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# **An Early Warning System for Systemic Banking Crises:**

## **A Robust Model Specification**

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# An Early Warning System for Systemic Banking

## Crises

(A Robust Model Specification)

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### Abstract

Using a panel dataset of 27 developed economies, estimated quarterly from 1980-2016, we develop a flexible systemic banking crisis early warning system (EWS). Evidence is provided that fitted multivariate logit probabilities, estimated recursively against documented crises, yield more informative crisis signals than any single macroeconomic, credit aggregate or asset price variable does independently. When the model robustness techniques of Young and Holsteen (2017) are applied, even stronger crisis signals are generated. Deciding which variables to include in the model is determined by adopting a signals-based approach to each prospective indicator, with the most informative yet robust variables identified in terms of their performance according to noise-to-signal ratios, weighted noise-to-signal ratios and an Alessi and Detken (2011) “usefulness” measure. The latter takes policy-makers’ preferences for false versus missed signals into account. The approach ensures a parsimonious yet effective EWS yielding forward-looking indicators that outperform all raw input indicators in crisis-signaling terms.

*JEL classification:* G01, G21, G28, E58.

*Keywords:* early warning system, systemic banking crises, macroprudential policy, model robustness, financial stability

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## Non-Technical Summary

During a systemic banking crisis, a country's financial and corporate sectors may experience a large number of defaults, whereby the impacted financial institutions and corporations face difficulties meeting their contractual obligations. During such periods, typically more than one bank faces the threat of insolvency and the state may be required to intervene in order to shore up confidence in the country's financial system. Although systemic crises tend to occur relatively infrequently they can be accompanied by spillover effects, damaging the wealth of the countries involved. As the crises unfold, other welfare-related problems may be observed such as a reduction in tax yield, increased unemployment and the imposition of corrective measures (such as austerity programmes). Since the financial crisis of 2008, significant effort has been expended in developing various systemic crisis Early Warning Systems (EWS), whose objectives' are to provide a consistently reliable advanced warning signal which will allow national authorities to consider the activation of macroprudential instruments early in the cycle. Such action would aim to reduce the risk of systemic crisis materialising or would aim to increase the resilience of the financial system in the event of such a shock. However, to-date, there are divergent views regarding the form that the EWS should take and what the "best" input variables ought to be. At the time of writing there is no generally accepted structural (i.e. theoretical) model that national authorities can deploy, hence an EWS that works well for country A may prove to be sub-optimal from country B's perspective.

In this paper, a new variant of an EWS is developed, one which incorporates the model-robustness ideas set forth by Young and Holsteen (2017), thus ensuring that only the most consistently important and relevant leading indicators, drawn from a superset of potential indicators as informed by the systemic crisis literature, are included in the final specification. Our EWS comprises only 8 raw input variables, chosen on the basis of their model robustness characteristics. These characteristics may be summarised as i) a consistently reliable contribution to, or detraction from, the likelihood of a systemic crisis, ii) consistent cross-model statistical significance and iii) level of influence on the other control variables comprising the benchmark specification. The output of the EWS is a dynamic crisis probability data series (each data point indicates the probability of a systemic crisis occurring within the ensuing "h" quarters, ( $2 \leq h \leq 8$ ), for each country in the sample, including Ireland. Due to its input variable parsimony the EWS is relatively easily maintained, thereby increasing its tractability as a monitoring tool. The output generated allows crisis probabilities to be benchmarked at the country level and the effectiveness of macroprudential policy measures to be correspondingly gauged over time. As crisis likelihood trends upwards in advance of a crisis, corrective actions may be considered and adopted in a timely fashion so as to offset the cost implications of a potential crisis to the greatest possible extent. The earlier the warning the greater the opportunity for "self-healing" adjustments to be made.

Because of the nature of the input data involved, the extension of the data sample backwards in time is straightforward. As a result of this, we can incorporate an increasing number and variety of systemic banking crises in our sample. This has the added benefit of allowing the EWS to encompass the harbingers of banking crises in a general sense, i.e. not just those which are particular to the Global Financial Crisis of 2008.

Our data sample consists of 20 quarterly-measured or “raw” indicators, including variables from a total of 27 economically-developed countries, covering the period 1980Q1 to 2016Q4. These indicators can loosely be grouped into macroeconomic, credit-aggregate and asset-price categories. The benchmark EWS contains input variables from each category and comprises local (i.e. measured at the country level) and global (the same data applies to all countries) data. We opt for developed economies for two specific reasons; 1) evidence that the most costly systemic banking crises emerge in and/or spill over from such countries and 2) data is more readily available and reliable in developed countries (see Laeven and Valencia (2013)). The crisis data is drawn from the new ECB Financial Stability Committee’s database as described in Lo Duca et al. (2017), supplemented where necessary by the IMF’s complementary dataset as discussed in Laeven and Valencia (2013). These datasets represent the most up-to-date and comprehensive systemic crisis information available at present.

We show that the main output of our EWS, which is the “point-in-time”, per-country probability of a systemic banking crisis occurring within the chosen forecast horizon (up to 8 quarters ahead) outperforms all other indicators in reliability terms. We further show that this property holds consistently across several widely-accepted signal-reliability measures. To our knowledge this paper represents the first such application of Young and Holsteen (2017)’s model-robustness enhancements to the EWS literature. The model robustness ideas addressed by Young and Holsteen (2017) have generated a lot of interest in recent years, with technological advancement facilitating more exhaustive empirical analysis than would have been typical heretofore. The benefits of the approach we adopt apply in a general econometric sense, aspects of which we describe in the paper’s concluding section.

# 1 Introduction

The development of an Early Warning System (EWS) for systemic banking crises presents several challenges. A fundamental decision concerns model choice, with two broad genres having come to prominence in the literature. Initial EWS models (covering the period 1998-2000) were typically univariate-based, a systemic crisis being flagged if the indicator (or, occasionally, several indicators simultaneously) exceeded a given threshold (see Kaminsky et al. (1998) and Demirgüç-Kunt and Detragiache (2000)). Multivariate binary-choice models, proponents argue, outperform their univariate signaling counterparts in crisis-prediction accuracy terms (see Davis and Karim (2008)<sup>1</sup>, Lo Duca and Peltonen (2013) and Sarlin and von Schweinitz (2017)). As well as model type, there are key decisions to be made involving cross-sectional versus panel data, single versus multi-country focus and variable selection. Furthermore, a trade-off is required in terms of sample time-frame versus data availability, giving rise to concerns that data may only reflect events preceding the most recent crisis, without being representative of crises generally.

In this paper, we concentrate on the implications to results and conclusions arising from such fundamental decisions, particularly those that relate to model specification and its inherent robustness. Young and Holsteen (2017) claim that model robustness, although crucially important in causality identification terms, rarely features in empirical research. They contend that robustness checking is frequently cursory rather than exhaustive, with results biased towards those specifications which serve to confirm the primary findings rather than contradicting them.<sup>2</sup> They present several examples showing how an ostensibly statistically significant variable is often crucially dependent upon the choice of the remaining covariates forming the estimation model. Given a set of pre-selected control variables,  $\{p\}$ , there are  $2^p$  possible control vector combinations. Thus, a coefficient distribution exists for each reference variable, with the point estimation for the coefficient dependent upon the accompanying control vector selected. In the absence of an agreed structural model to explain the emergence of systemic banking crises, there is a danger that causality may be ascribed to a particular variable that, in reality, may have its coefficient's distribution centered at or close to zero, with the reported coefficient drawn from either tail and implying, incorrectly, statistical significance. The converse is also possible, with potentially important variables reported as lacking significance simply because of the particular model specification adopted. Such variables may in fact be fundamentally important. Given the potentially significant costs involved in systemic banking crises, such imprecision is both unsatisfactory and unnecessary.<sup>3</sup>

By synthesizing the approach of Young and Holsteen (2017) within the parameters suggested by Lo Duca and Peltonen (2013) we make several contributions to the EWS

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<sup>1</sup> Davis and Karim (2008) suggest that univariate signals-based models work better for single country studies whereas multivariate models are better suited to multiple country / panel-data studies

<sup>2</sup> At the time of writing we have not found any article considering model robustness implications of systemic banking crises EWS.

<sup>3</sup> There is also the issue of reputational damage involved whenever a model fails to predict a crisis and/or too frequently issues false signals.

literature.<sup>4</sup> First, by reducing model uncertainty, we simplify the choice of instruments included in the EWS to eight readily-available input variables. Each of these is shown to have a consistently reliable role in terms of crisis signaling. Thus, it is less likely that the model contains a “knife edge” control variable whose inclusion/omission is critical to the crisis probabilities generated. This results in an easily-maintained yet flexible EWS. Second, we reconfirm that a combination of local and global variables yields a leading indicator series which is optimal in crisis-signaling terms (see Lo Duca and Peltonen (2013)).<sup>5</sup> This indicator, which represents our benchmark EWS output, is a logit-based fitted crisis probability, estimated recursively according to robust modeling specifications. It routinely outperforms all other leading indicators according to the Alessi and Detken (2011) “usefulness” metric. These include several “established” indicators such as asset prices, credit to GDP gap ratio and short-term interest rates (see Davis and Karim (2008), Rose and Spiegel (2012), Eichler and Sobański (2012) and Drehmann et al. (2011)). The recursively estimated characteristic of the indicator is highly relevant, given that all future model iterations will occur on an “at this point in time”, or recursive, basis. Third, by identifying and systematically excluding insignificant variables, we alleviate the lack of data problem inherently associated with the backwards extension of the sample time-frame. As our sample commences in 1980, a variety of systemic crises are incorporated. This ensures that any crisis probabilities generated are not particular to the 2008 financial crisis, but are representative of systemic banking crises in a more general sense. This, in turn, facilitates more meaningful policy-related discussions and planning activities in a timely fashion, as financial vulnerabilities increase. Finally, we report low probabilities of a systemic banking crisis occurring in any of our sample countries within the next eight quarters.

The paper is structured as follows. An overview of the panel, including the rationale for the selection of the countries involved, as well as the variables themselves, is outlined in section 2. An overview of the two modeling genres mentioned above is presented in section 3. The central results are detailed in section 4. Section 5 presents some concluding remarks.

## 2 Data

To perform the analysis, a panel comprising 27 developed economies with 20 different quarterly-measured indicators spanning the period 1980Q1 to 2016Q4 has been compiled. We focus on such countries for reasons of data availability and also because of an assumption that the most damaging of systemic crises are likely to emanate from, or at the very least spill over to banks in economically-developed countries. The variables included in the analysis, along with several summary statistics are shown in Table 1. In the absence of a universally-accepted structural model for systemic banking crises, variable selection is based in-part upon earlier research. Demirgüç-Kunt and Detragiache (2000) highlight the role played by high short-term interest rates and low GDP growth rates in the run-up to crises. Lo Duca and Peltonen (2013) argue that multivariate models comprising a

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<sup>4</sup> The former examine several classical economic theories, such as gender pay gap, from a model robustness perspective. The latter present a clear rationale for the blending of regional and global data in order to optimise systemic crisis prediction accuracy.

<sup>5</sup> Note, Lo Duca and Peltonen (2013) rely upon the 90th percentile value of a country’s financial stress index (CLIFS) as the dependent variable in their model (see also Duprey et al. (2017) and Lo Duca et al. (2017)) and augmented by Laeven and Valencia (2013)’s crisis database.

combination of local (country-specific) and global (common) variables yield relatively high crisis-prediction success rates. Out of approximately 200 variables considered, they identify equity price deviation from trend (global), credit to GDP ratio deviation from trend (global) and equity to GDP ratio deviation from trend (local) as their most useful leading indicators. Virtanen et al. (2016) make the case for the national credit-to-GDP ratio and debt-servicing costs whereas Alessi and Detken (2011) focus upon significant deviations of asset prices from their long-run trends.

