note that thus far there is zero overlap between determinants of recessions or IMF programs, suggesting little hope of finding a "robust" Early Warning Signal, one that predicts all different types of economic crises.

4.3 Early Warning Signals of Exchange Rate Crises

The exchange rate crisis indicator was constructed by Frankel and Saravelos (2011) for August 2008 to March 2009 following the Eichengreen, Rose and Wyplosz (1995) methodology. To capture crises in both fixed and flexible regimes and taking into account that IMF programs provide reserves in times of crisis, the FX pressure index measures the weighted average of the change in the exchange rate and reserves. The weights are determined by (the inverse) relative standard deviations of each series in order to compensate for differences in volatilities. A higher index captures a lower crisis incidence, since it indicates a stronger exchange rate and/or larger reserve accumulations.

As expected, a number of candidate regressors straightforwardly related to the external sector have strong influence on FX pressure. A depreciating real effective exchange rate (measured over the prior 5 years), lower remittances, and larger trade deficits all increase FX pressure. More interesting is the finding that lower bank liquidity-to-asset ratios also increase FX pressure, as do lower levels of domestic credit. Of secondary importance, exerting weak to moderate effects on FX pressure, are higher rates of inflation (as measured by the GDP deflator) and per capita GDP. The latter indicates once again that richer countries were those primarily impacted by the FX crisis. Note that again, with the exception of the GDP deflator, none of the Early Warning Signals that predict FX pressure overlaps with Early Warning Signals that predict other dimensions of crises.

4.4 Early Warning Signals of Banking Crises

Certainly the start of the 2008 crisis is closely related to the failures of the investment houses of Bear Sterns and Lehman Brothers. The questionable values of US toxic housing assets became quickly apparent, which reduced interbank market liquidity and credibility. Frankel and Saravelos (2011) suggest the key indicator that relates to banking crises: a country's bank liquid reserves to bank assets ratio. The indicator reports the ratio of domestic currency holdings and deposits with the monetary authorities to claims on other governments, nonfinancial public enterprises, the private sector, and other banking institutions as reported by the World Development Indicators. A lower liquidity to asset indicator is thought to reflect higher risk of banking crisis.

BMA reports the largest set of indicators for the bank liquidity ratio with 9 effective Early Warning Signals. Four Early Warning Signals can only be termed weakly effective, however, while two are decisive. The risk of a banking crisis was clearly elevated in high income countries (e. g., high per capita GDP, high and low income variables, as well as the Sub-Saharan Africa Dummy). With the collapse of trade credit, countries that relied heavily on goods exports also were at greater risk of banking crises, while relatively larger service exports as a per cent of GDP insulated countries from banking crises. Not surprisingly, lack of financial openness is also associated with a greater risk of a banking crisis.

One initially puzzling result from the BMA estimation suggests that higher rates of inflation in the 5 years prior to 2008 are associated with "lower risk" of banking crisis, in the sense that higher inflation produced higher liquidity to asset ratios. This may be an artifact of basic banking principles, where higher rates of inflation reduce incentives to lend, leading to a relative reduction of illiquid assets, which artificially inflates the ratio of liquid to non liquid assets. With fewer funds committed to rather illiquid investments, to minimize the impact of high inflation, banks are better prepared for liquidity crises.

5. Conclusion

To establish a direct comparison to the previous literature, we employ an identical set of Early Warning Signals that had been suggested by Frankel and Saravelos (2011). Indeed we utilize the same dataset with two important modifications. First, we update the dataset taking into account national, World Bank, and IMF data revisions. Second, we construct a balanced dataset where each regression covers the same sample of countries. The updated dataset is then utilized using Bayesian Model Averaging to address missing and omitted variable bias and address model uncertainty as part of the empirical strategy.

In contrast to the early 2008 crisis literature, which stipulated that none of the established Early Warning Signals existed for this particular crisis, we find that each dimension of the 2008 crisis is well identified by sets of parsimonious and distinct Early Warning Signals. This is important because it provides credence to the 60 year old literature that had been called into question when a number of studies did not find any indicators to alert countries of impending economic crises. This is primarily because BMA discovered and made use of better models than the single frequentist regressions run by the existing literature. The models that are shown to receive the greatest support from the data identify Early Warning Signals that surpassed high effect thresholds.

In contrast to the Frankel and Saravelos (2011) results, we cannot confirm a set of Early Warning Signals that alerted countries to all dimensions of the 2008 crisis. We can only surmise that our results differ from Frankel and Saravelos for 3 important reasons. First, Frankel and Saravelos rely on bivariate regressions that are subject to omitted variable bias. Second, Frankel and Saravelos regressions contain different subsamples of countries in each regression. This could imply that each Early Warning Signal actually alerts to crises in different subsets of countries. Third, Frankel and Saravelos do not account for model uncertainty, effectively stipulating that each of their bivariate regression is the true model, without a mechanism to juxtapose the performance of alternative models and theories. Once model uncertainty and omitted variable bias are addressed, parsimonious sets of Early Warning Signals identify each dimension of the 2008 crisis in the global sample. However, no one regressor can be identified as an Early Warning Signal for all dimensions at the same time.