Taken together, the input variables selected for analysis in this paper are drawn from this literature and can be loosely grouped into macroeconomic, domestic credit-aggregate and asset-price categories.<sup>6</sup> Extending the data coverage back to 1980 facilitates the capture of characteristics associated with crises occurring in the past 37 years, i.e. those associated with the modern era of globalisation, financial product innovation, de-regulation and technological advancement. Recognising that not all banking crises have the same root causes is of paramount importance, even if data availability issues are exacerbated as the number of variables increases. As mentioned in the introduction, the determination of a model-robust specification alleviates this problem to a considerable extent. All deviation-from-trend variables were estimated according to Hamilton (2017), who argues that trends estimated according to Hodrick-Prescott filters may be unreliable.<sup>7</sup>

The countries comprising our sample, together with the start and end-dates of any systemic banking crisis experienced, including data sources, are presented in Table 3, with the extent of variable coverage by country outlined in Table 4. We rely upon the recently developed systemic crisis database, described in Lo Duca et al. (2017), which itemises all known systemic banking crises in the EU area since 1980 (and earlier). To complete the systemic crisis information required we also make use of the crisis database developed by Laeven and Valencia (2013) for crisis details in non-EU countries, albeit with the caveat that this database does not document any crisis post-2012.<sup>8</sup>

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<sup>6</sup> Cross-correlations between the variables are illustrated in Table 2.

<sup>7</sup> Here, in each time series the 8th lead of the variable is regressed against the 4 prior lags, with the fitted values from the regression comprising the trend. Thus, for variable  $y$  we estimate the trend from the fitted values derived from regressing (OLS):-  $y_{t+8} = \alpha + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + \epsilon_t$

<sup>8</sup> There is a strong overlap between crisis definitions across the two datasets, as presented in the annexe of Lo Duca et al. (2017). There are differences in terms of post-crisis period classification but these are of limited concern, particularly where post-crisis observations have been removed (EWS user-controlled input parameter) from the specification.

### 3 Model

We estimate three separate measures of crisis-signaling strength per indicator variable, at several quarterly forecast horizons. In a first round of analysis indicators are treated independently. In a second round (based on signal strength rank) they are grouped to allow multivariate analysis to be considered. A third phase takes variable and model robustness characteristics into account, as set forth in section 3.2 below.

#### 3.1 Signaling

A useful leading indicator variable is one that generates a signal in anticipation of a crisis. In past studies signals are assumed to have been issued whenever the indicator breaches a (pre)defined threshold level. This may be a value associated with a low or high percentile based upon the indicator’s past distribution. Alternatively, the indicator may reach a level which represents a standard deviation (or greater) away from its trend, suggesting that an imbalance has accrued. Either way, whenever the specified threshold has been breached, this is treated as the indicator signaling a crisis, even though it may in reality be a temporary anomaly or merely be a short-lived period of fragility, with limited financial consequences.

To test the accuracy of such signals, comparisons with an actual crisis data variable (i.e. as confirmed by the data recorded in one of the crisis datasets we utilise) are made. If the signaling variable is “flashing” when an actual crisis occurred, this is treated as a correct signal. If no crisis occurs the indicator has issued a false signal. If an actual crisis occurs but the indicator is below the threshold this is considered a missed signal, i.e. the indicator failed to anticipate the crisis. By extension, a contingency matrix defining the possible relationship between signals and actual crises is defined, according to the following schema:

	Crisis Status	
	Systemic event within given horizon “h”	No Systemic event within given horizon “h”
The indicator is above the threshold $\Theta$ (i.e. signal is generated)	A (correct signal)	B (false signal)
The indicator is below the threshold $\Theta$ (i.e. no signal generated)	C (missed signal)	D (correct absence of signal)

Thus, at each point in time the relationship between the indicator and the crisis variable can be categorised as existing in one of four possible states, two of which are accurate and two of which are incorrect (considered respectively, signals and noise). False signals, “B”, are typically considered to be a Type I error and missed signals, “C”, are considered to be Type II errors, in keeping with econometric hypothesis-testing nomenclature. Several variations of the noise-to-signal ratio (NTSR) are then considered with preference given to variables that generate more signal than noise, i.e. the lower the ratio the better (see below).

There is always a trade-off to be made between the choice of threshold and the frequency of Type I and Type II errors. For instance, one could set a high threshold level, such as the 99th percentile level. By definition, the indicator will only exceed this threshold 1% of the



time and so the potential for accurate crisis prediction is reduced, as will the Type I error count. However, by setting such a high threshold there will be an increased likelihood of Type II errors, where the variable has failed to signal an actual crisis. As thresholds are varied there can be a reduction in one error type count, but often at the expense of an increase in the other. There are also costs associated with each error category, both real and in terms of reputational damage. Weighing up such costs, the modeler may prefer one error type over another and so he/she may express such preferences in terms of weights applied to each, as described below. Thus any EWS threshold choice requires careful consideration. Thresholds may be exogenously defined (i.e. ex-ante and static) or dynamic (see Sarlin and von Schweinitz (2017), implying a moving threshold as more data is added or estimated over time. Our approach is to generate signals for each variable's breach of every percentile level from 1-99 and, from there, to establish the percentile yielding the most accurate signals for all variables.

More specifically, we gauge signal reliability according to three well-established measures from the literature, each of which is based upon the contingency matrix above. These are 1) the noise-to-signal-ratio (see Kaminsky et al. (1998) and Borio and Drehmann (2009)), 2) a weighted noise-to-signal-ratio (see Borio and Drehmann (2009)) and 3) a "usefulness" score (see Alessi and Detken (2011) and Lo Duca and Peltonen (2013)). Measure (1) does not take policy makers' preferences for missed and/or false signals into account. The lower the score, the higher the proportion of signal, relative to noise, is generated by the variable. Any score less than 1 implies a higher signal than noise ratio, implying a leading indicator property. For every threshold  $\Theta$  (ranging from the 1st to the 99th percentile) NTSR is calculated thus:

$$NTSR = (B/(A + B))/1 - (C/(C + D)) \quad (1)$$

For each variable we record the optimal (lowest) NTSR achieved as well as its corresponding percentile value. The second performance measure (2), weighted noise-to-signal-ratio (WNTSR), is a variant of equation 1, yet it also takes policy makers preferences into account. As before, the lower the WNTSR the more signal (relative to noise) is evident. WNTSR is calculated as per the following:

$$WNTSR = (1 - \omega).(B/(A + B)) + (\omega).(C/(A + C)) \quad (2)$$

Here, the parameter  $\omega$  is a weighting parameter, ( $0 < \omega < 1$ ), illustrating the relative importance a policy maker applies to missed signals (category "C") relative to false signals (category "B") in the contingency matrix. Thus, for a value of  $\omega = 0.5$ , a policy maker is indifferent between Type I and Type II errors. With  $\omega < 0.5$  the policy maker is less concerned about missing signals and is more concerned with the cost and, possibly, reputational damage resulting from acting upon potentially false signals. Lo Duca and Peltonen (2013) and Alessi and Detken (2011) also calculate a "usefulness" measure (3), which gives greater prominence to such preferences (see also Demirgüç-Kunt and Detragiache (2000)) Usefulness, "U", is calculated according to the following:

$$U = \text{Min}[\omega, 1 - \omega] - L(\omega) \quad (3)$$

Here  $\text{Min}[\omega, 1 - \omega]$  is defined as the loss to the policymaker caused by disregarding the indicator's crisis signal, whereas  $L(\omega)$  represents a loss function associated with acting upon

the indicator's signal. As mentioned previously, the usefulness measure takes error Types I and II, as well as policymakers' preferences, into account:

$$L(\omega) = \omega * (C/(A + C)) + (1 - \omega) * (B/(B + D)) \quad (4)$$

The objective is to minimise loss function  $L(\omega)$ , thus higher values of  $U$  are preferred. According to this schema, any value of  $U > 0$  suggests a potentially informative systemic crisis signal being issued by the variable in question. Variables returning a value of  $U < 0$  are considered "noisy" and are reported in tables with a score of 0. The three measures do not interact per se, instead they are estimated consecutively per each iteration of the EWS with the results reported separately.

Having ranked each variable according to each of these measures, a subset of the best-performing variables is included in a multi-variate logit setting. Typically the dependent variable  $C_{it}$  takes the value of "1" if country  $i$  experiences a systemic banking crisis in quarter "t" as per the Lo Duca et al. (2017) and Laeven and Valencia (2013) databases. The model is augmented as suggested by Lo Duca and Peltonen (2013) in that an "ideal" leading indicator is artificially created. This depends upon a user-input forward-looking horizon "h". Thus, the model's dependent variable  $Y_{it}$  is set to 1 in each quarter "q" prior to the actual crisis so long as  $q \leq h$ . By construction,  $Y$  perfectly signals a systemic crisis within the next  $h$  quarters. Having determined  $Y$ , we estimate the following model:

$$\log \left( \frac{P[Y_{it} = 1|Z_{it}]}{P[Y_{it} = 0|Z_{it}]} \right) = \alpha + \beta Z_{it} + \epsilon_{it} \quad (5)$$

In this specification, vector  $Z_{it}$  contains the most informative variables emanating from the univariate signal generation analysis conducted earlier. In the final round of analysis,  $Z_{it}$  is composed of eight variables selected on the basis of their respective model robustness characteristics, as described below.

### 3.2 Model Robustness

Consider the familiar baseline linear regression model:

$$Y_t = \alpha + \beta X_t + \epsilon_t \quad (6)$$

Typically, having collected a sample of data, a point estimate  $b$  of the unknown parameter  $\beta$  is determined via OLS regression. The estimate is not definitive but is based partly on random chance. Assuming  $K$  possible samples that could have been drawn from set  $\{S1..Sk\}$ , there is a distribution of  $b$  estimates such that the point estimate of  $b$  is just one that could have been drawn from  $\{b1..bk\}$ . Via repeated sampling, with mean value  $\bar{b}$ , the standard error of coefficient  $b$  is given by:

$$\sigma_s = \sqrt{\frac{1}{K} \sum_{k=1}^K (b_k - \bar{b})^2} \quad (7)$$

Extending this scenario to a multivariate specification where  $X$  now takes on a vector composition, Equation 6 implicitly assumes that the "true" model is known, i.e. that we know the exact required composition of  $X$ . If model uncertainty is admitted (which it often isn't), there are more than  $K$  estimates to be considered in terms of each  $b$ 's distribution. For example, if a set of possible models  $\{M1..Mw\}$  are available, there is an additional set of possible  $b$  estimates,  $\{b1..bw\}$ , depending upon model choice. Then the total standard error,  $\sigma_t$ , with mean value  $\bar{b}$ , of each coefficient is as follows:

$$\sigma_t = \sqrt{\frac{1}{KW} \sum_{w=1}^W \sum_{k=1}^K (b_{kw} - \bar{b})^2} \quad (8)$$

The EWS sample data comprises 20 raw indicators. Thus for each variable, depending upon the choice of the accompanying control vector, there are  $2^{19}$  model specifications involving each of the possible control variable combinations. Young and Holsteen (2017) provide a toolkit enabling the assessment of each input variable. Because each possible model specification is executed, this allows a distribution for each  $b$  coefficient to be developed and analysed, including its coefficient mean together with the corresponding standard error. The toolkit also reports each coefficient's sign, along with the proportion of positive, negative and statistically significant values associated with its distribution. Furthermore, the marginal impact of the inclusion of each variable upon the distribution mean is provided, enabling both important as well as insignificant control variables to be identified for each potential crisis indicator.<sup>9</sup>

## 4 Results

The univariate signaling results are initially presented for each of the three signaling metrics described above. Following this, the most informative variables are combined into a logit model specification with the crisis signaling properties of the logit's fitted probability series compared with those of the "raw" input indicators. Later, having adjusted the model according to the analysis recommended by Young and Holsteen (2017), the re-fitted probabilities are again assessed, with the results presented alongside those achieved in the preceding analysis. Thus, the benefits of the robust-modeling approach can be readily established.

### 4.1 Univariate Signals

The univariate NTSR results are presented in Table 5 where the optimal percentile and corresponding NTSR values are shown for each forecasting horizon "h" up to 8 quarters ahead. The lower the NTSR value the more signal content is provided by the variable. A score of 1 or greater means there is more noise than signal in the variable, even for optimal percentiles. There is a minimum accuracy requirement of 25% of actual crises successfully signaled before a result is reported (see Borio and Drehmann (2009)). According to this latter criterion, losses only on the S&P 500 index variable fails to meet the minimum

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<sup>9</sup> Note, Young and Holsteen (2017) deliberately provide limited guidance as to when, or if, a variable ought to enter a model specification. The researcher forms his / her opinion on this subject depending upon the economic theory being tested along with the robustness results achieved.

threshold. In addition, for this iteration of the EWS, all post crisis-emergence observations have been removed from the sample, although multiple crises per country are allowed so long as there are quarters separating them where no crisis was observed.

With a look-ahead horizon of 1 quarter, the most informative variables are i) the country level index of financial stress (CLIFS), ii) the standardised credit-to-GDP gap and iii) the local credit-to-GDP gap. Each of these are local variables. The CLIFS index is a composite measure made up of several financial variables, as described in Table 1. These, in turn, are known to reflect multiple prevailing market-related financial stress conditions (see Duprey et al. (2017)). Credit-to-GDP ratios are useful for assessing the level of indebtedness of a country. The local version of this variable may also reflect instances of property-related asset mispricing, such as sometimes occurs during a property bubble. During such periods, any post-shock correction of the property market can be very damaging financially. The repercussions impact banks and borrowers directly, but where sovereign intervention is also required, the damage can extend to the sovereign also.

As the forecast horizon extends the NTSR scores tend to improve, with the CLIFS index consistently shown to be the best leading univariate indicator. However, the percentile values associated with the optimal signals are generally low, damaging the CLIFS' credentials as the preferred leading indicator. By definition the CLIFS index will exceed the 2nd percentile (see Table 5) 98% of the time, thus there will be relatively many false signals. On this basis, the standardised credit-to-GDP ratio is marginally preferable as its optimal signals occur at slightly higher percentiles. Several variables such as the national GDP growth rate and the percentage deviation of house prices from trend remain above or close to 1 for all values of "h". Such series are deemed noisy, generating considerably less-reliable crisis signals.

The results reported in Table 5 do not take policy preferences for missed / false signals into account. To accommodate these preferences attention turns to the second NTSR metric, with user-input weights allocated (representing  $\omega$ ) as per Equation 2. These results are presented in Table 6. Once again the optimal percentile and corresponding WNTSR score for each indicator is shown for each of up to 8 quarters ahead, with results interpreted as per those of Table 5. By way of contrast, no minimum crisis signaling success requirement is set, a configuration of the EWS which, as shall be observed, has a marked bearing on the results reported. Now, the S&P index (losses only) variable is the best-performing indicator at all forecasting horizons. In ranking terms, this is followed by the credit-to-GDP ratio, with inflation a close third. Unlike Lo Duca and Peltonen (2013), we find that local variables tend to outperform global variables for each of the first two signal metrics considered. However, it must be noted that best-performing variables appear optimal at extreme percentile levels. These tend to be either very low, (i.e. 2nd percentile), or very high, (i.e. 99th percentile), thereby rendering them highly prone to Type I or Type II errors as described before. Thus, the importance of setting a minimum successful crisis signaling threshold is reinforced, as recommended by Borio and Drehmann (2009), Sarlin and von Schweinitz (2017) and Alessi and Detken (2011).

Because of the above issues, our preferred measure is "usefulness" as defined by Alessi and Detken (2011). Results for this are reported in Table 7. Unlike the NTSR and WNTSR measures, the higher the score achieved the better the crisis signal performance of the indicator. This implies a relatively low loss function attributable to noisy data. According to Table 7, the most useful crisis signaling variables are i) the credit-to-GDP ratio, ii) the CLIFS

index and iii) the real short-term interest rate. The latter variable often enters the literature on systemic crisis determinants, (see Demirgüç-Kunt and Detragiache (1998, 2000), Davis and Karim (2008) and Eichler and Sobański (2012)), given its potential adverse affect upon borrowers' ability to repay loans, bank and firm funding costs and investment hurdle rates. For this table, we revert to a configuration of the EWS as per Table 5, setting  $\omega = 0.5$ , the minimum required successful crisis signaling ratio = 25% and with  $h$  ranging from 1-8 as before. The national (local) GDP growth rate fails to meet the minimum threshold at short forecasting horizons, as does the percentage deviation of local GDP from its trend for  $h = 8$ . The loss function is increasing in  $h$  which is what one might intuitively expect.

In terms of identifying the most informative variables to take to the next stage of the analysis, there is a degree of consistency across the three measures evaluated. The credit-to-GDP ratio appears to be the most consistent leading indicator but selecting the top indicators is not automatic, a degree of subjectivity is required surrounding the variable inclusion/exclusion cut-off point. This may be problematic, not just from a crisis-signaling perspective, but also with regard to adopting a policy stance in relation to thresholds that may have been breached by variables. Borio and Drehmann (2009) deal with this issue by only considering a signal as having been issued when multiple variables have simultaneously breached their ex-ante defined crisis-signaling thresholds. Whilst this approach has the advantage of reducing the volume of false signals generated, it has the disadvantage that variable selection can be either complex (in terms of justifying variable choice) or arbitrary. Furthermore, it entails an inherent assumption that all crises have similar characteristics and trajectories, when in fact the literature reveals that different crises have a variety of underlying root causes and outcomes (see Richter et al. (2017)). In addition, the joint threshold-breaching approach becomes increasingly difficult to achieve as more variables are added to the conditioning function, thereby increasing the likelihood of missed signals.

We overcome this difficulty via the simple expedient of ranking each variable according to each of the measures considered and selecting the top 10 variables to include in the EWS.<sup>10</sup> The following variables are selected on this basis:

- |                              |                                       |
|------------------------------|---------------------------------------|
| 1. Credit-to-GDP ratio       | 6. %Deviation Global GDP from trend   |
| 2. Short-term interest rates | 7. %Deviation Local GDP from trend    |
| 3. S&P 500 index             | 8. %Deviation Unemployment from trend |
| 4. Losses only S&P 500 index | 9. Standardised Credit-to-GDP ratio   |
| 5. Global GDP growth rate    | 10. Inflation                         |

Systemic crisis probabilities are fitted post-estimation for each value of  $h = 1..8$  as before. Lo Duca and Peltonen (2013) make the case for the inclusion of a combination of both local as well as global variables because, they argue, the resulting fitted crisis probabilities tend to yield better crisis signals in univariate models than any of the raw indicators considered thus far. The ranked variables listed above fulfill this condition. Four new fitted probability series are estimated, the first of which is generated using local variables only. For the second series, only global variables are included. The third comprises a combination of local and global

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<sup>10</sup> We are not imparting systemic crisis causality to any variable in the EWS. For example, we are not saying that an increase in real short-term interest rates causes crises. Rather, we are saying that there is a lagged correlation between interest rate spikes and banking crises further downstream.

variables estimated over the full sample horizon. In the fourth specification, probabilities are estimated on a recursive basis using combined local and global variables.

The recursive specification represents a model most closely resembling the information available to supervisory authorities on a coincident or “point in time” basis. Having estimated each of the four series the univariate analysis is repeated for each, with results contrasted to those achieved using “raw” input variables as outlined earlier in Tables 5 - 7.<sup>11</sup>

## 4.2 Univariate Signals vs Fitted Logit Probabilities

Tables 5 - 7 are replicated as Tables 8 - 10, this time including the four new series also displayed as per the above criterion.

The NTSR results are presented in Table 8. All four fitted crisis probability series contain useful leading indicator properties with 1/2 of them representing an improvement over the best of the raw input indicators (CLIFS index). Dominating this group for all forecasting horizons,  $h$ , is the full-sample estimated series combining local and global variables. This specification comprises all the variables listed above. As found by Davis and Karim (2008) and Lo Duca and Peltonen (2013), a multivariate-based EWS appears to work best for panel data involving more than one country. We see further evidence of this in relation to the WNTSR and usefulness scores achieved by these series as presented in Tables 9 and 10. In Table 9, the recursively estimated series ranks first or second relative to all other variables but does so at the 99th percentile level. As before, the fact that optimal percentiles are either very low or very high results from having not imposed any minimum successful crisis accuracy threshold, *ex ante*. In Table 10 the recursively-estimated series dominates the other fitted series in terms of the usefulness metric from  $h = 2 - 8$  and comes close to matching or exceeding the best leading “raw” indicator (credit-to-GDP ratio).

These results reinforce what others have found in earlier research but, given the potential advantages accruing from the model robustness techniques of Young and Holsteen (2017), it may be possible to generate even stronger crisis signals than any achieved thus far and to do so within a more consistently reliable framework.<sup>12</sup> That this is, in fact, possible is demonstrated in the following section.

## 4.3 Model Robust Leading Indicators

Before these results are presented, a justification for the selection of the variables comprising the final “robust” EWS specification is necessary. Each of the raw input indicators are subjected to a model robustness assessment, as described in subsection 3.2. Space does not permit presentation of the results for each of the twenty indicators, however the results for two variables are sufficient to highlight the advantages accruing from the procedure

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<sup>11</sup> There is a lag associated with the availability of several core EWS input variables, such as GDP, house prices and unemployment etc. This reduces the effectiveness of any EWS as a truly coincident indicator of crises, however the comment made in the text refers to the “best available” information. The lookahead horizon = 8 ameliorates this issue to an extent.

<sup>12</sup> This statement is made in the context of the results achieved in our EWS rather than in comparison with alternative EWS’s developed and maintained elsewhere.



generally. From there, a summary of the results achieved is described and choices made concerning the makeup of the benchmark robust EWS specification.

The robustness analysis reveals real short-term interest rates to be the most relevant variable (see Table 11). For each of the 524,288 models assessed, the variable is reported with statistically significant positive coefficients 100% of the time. Its robustness ratio, equivalent to a t-statistic, is 5.5, hence its strong statistical significance in all possible model combinations where it is included. The mean coefficient (log odds-ratio) is 76.26 but the maximum marginal variation of this mean value, associated with the inclusion of particular control variables, stems from the inclusion of the S&P 500 index (losses only) variable, which increases the mean by only 11.5% when included. Thus short-term interest rates are strongly, yet independently, associated with signaling crises in all multi-variate logit models estimated.