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Table 1

	Balance of Payments		**GDP Growth**		**FX Pressure**		**Banking Crisis**	
	Incl. Prob	**Post. Mean**	**Incl. Prob**	**Post. Mean**	**Incl. Prob**	**Post. Mean**	**Incl. Prob**	**Post. Mean**
xgoodsgdp							**96.7**	-0.754
cpiavlast5years	**100**	1.362					**95.8**	0.382
subsaharan							**80.6**	-0.204
gdppercapitapppcurrentusd			na	na	**66.9**	-0.292	**79.7**	-0.465
xgservicegdp							**73.8**	0.669
lowincome			**100**	0.310			**57.7**	0.146
reserves_perc_gdp_constr	**82.6**	-1.360					**57.4**	0.147
financiallyclosed							**53.8**	-0.111
cpi2007							**51.7**	-0.275
Domesticcredittotal_pct_gdp					**100**	0.568		
remittancesreceived_pct_gdp					**100**	0.499		
reer5yr					**100**	-0.320		
tradebalance_pct_gdp	**62.1**	-0.805			**99.2**	0.548		
bankliquidrestoass					**96.3**	0.310	na	na
gdpdeflator_pct_annual			**54.4**	-0.102	**79.7**	-0.215		
upperincome			**100**	-0.354				
ca_pct_gdp			**99.5**	0.679				
mena			**98.6**	0.221				
Credit_domestic_pctgdp_5yr_rise			**92.2**	-0.221				
caavlast5yrs_pct_gdp			**91.7**	-0.422				
reserveschangesusd			**68.2**	-0.113				
foreignassetsnetlcucurrent			**60.4**	0.096				
reservesusd	**66.8**	-5.108						

All regressors from Appendix Table 1 are included the investigation of each crisis determinant. We only report results for candidate regressors whose inclusion probability exceeds 2.5 percent. Banking Crisis does not include the liquidity to asset ratio as a regressor and the real GDP growth runs do not include regressors related to GDP.

Appendix Table 1

	Mean	StDev	Min	Max	Description
fx_res_index	0.127	0.171	-0.489	0.515	Exchange market pressure from August 2008 to March 2009
imf_all	0.269	0.446	0.000	1.000	1 if country accessed SBA, PRGF or ESF from Jul 08 – Dec 2011
realgdp	2.612	7.435	-19.850	20.100	% Change in annual real GDP 2008
bankliquidrestoass	10.470	9.828	0.104	50.260	Bank liquid reserves to bank assets ratio (%)
businessdisclosure	5.462	2.784	0.000	10.000	Business extent of disclosure index (0=less disclosure to 10=more)
ca_pct_gdp	-3.099	10.730	-28.920	27.290	Current account balance (% of GDP)
ca2007_pct_gdp	-3.099	10.730	-28.920	27.290	CA2007%GDP
caavlast5yrs_pct_gdp	-2.053	7.982	-23.820	22.980	CAAvLast5Yrs%GDP
consumption_pct_gdp	79.800	14.660	40.270	119.200	Final consumption expenditure, etc. (% of GDP)
cpi2007	5.902	3.633	0.058	16.690	CPI2007
cpiavlast5years	5.847	5.177	-0.046	38.060	CPIAvLast5Years
credit_domestic_pct_gdp	0.753	0.560	-0.164	2.127	Domestic Credit % of GDP
credit_domestic_pctgdp_5yr_rise	0.083	0.257	-0.758	0.920	Domestic Credit % of GDP 5yr rise (2007-2002)
creditdepthofinfo	3.753	2.031	0.000	6.000	Credit depth of information index (0=low to 6=high)
currenttransfersreceiptsusd	6.E+09	8.E+09	0.E+00	4.E+10	Current transfers, receipts (BoP, current US$)
currenttransfersusd	-2.E+09	1.E+10	-1.E+11	4.E+10	Net current transfers (BoP, current US$)
domesticcreditbybanks_pct_gdp	80.120	62.250	-16.370	294.200	Domestic credit provided by banking sector (% of GDP)
domesticcreditlcu	6.E+13	2.E+14	-1.E+10	2.E+15	Net domestic credit (current LCU)
domesticcredittotal_pct_gdp	70.460	54.620	8.183	210.100	Domestic credit to private sector (% of GDP)
eapacific	0.129	0.337	0.000	1.000	EA&Pacific
euroarea	0.140	0.349	0.000	1.000	EuroArea
fdicurrentusd	-1.E+09	3.E+10	-1.E+11	1.E+11	Foreign direct investment, net (BoP, current US$)
fdiinflows_pct_gdp	10.440	39.280	-14.370	380.300	Foreign direct investment, net inflows (% of GDP)
fdiinflowsusd	2.E+10	5.E+10	-8.E+09	2.E+11	Foreign direct investment, net inflows (BoP, current US$)
financiallyclosed	0.204	0.405	0.000	1.000	1 if in bottom 30 pctile in Chinn & Ito (2008) financial openness index
foreignassetsnetlcucurrent	1.E+13	7.E+13	-3.E+11	5.E+14	Net foreign assets (current LCU)
gdpdeflator	1.E+03	1.E+04	9.E+01	1.E+05	GDP deflator (base year varies by country)
gdpdeflator_pct_annual	6.901	5.242	-3.833	22.750	Inflation, GDP deflator (annual %)
gdpgrowth2007	5.943	3.745	-2.129	25.050	GDPgrowth2007
gdpgrowthlast5yrs	5.423	3.152	-0.887	21.470	Average GDP growth last 5 years
gdppercapitagrowth	4.856	3.803	-2.107	23.640	GDP per capita growth (annual %)
gdppercapitapppcurrentusd	2.E+04	1.E+04	8.E+02	8.E+04	GDP per capita, PPP (current international $)