By contrast, Table 12 presents a similar analysis for the S&P500 index variable. A low robustness value of 0.3117 is achieved. Positive coefficients are reported in 50% of the 524,288 models and negative coefficients in the remainder. The negative coefficients are never reported with statistical significance, and only 46% of the positive coefficients are statistically significant. The variable's mean coefficient of 0.9299 is heavily influenced by the inclusion of multiple controls, most notably the losses only on the S&P500 index variable (perhaps unsurprisingly). However the mean value coefficient is doubled whenever real short-term interest rates are included. Thus endogeneity between these variables is strongly suggested. The distribution is multi-modal and does not take on anything that approximates a normal shape. The inclusion of this variable in the EWS would be problematic and would require very careful consideration in terms of the additional controls that would be required. Significant uncertainty would surround the interpretation of any such coefficient reported, as doubt would exist concerning where in the distribution the coefficient result was drawn from.

The kernel densities associated with these variables are presented in Figures 1 and 2. The differences between the two plots graphically illustrate the issues described above.

The robustness results for all 20 input variables are summarised in Table 13. The reference variable is listed at the top of a column with the marginal impact of each control variable upon the mean value of the coefficient below. Where this impacts the reference variable's mean value by more than 5%, the cell is shaded. Also reported are analysis summary statistics including the robustness ratio. Reading across the rows, one can identify the variables with a consistently high influence on the mean coefficient values achieved by the various reference variables under model robustness tests. Thus, a picture of robustness (robustness ratio) versus global influence emerges. Depicting this graphically allows for the most and least important variables to be identified. This is shown in Figure 3. Variables falling in the shaded area in the southwestern corner of the figure are omitted on the basis of low robustness and/or little model influence. Eight variables remain for inclusion in the EWS and these are as described below:-

#### 4.4 Robust Model Fitted Probabilities

Using the results described above the following variables are selected for inclusion in the benchmark EWS:

- |  |  |
|--|--|
| 1. Real short-term interest rates                | 5. %Deviation unemployment from trend      |
| 2. Losses only S&P 500 index                     | 6. Credit-to-GDP ratio                     |
| 3. %Deviation house prices from trend            | 7. Country level index of financial stress |
| 4. %Deviation household credit growth from trend | 8. House price index                       |

These variables have exhibited a relatively high robustness score or are shown to have strong and consistent model influence or both. They can be thought of as constituting the model robust determinants of systemic banking crises (see Demirgüç-Kunt and Detragiache (1998, 2000)). The analysis shows that a spike in short-term interest rates or a sudden shock to asset prices (recorded via losses on the S&P 500 index) can lead to significantly higher crisis likelihoods. Borrowers' ability to repay loans is adversely affected, especially in highly-leveraged countries, as the inclusion of the credit-to-GDP and household credit growth rate variables highlight. Also, when house prices deviate significantly above their long-term trend there is elevated crisis risk, as two of the variables suggest. Supporting the use of the CLIFS index by Lo Duca and Peltonen (2013) as a proxy crisis variable, we find that low CLIFS levels tend to precede crises, as do low unemployment rates. Overall, our findings support the general view that leverage and its role in fueling asset / house price bubbles is a reliable leading crisis indicator, particularly in countries where there is low unemployment and low financial stress. Thus, systemic pressures may be accumulating in the background with any financial imbalances only being revealed when the crisis unfolds. Consequently, the need for counter-cyclical policy measures such as LTV (loan-to-value), LTI (loan-to-income) and CCyB (counter-cyclical capital buffers) is reinforced.

Given the composition of, as well as the narrative associated with, the above list, we present the full-sample combined results as well as the recursively estimated combined results for a "benchmark" model-robust EWS specification. Results for the NTSR, WNTSR and usefulness measures are re-presented in Tables 14 - 16, the final two rows of each table representing the output from said benchmark EWS.

The advantages accruing from the model robustness analysis are clear. NTSR scores for these series represent a significant improvement over any crisis-signaling power evident thus far, particularly in the case of the recursively estimated series (see Table 14). The initial recursive estimation window is from 1980Q1 - 2004Q1. Optimal thresholds are high but do not give rise to any undue missed signal concerns. There is variation across optimal percentiles in the choice for  $h$ , reinforcing the need to be careful in terms of becoming fixed on any one optimal indicator threshold. As data or parameters are added these are prone to change. Note, the NTSR measure neglects policy preferences vis-a-vis false/missed signals. This shortcoming is addressed in Table 15 and once again the benchmark model's output significantly outperforms any other potential leading indicator. As before, no minimum accuracy threshold was set, with the best signals remaining rooted at either very high or low percentiles. Thus, the same Type I and II dangers persist.

Table 16 recreates our preferred metric, this being the Alessi and Detken (2011) usefulness measure. Once again, the recursively-estimated fitted probability series yields the best performing indicator of all measures examined thus far, and does so within a reasonably tractable percentile range (40-91, depending upon  $h$ ). Taking the results of Tables 14-16 together, a compelling case can be made for the recursively-estimated fitted probability forming the centerpiece of the systemic crisis EWS. Subject to the policy-maker's preference



for the costs associated with false signals, a supervisory authority might refrain from issuing a crisis warning unless, in the spirit of Borio and Drehmann (2009), several additional indicators, such as the level of global GDP and the credit-to-GDP ratio, were all simultaneously in breach of their thresholds. Such an approach would mitigate the likelihood of reporting or acting on a false signal.

To reinforce these findings, we present further graphical evidence in favour of the recursively estimated probabilities in Figure 4. This depicts the receiver operator characteristic (ROC) curve for each of the recursive, full sample combined and one of the best-performing input variables (credit-to-GDP ratio). The ROC curve plots the ratio of true-positive to false-positive signals generated in logistic models, where the reference variable is the binary dependent variable. We build the reference variable (the ideal indicator series as described above) for each forecasting horizon extending from 2-8 quarters ahead. The larger the area under the curve the more reliable the signal generated from the associated explanatory variable. Regardless of the horizon involved, the recursively estimated crisis probability series dominates.

#### 4.5 Current Systemic Crisis Probabilities

Figure 8 shows the changing fitted crisis probabilities for three countries, Ireland, Italy and Spain with the global financial crisis era shaded. As these countries were particularly badly impacted by the financial crisis of 2008, we wish to examine whether any advance warning might have been apparent prior to the onset of the crisis in these countries. The particular series depicted are the fitted EWS probabilities based upon the recursively-estimated specification. Note Sarlin and von Schweinitz (2017) recommend setting the crisis probability threshold both exogenously and on a non-varying basis. They set 0.2 as a threshold guideline in terms of issuing crisis warnings. This guideline is adopted along with an upper threshold of 0.6. On this basis, according to the EWS, all three countries breached the threshold prior to the outbreak of the financial crisis in 2008. Crisis probabilities increase dramatically before the outbreak of the crisis, behaviour which the EWS ought to reflect. However, Italy does not experience a threshold breach during the ensuing sovereign debt crisis era - even though it experienced severe bank capitalisation difficulties during this period and subsequently. This double-peak feature is apparent for each country depicted but to a lesser extent in the case of Italy. Similar series are generated for each of the 27 countries in the sample.

Note how crisis probabilities had declined below the threshold prior to the sovereign debt crisis, a feature common to almost all countries examined. There are also periods where the threshold is breached for certain countries (e.g. US in 1994, not shown) but no crisis actually occurs. The early warning system represents a **guide to crisis** only and is **not infallible**.<sup>13</sup> Each series was fitted on the basis that all observations remain in the sample during the

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<sup>13</sup> A fitted probability is only generated for a given country/quarter combination if data for all eight variables driving the model is available. So fitted crisis likelihood remains vulnerable to the delay (lag) associated with generating the various input series, e.g. GDP-related data. This is a failing common to all systemic crisis EWS's.

logit estimation, ensuring that there are no gaps in model predicted values.<sup>14</sup> The look ahead parameter was set to 8 quarters but can be any value in the range from 1-8 quarters. Hence, the end point of each series represents the estimated likelihood of a systemic crisis in the corresponding country (as of 2016Q2) up to 2018Q2.

## 5 Conclusions

We develop a benchmark multivariate EWS combining local / global variables, with coefficients estimated recursively according to model-robust pre-selection criteria, whose output is a leading systemic crisis indicator which is almost always optimal in “usefulness” terms (see Alessi and Detken (2011) and Lo Duca and Peltonen (2013)). Evidence is presented that a clear signal was generated for many countries impacted by the 2008 crisis up to 8 quarters in advance. Future iterations of the EWS are constrained to run on a recursive basis, however this is not as disadvantageous as one might suppose, given that the EWS frequently yields strong signals in such circumstances.

Having developed the EWS by taking guidance from the model robustness techniques recommended by Young and Holsteen (2017), we make several contributions. The first concerns model parsimony via the reduction of model composition concerns. Absent a structural model for crises, academics have tested hundreds of variables / combinations thereof, since 2008, in the search for a consistently strong leading crisis indicator. Without theoretical constraints, models may and have become intractable and cumbersome, with significant uncertainty surrounding the merit or otherwise of variable inclusion and with further uncertainty concerning the reliability of the point estimates generated upon model execution. Young and Holsteen (2017) show that it is possible to ameliorate several of these issues. Secondly, in the context of our EWS, confidence is increased that the model contains no knife-edge variable whose inadvertent inclusion / omission would greatly impact the accuracy and reliability of the leading indicator(s) generated. In addition, endogeneity concerns are reduced, with such variables being de-facto identified via the accompanying exhaustive robustness-testing process. Variables with limited-to-no crisis-probability implications are clearly identified and may safely be omitted from the end specification, resulting in a powerful yet easily maintained system.

The benchmark EWS comprises only eight variables namely i) real short-term interest rates, ii) losses only on the S&P 500 index, iii) percentage deviation of house prices from trend, iv) percentage deviation of household credit from trend, v) percentage deviation of unemployment from trend, vi) credit to GDP ratio, vii) country level index of financial stress and viii) house price index. As such, it can be maintained with minimal effort. There is a mixture of local and global factors as highlighted by Lo Duca and Peltonen (2013) just as there are macroeconomic, credit aggregate and asset-price factors taken into consideration. Thus the core characteristics associated with crises, as established in the literature, are well represented in the benchmark specification. The benchmark EWS, i.e. the specification that generates recursively estimated fitted crisis probabilities, performs well in terms of

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<sup>14</sup> Note that the dependent variable, the ideal crisis indicator, is formed in exactly the same way as before with the indicator set to 1 in the lookahead horizon preceding the onset of a crisis only, all other instances of the dependent variable are set to 0.

signaling crises in a timely fashion (see Fig. 8) and currently suggests low probabilities of any crisis emerging in any of the sample countries within the next eight quarters. Because of its parsimony, the backward extension of the panel data (in our case to 1980) is more feasible. This in turn facilitates a better understanding of the factors driving systemic crises in a more general sense, as opposed to those which are peculiar to the 2008 global financial crisis and which form the basis of most recent studies.

Having described the benefits associated with our approach, a word of caution is advisable. Any EWS issues warnings only, it does not predict crises per se. There will always be a trade-off to be made between setting crisis probability thresholds and dealing with the ensuing false signal / missed signal dichotomy involved. By extension, there is also a degree of subjectivity surrounding the extent to which bank supervisors are comfortable with these Type I and Type II errors and any implicit reputational damage involved. Nevertheless, once the policy maker has adopted a suitable crisis probability "threshold window", the EWS allows for timely intervention to help deflect the scale and extent of the damage which might otherwise be wrought and to allow all relevant macroprudential policy instruments to be activated in an orderly fashion as required.

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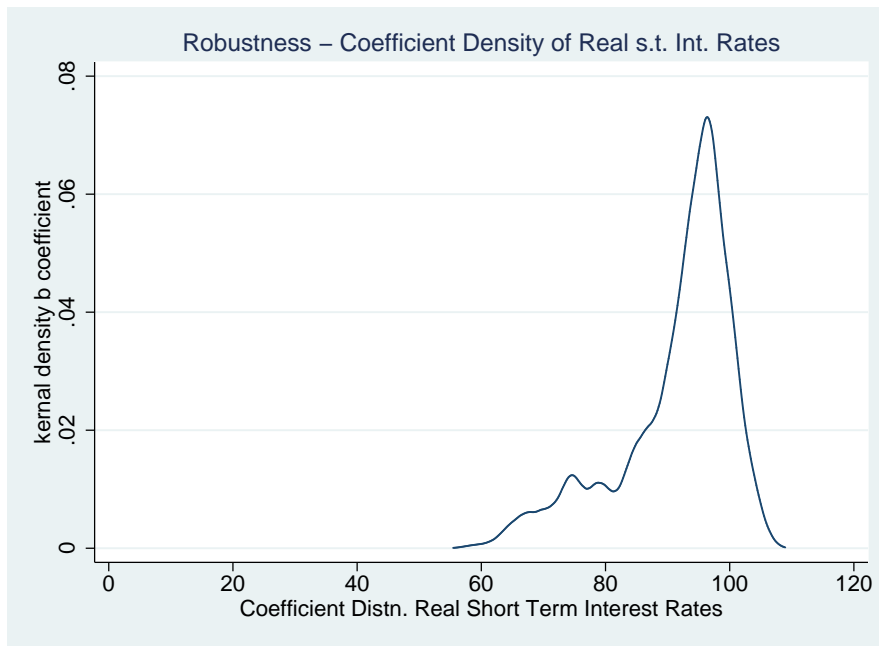