Appendix Table 1 continued

	Mean	StDev	Min	Max	Description
gdppppcurrentusd	6.E+11	2.E+12	4.E+08	1.E+13	GDP, PPP (current international $)
govexp_pct_gdp	18.330	8.356	3.364	42.500	General government final consumption expenditure (% of GDP)
incomenetbopusd	-3.E+08	2.E+10	-4.E+10	1.E+11	Net income (BoP, current US$)
investment_pct_gdp	25.010	6.271	12.970	43.300	Gross capital formation (% of GDP)
latamcarribean	0.183	0.389	0.000	1.000	LatAm&Carribean
legalrightsindex	5.892	2.420	0.000	10.000	Strength of legal rights index (0=weak to 10=strong)
lowincome	0.129	0.337	0.000	1.000	LowIncome
m2_pct_gdp	86.070	143.300	16.150	1349.000	Money and quasi money (M2) as % of GDP
m2growth_pct_	18.700	13.930	-25.340	73.210	Money and quasi money growth (annual %)
m2lcu_100mil	5.E+05	2.E+06	3.E+00	2.E+07	Money and quasi money (M2) (100 bil LCU)
mena	0.086	0.282	0.000	1.000	ME&NA
merchandisetrade_pct_gdp	81.960	51.830	21.540	347.500	Merchandise trade (% of GDP)
mgoodsgdp	-42.200	25.350	-176.600	-8.752	Imports Goods (% of GDP)
mgservicegdp	-52.330	31.040	-197.100	0.000	Imports Goods and Services (% of GDP)
northamerica	0.022	0.146	0.000	1.000	NorthAmerica
portfolioinvequityusd	7.E+09	4.E+10	-1.E+11	3.E+11	Portfolio investment, equity (DRS, current US$)
publicdebtgdp	44.520	32.510	3.742	187.700	Public Debt (% of GDP)
realintrate	0.165	3.641	-9.811	13.800	Real Interest Rate (%)
reer5yr	107.200	18.080	68.900	170.500	REER5yr_pct_rise (+ = appreciation)
reerdev10yravg	104.700	16.470	62.390	153.900	REERDevFrom10yrAv
remittancesreceived_pct_gdp	4.933	7.482	0.000	39.370	Workers' remittances and compensation, received (% of GDP)
reserves_perc_gdp_constr	0.200	0.174	0.004	0.976	Foreign Exchange Reserves (% of GDP)
reserveschangesusd	-6.E+09	6.E+10	-5.E+11	2.E+11	Foreign Exchange Reserves ($)
reservesusd	6.E+10	2.E+11	4.E+07	2.E+12	Total reserves (includes gold, current US$)
savings_pct_gni	12.060	13.310	-33.720	53.500	Savings (% of GNI)
savingsdomestic_pct_gdp	19.760	15.260	-22.000	59.730	Gross domestic savings (% of GDP)
southasia	0.032	0.178	0.000	1.000	SouthAsia
subsaharan	0.129	0.337	0.000	1.000	Sub-Saharan
tradebalance_pct_gdp	-5.350	16.420	-52.150	39.620	Trade Balance % of GDP
upperincome	0.333	0.474	0.000	1.000	UpperIncome
xgoodsgdp	35.510	26.130	3.939	170.900	Exports Goods (% of GDP)
xgservicegdp	47.860	33.600	0.000	218.900	Exports Goods and Services (% of GDP)

Source: Frankel and Saravelos (2011), World Bank Development Indicators, IMF International Financial Statistics, and IMF staff estimates.