FIG. 1. Coefficient Density - Real Short-term Int. Rates

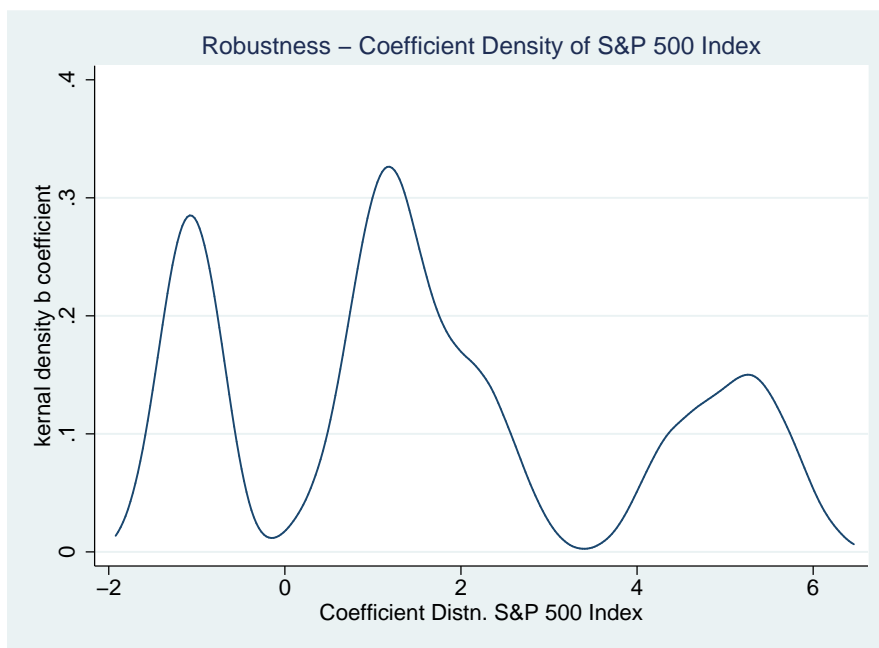


FIG. 2. Coefficient Density - S&P 500 Index

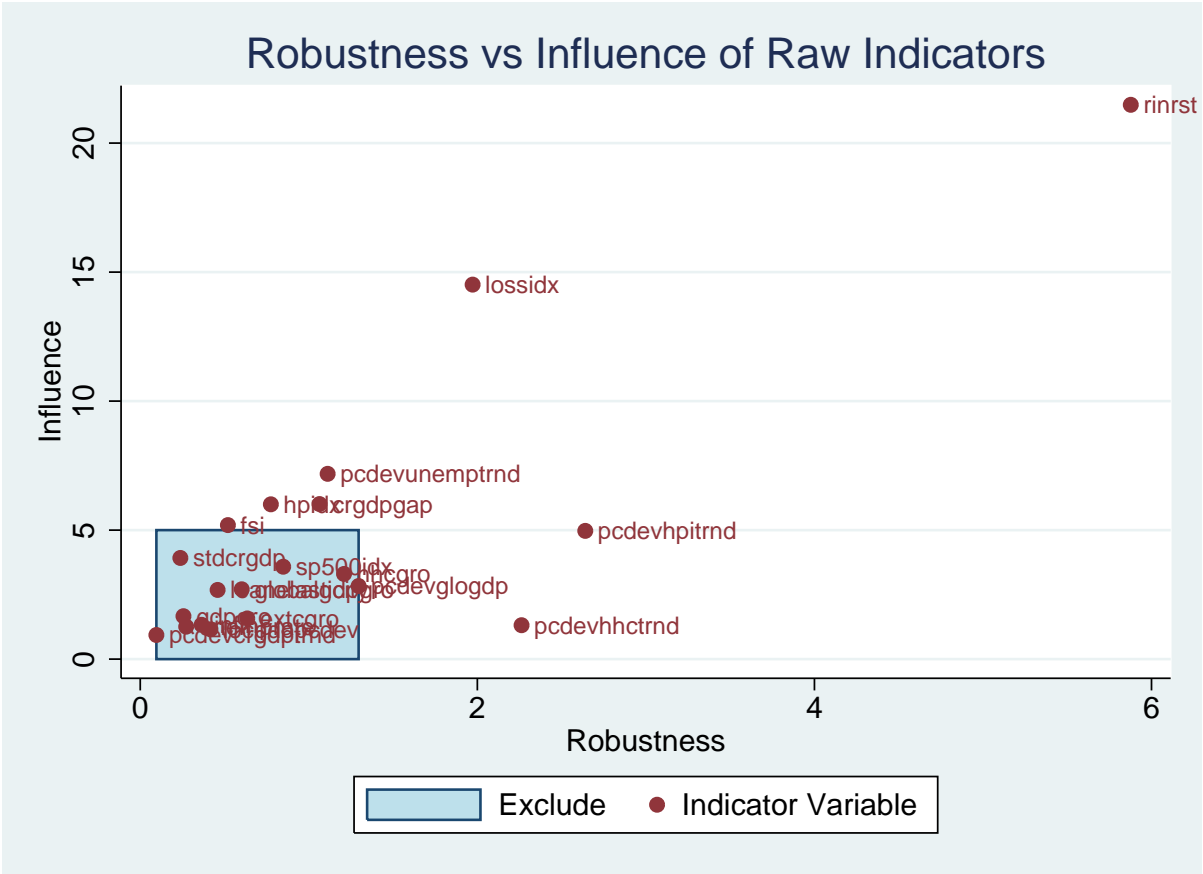


FIG. 3. Robustness vs Influence of Input Variables

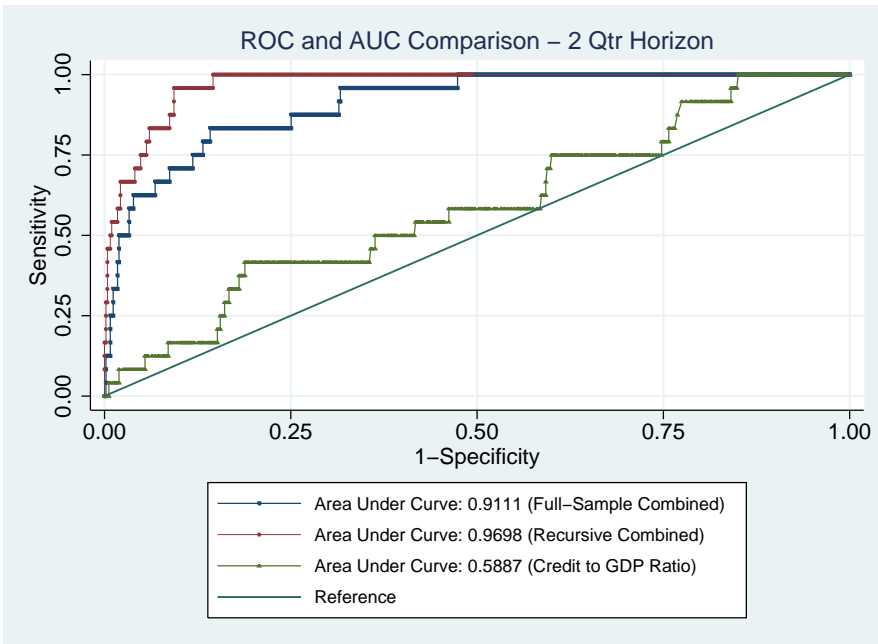


FIG. 4. ROC Relative to 2-qtr ideal indicator

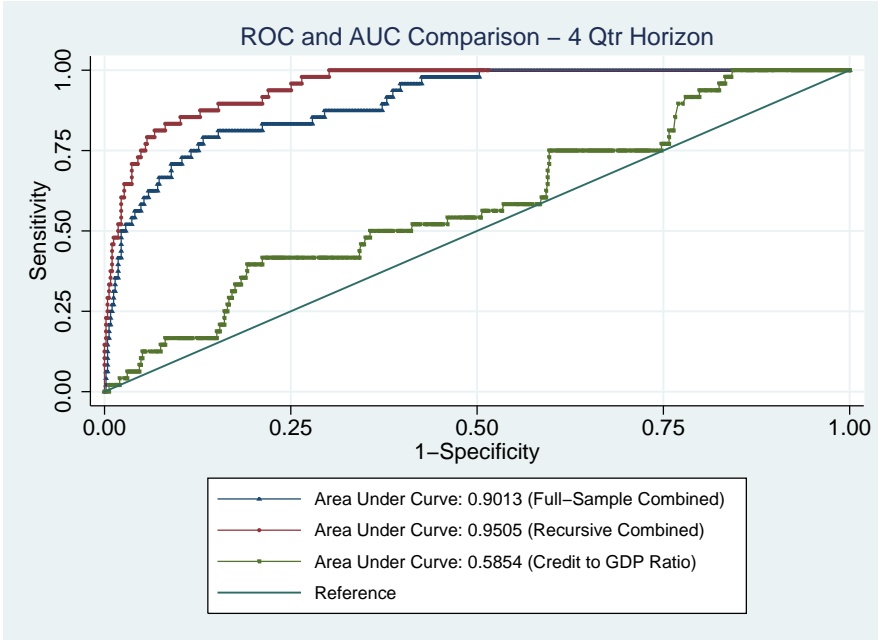


FIG. 5. ROC Relative to 4-qtr ideal indicator



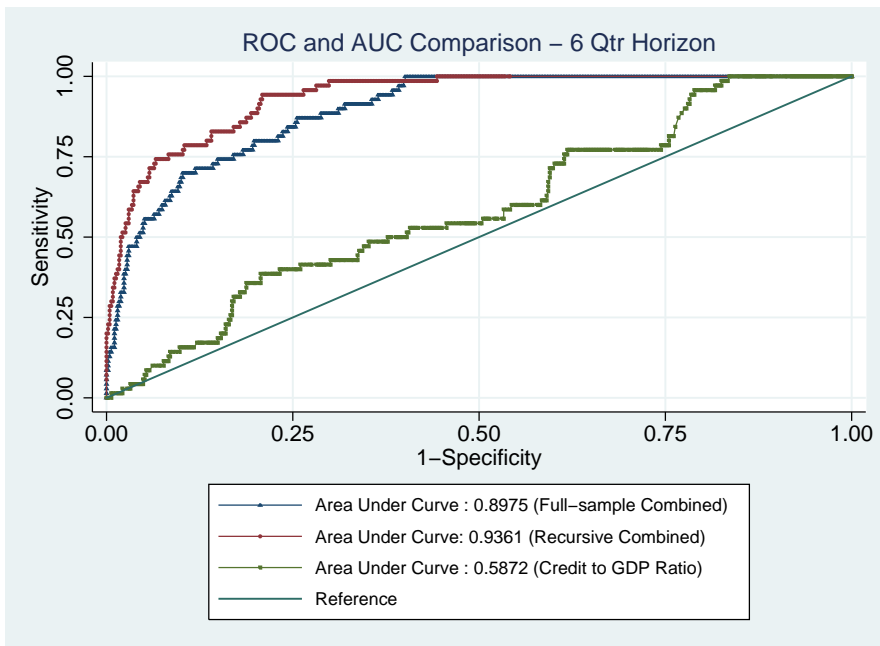


FIG. 6. ROC Relative to 6-qtr ideal indicator

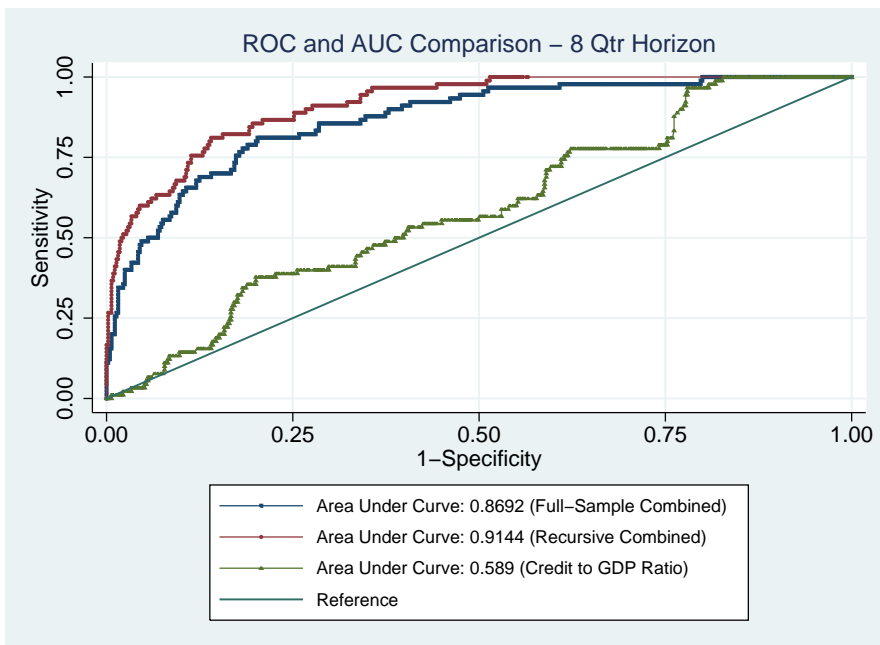


FIG. 7. ROC Relative to 8-qtr ideal indicator

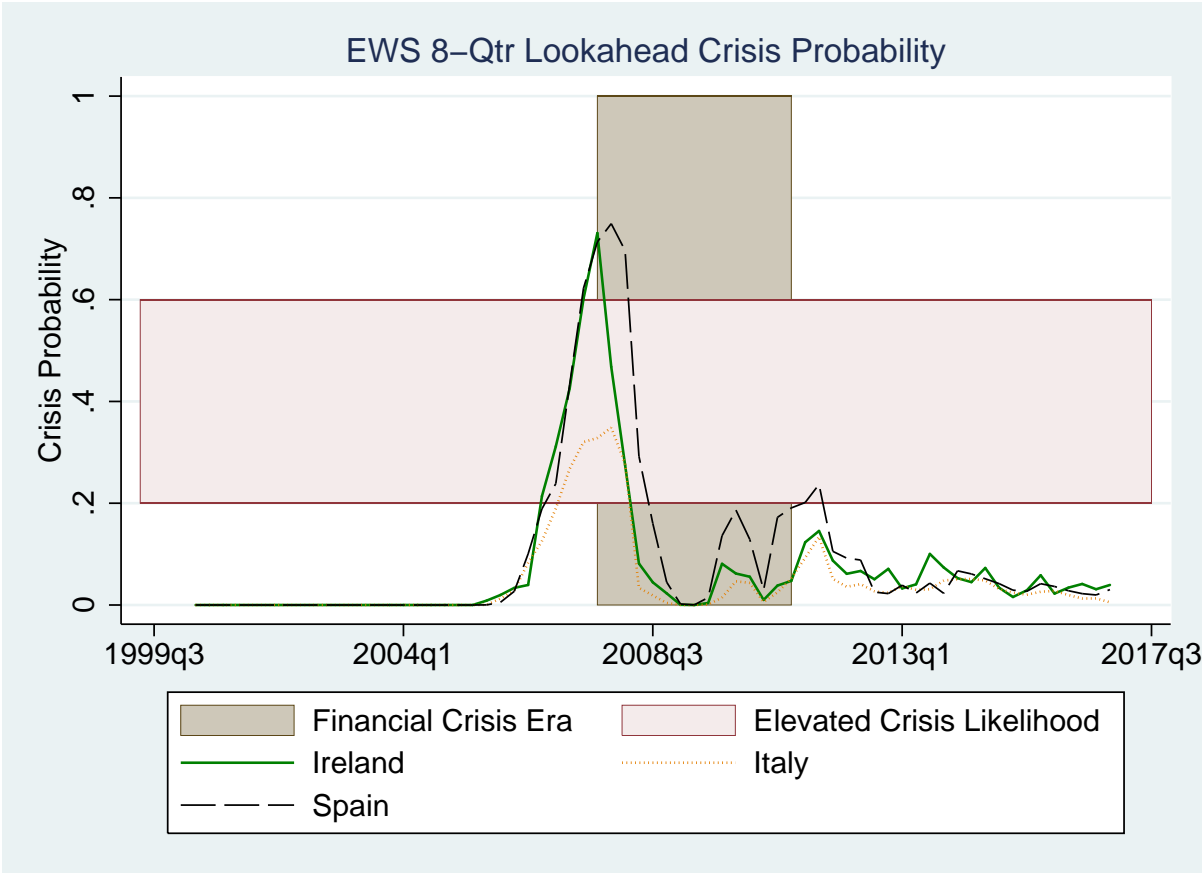


FIG. 8. Crisis Probabilities

TABLE 1. Variable Description and Summary Statistics

	Summary statistics				Description	Obs	Countries	Coverage	Source
	Mean	SD	Min	Max					
Household Credit Growth Rate	0.0170	0.0543	-0.3180	0.3020	Growth rate in lending by banks to households from current quarter to same quarter y-o-y	2200	27	1980Q2-2016Q4	BIS - Total Credit Statistics
Inflation	0.3108	3.6785	-0.0613	169.0423	Growth rate in CPI from same quarter y-o-y	3922	27	1980Q1-2016Q4	OECD - Statistics
GDP Growth Rate	0.0232	0.0302	-0.1869	0.2167	Growth rate in Gross Domestic Product from same quarter y-o-y	3563	26	1980Q1-2016Q4	OECD - Long Data Series
Real Short-term Interest Rates	0.0642	0.0641	-0.0084	0.6084	Based on inflation adjusted three month money market rates	3227	26	1980Q1-2016Q4	OECD - Statistics*
Credit to GDP Ratio	132.5651	62.2238	9.4000	455.3000	Ratio of total credit extended (all borrowers) over National GDP	3690	27	1980Q1-2016Q4	BIS - Total Credit Statistics
External Claims Growth	0.0244	0.1104	-0.5490	2.9640	Change in total foreign currency assets of BIS reporting banks y-o-y	3277	27	1980Q2-2016Q4	BIS - Locational Banking Statistics
CLIFS Index	0.1359	0.1103	0.0117	0.8445	Based on increasing volatility across Bond Markets, Interest Rates (and Spreads), Equity Markets and Exchange Rates (see Duprey et al. (2017) and Hollo et al. (2012))	1139	17	2000Q1-2016Q3	ECB - Statistical Data Warehouse
S&P 500 Index	0.0989	0.1691	-0.3968	0.5294	Capturing equity prices, this is the Standard & Poors index of 500 leading corporations (composition varies depending upon market capitalisation of constituent firms)	3996	27	1980Q1-2016Q4	Yahoo Finance Historical Data
Losses only S&P 500 Index	0.0316	0.0764	0.0000	0.3968	Same as above except positive changes are set to zero and losses are multiplied by -1, so that only losses on the index are considered	3996	27	1980Q1-2016Q4	Yahoo Finance Historical Data
Global GDP Growth Rate	0.0075	0.0163	-0.0475	0.0559	Average growth rate of GDP (converted to US\$) of US, UK, Japan, Germany and France	3969	27	1980Q1-2016Q4	OECD - Long Data Series, exchange rates from Federal Reserve Bank of Cleveland
% Deviation Local GDP Growth from Trend	0.6245	19.8923	-314.7358	657.2866	Based upon Hamilton (2016) filter with forward lag = 8 regressed against past 4 lags of GDP. Predicted values form trend, cycle is actual - trend, growth rate is change in cycle as a proportion of trend	3459	26	1981Q1-2016Q4	OECD - Long Data Series
% Deviation Global GDP from Trend	-0.0682	0.0560	-0.2313	0.0048	See % Deviation of GDP growth rate for mechanics of the calculation	3888	27	1981Q1-2016Q4	OECD - Long Data Series, exchange rates from Federal Reserve Bank of Cleveland
% Deviation Household Credit Growth from Trend	0.7379	3.1966	-42.1072	28.8641	See % Deviation of GDP growth rate for mechanics of the calculation	2073	27	1981Q2-2016Q4	BIS - Total Credit Statistics
Unemployment Rate	0.0762	0.0387	0.0189	0.2773	Unemployment Rate based upon the number of people not working as a % of total workforce	2412	25	1980Q4-2016Q4	OECD - Long Data Series
% Deviation Unemployment Rate from Trend	-0.0305	0.1613	-0.7407	0.4594	See % Deviation of GDP growth rate for mechanics of the calculation	2297	25	1981Q4-2016Q4	OECD - Long Data Series
House Price Index	143.1362	88.5106	19.8300	473.3190	House Price Index in Levels, with 1995 as the Index year (=100)	2664	17	1980Q1-2016Q4	BIS - Long Property Price Series
% Deviation House Price Index from Trend	-0.1162	0.1223	-0.9738	0.3412	See % Deviation of GDP growth rate for mechanics of the calculation	2592	17	1981Q1-2016Q4	BIS - Long Property Price Series
% Deviation Credit to GDP Ratio from Trend	-0.0486	0.0798	-2.4909	0.6283	See % Deviation of GDP growth rate for mechanics of the calculation	3582	27	1981Q1-2016Q4	BIS - Total Credit Statistics
Standardised Credit to GDP Ratio	0.0000	1.0000	-1.9783	5.1841	For each country calculate mean and std. deviation credit to GDP ratio. Calculate standard score as (ratio-mean)/std. deviation	3689	27	1980Q1-2016Q4	BIS - Total Credit Statistics
Loan Elasticity	-0.0002	0.2523	-7.2500	5.5000	% change in total credit extended / % change in GDP growth rate at the national level.	2113	26	1980Q2-2016Q4	BIS - Total Credit Statistics and OECD - Long Data Series

\* - Data for Brazil sourced via Federal Reserve Bank of Cleveland.

This table presents information identifying the name and number of countries in the panel. Crisis start and end dates are also presented based upon the ECB's macroprudential policy assessment group's systemic crisis database (covering primarily European countries) and supplemented where necessary by Laeven and Valencia's (2012) systemic crisis database.

TABLE 2. Pairwise Variable Correlation

	Bank Crisis	H/hold Credit Growth	Inflation	Nat. GDP Growth	Real short term Interest	Credit GDP Ratio	External Claims Growth	CLIFS	S&P S&P 500 Index	Losses only S&P	Global GDP Growth	% Devn. Local GDP	% Devn. Global GDP	% Devn. H/hold Credit	Unemp. Rate	% Devn. Unemp. Rate	House Price Index	% Devn. House Prices	% Devn. Credit GDP	Std. Credit GDP	Loan Elasticity	
Banking Crisis	1																					
Household Credit Growth Rate	-0.0813*	1																				
Inflation	0.0486*	0.0607*	1																			
GDP Growth Rate	-0.3304*	0.1083*	-0.0303	1																		
Real Short Term Interest Rate	-0.0035	0.0807*	0.2694*	0.1061*	1																	
Credit to GDP Ratio	0.1899*	-0.0427	-0.0634*	-0.1488*	-0.589	1																
External Claims Growth	-0.0911*	0.2103*	0.0308	0.1180*	0.1039*	-0.0466*	1															
CLIFS Index	0.4168*	-0.0964*	0.0159	-0.4871*	0.0653	0.1395*	-0.1309*	1														
S&P 500 Index	-0.0667*	-0.0539	0.0011	0.1834*	0.0765*	-0.0908*	0.0466*	-0.3696*	1													
Losses only S&P 500 Index	0.0741*	0.0496	-0.0153	-0.2412*	-0.0498	0.0543*	-0.0495*	0.4462*	-0.7708*	1												
Global GDP Growth Rate	0.1387*	-0.0605*	-0.0605*	-0.1157*	-0.5963	0.4479*	-0.0894*	0.0777*	-0.1420*	0.0719*	1											
% Deviation Local GDP from Trend	0.0113	0.0088	0.0107	-0.0252	0.0146	0.0056	-0.011	0.0232	-0.0013	-0.0133	-0.0135	1										
% Deviation Global GDP from Trend	0.1037*	0.1432*	-0.0323	-0.0075	-0.4837*	0.3391*	-0.0236	-0.0449	-0.0213	0.8939*	-0.0764*	-0.0222	1									
% Deviation Household Credit from Trend	0.0426	-0.0699*	-0.0152	-0.0877*	-0.0217	0.0172	-0.0352	0.0933*	-0.0372	0.0458	0.027	-0.0053	-0.0022	1								
Unemployment Rate	0.2742*	-0.0620*	0.02	-0.1602*	0.1176*	-0.2174*	-0.0706*	0.1395*	0.0681*	-0.0797*	0.0809*	0.0188	0.0569*	0.011	1							
% Deviation Unemployment Rate from Trend	0.0822*	-0.1285*	0.0129	0.0771*	0.0509	-0.0949*	-0.0556	-0.1499*	0.1851*	-0.2003*	-0.0589*	-0.0067	-0.0814*	-0.0263	0.4016*	1						
House Price Index	0.0890*	0.0004	-0.4117*	-0.0695*	-0.5969*	0.6981*	-0.0354	0.1307*	-0.1417*	0.0706*	0.7783*	-0.0079	0.6267*	0.0169	-0.0547	-0.2853*	1					
% Deviation House Price Index from Trend	0.1157*	-0.0721*	-0.5644*	-0.2644*	-0.5980*	0.4945*	-0.0443	0.3681*	-0.0934*	0.0644*	0.5348*	0.0203	0.5063*	0.029	0.0817*	-0.1204*	0.3640*	1				
% Deviation Credit to GDP ratio from Trend	0.1048*	-0.1222*	0.0153	-0.2036*	-0.3694*	0.2394*	-0.0544*	0.0238	-0.0058	-0.0056	0.1708*	0.004	0.1586*	0.0107	-0.0757*	0.0865*	0.2253*	0.3850*	1			
Standardised Credit to GDP ratio	0.1911*	-0.0419	-0.0633*	-0.1500*	-0.5885*	0.9999*	-0.0463*	0.1435*	-0.0906*	0.0546*	0.4474*	0.0057	0.3389*	0.017	-0.2165*	-0.0960*	0.6975*	0.4955*	0.2382*	1		
Loan Elasticity	-0.0073	0.1335*	0.0222	0.0205	0.0217	0.0075	0.0277	-0.0276	-0.0387	0.0475	-0.0206	-0.6689*	0.0293	-0.0068	-0.0632*	-0.0838*	-0.0075	-0.0402	-0.012	0.0074	1	

This table presents pairwise correlations for the main variables for our sample of 27 countries measured quarterly over the period 1980 - 2016. Correlations shaded in grey denote that they are statistically significant at a minimum of the 10% level. The banking crisis variable is drawn from the ECB FSC's Macroprudential policy working group database supplemented where necessary by Laeven & Valencia (2013). Household credit measures growth in lending at national level to households for all types of credit. Inflation measures changes to a basket of consumer items from the current quarter to the same quarter 1 year previously. GDP growth rate is annual growth rate measured on quarterly year-over-year basis. Real short-term interest rates are the 3 month central bank lending rates, inflation adjusted. Credit to GDP gap is the ratio of credit extended relative to GDP. External claims growth measures changes in foreign currency claims measured quarterly on a year over year basis. The CLIFS index is a variant on the composite index of systemic stress (CISS) index which measures the strength of equity, interest rate, currency and corporate bond spread correlation changes.

TABLE 3. Countries and Systemic Crises Summary

	Crisis Start	Year(s) End	Source
<b>Argentina</b>	1980Q1 1989Q1	1980Q4 1989Q4	Laeven and Valencia (2012)
<b>Australia</b>	-	-	Laeven and Valencia (2012)
<b>Austria</b>	2007Q4	2014Q1	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Belgium</b>	2007Q4	Ongoing	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Brazil</b>	1990Q1 1994Q1	1990Q4 1994Q4	Laeven and Valencia (2012)
<b>Canada</b>	-	-	Laeven and Valencia (2012)
<b>China</b>	1998Q1	1998Q4	Laeven and Valencia (2012)
<b>Denmark</b>	1987Q1 2008Q1	1995Q1 2013Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Finland</b>	1991Q3	1996Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>France</b>	1991Q2 2008Q2	1995Q1 2009Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Germany</b>	2001Q1 2007Q3	2003Q4 2013Q2	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Greece</b>	2010Q2	Ongoing	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Hungary</b>	1991Q1 2008Q3	1995Q4 2010Q3	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Ireland</b>	2008Q3	2013Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Italy</b>	1991Q3 2011Q3	1997Q4 2013Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Japan</b>	1997Q3	1997Q4	Laeven and Valencia (2012)
<b>Luxembourg</b>	2008Q1	2010Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Netherlands</b>	2008Q1	2013Q2	ECB MPG/AWG Systemic Crisis Database (2016)
<b>New Zealand</b>	-	-	Laeven and Valencia (2012)
<b>Norway</b>	1991Q1	1991Q4	Laeven and Valencia (2012)
<b>Poland</b>	1981Q1	1994Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Portugal</b>	1983Q1 2008Q4	1985Q1 Ongoing	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Spain</b>	1980Q1 2009Q1	1985Q3 2013Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Sweden</b>	1991Q1 2008Q3	1997Q2 2010Q4	ECB MPG/AWG Systemic Crisis Database (2016)
<b>Switzerland</b>	2008Q1	2008Q4	Laeven and Valencia (2012)
<b>United Kingdom</b>	1991Q3 2007Q3	1994Q1 2010Q1	ECB MPG/AWG Systemic Crisis Database (2016)
<b>United States</b>	1988Q1 2007Q4	1988Q4 2011Q4	Laeven and Valencia (2012)

This table presents information identifying the name and number of countries in the panel. Crisis start and end dates are also presented based upon the ECB's macroprudential policy assessment group's systemic crisis database (covering primarily European countries) and supplemented where necessary by Laeven and Valencia's (2012) systemic crisis database.

\* Note, crisis data for Brazil is sourced via the Federal Reserve Bank of Dallas (FRED) statistical data warehouse.

TABLE 4. Variable Coverage By Country

	H/hold credit Growth	Inflation	Nat. GDP Growth	Real s.t. Int. rate	Credit GDP Ratio	Ext. claims Growth	CLIFS	S&P 500 Index	Losses only S&P	Global GDP Growth	% Devn. Local GDP	% Devn. Global GDP	% Devn. H/hold Credit	Unemp. Rate	% Devn. Unemp. Rate	House Price Index	% Devn. House Prices	% Devn. Credit GDP	Std. Credit GDP	Loan Elasticity
Argentina	96	148	92	0	128	84	0	148	148	147	88	144	89	0	0	0	0	0	124	128
Australia	114	147	148	148	147	76	0	148	148	147	144	144	109	145	145	141	148	144	143	147
Austria	71	147	148	110	147	147	67	148	148	147	144	144	67	145	145	141	0	0	143	147
Belgium	72	147	148	148	147	147	67	148	148	147	144	144	68	72	72	68	148	144	143	147
Brazil	75	143	80	90	83	56	0	148	148	147	76	144	71	139	139	135	0	0	79	83
Canada	107	147	148	148	147	147	0	148	148	147	144	144	103	145	145	141	148	144	143	147
China	84	147	0	71	124	84	0	148	148	147	0	144	80	0	0	0	0	0	120	124
Denmark	72	147	148	120	147	147	67	148	148	147	144	144	68	108	108	104	148	144	143	147
Finland	72	147	148	120	147	129	67	148	148	147	144	144	66	76	76	72	148	144	143	147
France	72	147	148	148	147	147	67	148	148	147	144	144	67	56	56	52	148	144	143	147
Germany	72	147	148	148	147	147	67	148	148	147	144	144	67	145	145	141	148	144	143	147
Greece	76	147	148	91	147	52	67	148	148	147	144	144	72	108	108	104	0	0	143	147
Hungary	72	143	84	95	108	84	67	148	148	147	80	144	68	72	72	68	0	0	104	108
Ireland	72	147	148	132	148	147	67	148	148	147	144	144	68	108	108	104	148	144	144	147
Italy	71	147	148	148	147	147	67	148	148	147	144	144	67	76	76	72	148	144	143	147
Japan	76	147	148	59	147	147	0	148	148	147	144	144	72	145	145	141	148	144	143	147
Luxembourg	59	147	148	73	59	147	67	148	148	147	144	144	54	40	40	36	0	0	55	59
Netherlands	72	147	148	124	147	147	67	148	148	147	144	144	67	76	76	72	148	144	143	147
New Zealand	108	147	115	148	148	84	0	148	148	147	111	144	104	124	124	120	148	144	144	148
Norway	84	147	148	148	147	132	0	148	148	147	144	144	80	68	68	64	148	144	143	147
Poland	71	107	84	102	99	84	67	148	148	147	80	144	66	97	97	89	0	0	95	99
Portugal	72	147	148	124	147	76	67	148	148	147	144	144	68	76	76	72	0	0	143	147
Spain	87	147	148	148	147	132	67	148	148	147	144	144	81	72	72	68	148	144	143	147
Sweden	71	147	148	140	147	147	67	148	148	147	144	144	65	64	64	60	148	144	143	147
Switzerland	84	147	148	148	147	147	0	148	148	147	144	144	79	39	39	24	148	144	143	147
United Kingdom	71	147	148	148	147	147	67	148	148	147	144	144	67	71	71	67	148	144	143	147
United States	147	147	148	148	147	146	0	148	148	147	144	144	140	145	145	141	148	144	143	147

This table presents information concerning the variable coverage (number of observations) per variable per country over the period 1980 Q1 to 2016 Q4. In general, macroeconomic data such as GDP, inflation and unemployment data is readily available extends fully back to 1980 Q1 whereas other variables, e.g. the country level index of financial stress (CLIFS) is only available from 2000 Q1 onwards and so has weaker coverage. Data on China and Argentina is sparse for several variables however, given that parts of our analysis requires all observations post the initial crisis to be removed, this reduces the implications stemming from such omissions.

TABLE 5. Univariate Signals - Noise To Signal Ratio (NTSR)

This table shows the NTSR results achieved for each of the 20 raw input variables examined. NTSR scores < 1 contain more signal than noise and are preferred. The lower the NTSR value reported the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding NTSR results depicted. In this instance of the EWS  $\omega$  was set to 0.5 meaning the policy maker is indifferent between false and missed signals. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. A minimum crisis-anticipation accuracy of 25% is required for results to be reported, a criterion which S&P 500 losses only fails to achieve. The best signal is generated by the CLIFS index as this has the lowest NTSR.

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Noise-to-Signal Ratio							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
		Household credit growth	Local	8	8	8	8	78	8	8	8	0.99099	0.98181	0.97848	0.97103	0.95477	0.95914
Inflation	Local	2	2	2	2	10	2	2	2	0.99601	0.98984	0.98572	0.98154	0.97151	0.96728	0.96111	0.95913
National GDP growth rate	Local	2	2	2	2	32	2	2	2	1.00613	1.01243	1.0141	1.01581	1.00401	1.01215	1.00716	1.00333
Real Interest Rate (short-term)	Local	2	2	2	2	39	2	2	2	0.99809	0.99731	0.99793	0.99856	0.97717	0.99775	0.99733	0.99691
Credit to GDP Ratio	Local	2	2	2	2	42	2	2	2	0.99543	0.99112	0.98674	0.98231	0.95319	0.9713	0.967	0.96264
External claims growth rate	Local	7	6	6	7	81	6	7	7	0.99544	0.97976	0.97839	0.97033	0.95939	0.96102	0.95387	0.95004
CLIFS Index	Local	2	2	2	2	4	2	2	2	0.98616	0.97537	0.96441	0.95328	0.9438	0.93422	0.92369	0.913
S&P 500 Index	Global	7	7	8	8	29	7	7	7	1.00599	1.01214	1.02101	1.02961	0.96049	1.0349	1.03624	1.04279
Losses only S&P 500 Index	Global	2	2	2	2	.	2	2	2	.	.	.	.	.	.	.	.
Global GDP Growth rate (4-bloc average)	Global	6	6	6	4	26	4	6	6	1.00235	1.00081	0.99658	0.9909	0.95647	0.99104	1.00378	1.01016
% Deviation National GDP from trend	Local	15	15	15	15	78	16	16	17	0.99678	0.99505	0.98856	0.99309	0.99155	1.00059	1.0065	1.00384
% Deviation Global GDP from trend	Global	31	31	31	31	98	31	30	29	1.00146	1.0016	1.00449	1.00326	0.97456	0.9999	1.00699	1.00603
% Deviation Household credit from trend	Local	8	8	8	8	17	8	9	9	0.99835	0.99521	0.99643	1.00067	0.9715	1.00252	0.98874	0.9885
Unemployment Rate	Local	2	2	2	2	6	2	2	2	0.99932	0.99862	0.99676	0.99602	0.99423	0.99554	0.99409	0.99383
% Deviation Unemployment Rate - Trend HP	Local	4	4	4	4	24	4	4	4	1.00118	0.99862	0.99601	0.99846	0.97189	0.99741	0.99422	0.99364
House price index	Local	2	2	2	2	73	2	2	2	1.00269	1.00544	1.00826	1.01116	0.96989	1.0154	1.01759	1.01984
% Deviation House Prices from Trend	Local	40	48	56	56	88	56	55	52	1.001	1.00696	1.01735	1.02221	1.0086	1.03638	1.0442	1.04304
% Deviation Credit to GDP from trend	Local	37	37	36	32	83	28	27	27	1.0038	1.00769	1.01185	1.00885	0.98045	1.00202	0.99923	0.99344
Standardised Credit to GDP ratio	Local	13	13	13	13	91	13	13	13	0.99286	0.98558	0.98003	0.97436	0.96524	0.96391	0.96141	0.95692
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	15	15	16	16	58	18	18	18	0.99109	0.98569	0.98947	0.98522	0.97703	0.98392	0.97803	0.98709

TABLE 6. Univariate Signals - Weighted Noise To Signal Ratio (WNTSR)

This table shows the weighted NTSR results achieved for each of the 20 raw input variables examined. WNTSR scores <1 contain more signal than noise and are preferred. The lower the WNTSR reported the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding WNTSR results depicted. In this instance of the EWS,  $\omega$  was set to 0.45. The policy maker is 45% comfortable with a missed signal and 55% comfortable with a false signal. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. No minimum crisis-anticipation accuracy is required.

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Weighted Noise-to-Signal Ratio							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
		Household credit growth	Local	2	2	2	2	2	2	2	2	0.9707	0.9564	0.9527	0.9366	0.9429	0.9472
Inflation	Local	2	2	2	2	2	2	2	2	0.5913	0.5791	0.5750	0.5698	0.5622	0.5529	0.5463	0.5432
National GDP growth rate	Local	2	2	2	2	2	2	2	2	0.8778	0.8740	0.8530	0.8398	0.8235	0.8082	0.7912	0.7785
Real Interest Rate (short-term)	Local	2	2	2	2	2	2	2	2	0.6619	0.6561	0.6543	0.6507	0.6445	0.6385	0.6325	0.6267
Credit to GDP Ratio	Local	2	2	2	2	2	2	2	2	0.5793	0.5733	0.5672	0.5612	0.5530	0.5476	0.5421	0.5365
External claims growth rate	Local	2	2	2	2	2	2	2	2	0.9577	0.9428	0.9194	0.9061	0.8980	0.8939	0.8929	0.8874
CLIFS Index	Local	2	2	99	99	99	99	99	99	0.7869	0.7768	0.8048	0.8078	0.7460	0.7476	0.7487	0.7496
S&P 500 Index	Global	2	2	2	2	2	2	2	2	0.9372	0.9403	0.9488	0.9486	0.9351	0.9136	0.9104	0.9028
Losses only S&P 500 Index	Global	2	2	2	2	2	2	2	2	0.5438	0.5380	0.5323	0.5265	0.5209	0.5153	0.5097	0.5041
Global GDP Growth rate (4-bloc average)	Global	2	2	2	2	2	2	2	2	0.9614	0.9375	0.9305	0.9164	0.9150	0.9097	0.9099	0.9144
% Deviation National GDP from trend	Local	2	2	2	2	2	2	2	2	0.9834	0.9787	0.9739	0.9615	0.9644	0.9663	0.9677	0.9688
% Deviation Global GDP from trend	Global	3	2	2	2	2	2	2	2	0.9827	0.9831	0.9701	0.9721	0.9732	0.9740	0.9746	0.9750
% Deviation Household credit from trend	Local	2	2	2	2	2	2	2	2	0.9820	0.9637	0.9696	0.9726	0.9658	0.9346	0.9290	0.9232
Unemployment Rate	Local	2	2	2	2	2	2	2	2	0.7336	0.7276	0.7175	0.7126	0.7085	0.7039	0.6970	0.6922
% Deviation Unemployment Rate - Trend HP	Local	2	2	2	2	2	2	2	2	0.9854	0.9739	0.9597	0.9599	0.9537	0.9429	0.9329	0.9233
House price index	Local	2	2	2	2	2	2	2	2	0.7224	0.7171	0.7118	0.7066	0.6999	0.6936	0.6877	0.6819
% Deviation House Prices from Trend	Local	2	2	2	2	2	2	2	2	0.9838	0.9795	0.9752	0.9708	0.9664	0.9621	0.9577	0.9534
% Deviation Credit to GDP from trend	Local	5	5	5	5	2	2	2	2	0.9850	0.9818	0.9857	0.9877	0.9788	0.9694	0.9603	0.9515
Standardised Credit to GDP Ratio	Local	2	2	2	3	3	3	3	3	0.9519	0.9494	0.9511	0.8979	0.8931	0.8919	0.8939	0.8948
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	2	3	2	2	2	2	2	2	0.9809	0.9574	0.9776	0.9592	0.9519	0.9539	0.9553	0.9563



TABLE 7. Univariate Signals - Usefulness

This table shows the usefulness results achieved for each of the 20 raw input variables examined. Scores >0 contain more signal than noise and are preferred. The greater the usefulness the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding usefulness results depicted. In this instance of the EWS,  $\omega$  was set to 0.5 The policy maker is indifferent between the costs associated with a missed signal as with a false signal. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. A minimum crisis-anticipation accuracy of 25% is required, a criterion which National GDP fails to achieve within these parameters (up to 6 quarter forecast horizon).

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Usefulness							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
		Household credit growth	Local	57	58	58	58	58	58	58	58	0.09835	0.08796	0.07759	0.07615	0.07965	0.07526
Inflation	Local	27	27	50	17	17	17	17	17	0.08057	0.06128	0.0489	0.04534	0.04546	0.04806	0.04807	0.04821
National GDP growth rate	Local	0	0	0	0	0	0	33	33	0	0	0	0	0	0	0.00172	0.0047
Real Interest Rate (short-term)	Local	44	41	40	39	39	34	27	25	0.1086	0.09766	0.08539	0.071	0.05535	0.04266	0.03528	0.03101
Credit to GDP Ratio	Local	44	44	43	43	42	41	41	41	0.11884	0.12011	0.11657	0.11098	0.11373	0.11434	0.11251	0.10959
External claims growth rate	Local	61	80	82	80	81	81	81	79	0.06467	0.0763	0.06219	0.06424	0.06434	0.06	0.05494	0.05234
CLIFS Index	Local	7	2	2	2	2	4	4	2	0.1037	0.09805	0.09911	0.10019	0.09694	0.09784	0.09882	0.09881
S&P 500 Index	Global	26	29	29	29	29	29	17	17	0.04517	0.05166	0.05448	0.05279	0.05457	0.05834	0.05755	0.05935
Losses only S&P 500 Index	Global	84	84	84	84	84	84	84	99	0.06247	0.05642	0.05024	0.04049	0.02137	0.01066	0.00284	0.00125
Global GDP Growth rate (4-bloc average)	Global	42	42	20	26	26	26	26	26	0.06722	0.06122	0.05939	0.05087	0.05338	0.05058	0.05277	0.05098
% Deviation National GDP from trend	Local	8	82	71	80	78	70	70	0	0.03914	0.02924	0.03621	0.02253	0.01788	0.00393	0.00146	0
% Deviation Global GDP from trend	Global	98	98	98	92	92	92	92	81	0.03361	0.02053	0.01623	0.02329	0.0323	0.03625	0.03926	0.04671
% Deviation Household credit from trend	Local	18	18	18	18	17	17	17	17	0.06301	0.06368	0.06437	0.06507	0.06808	0.06341	0.06017	0.05602
Unemployment Rate	Local	37	27	3	3	6	52	52	50	0.01655	0.01448	0.0157	0.01473	0.01382	0.01354	0.01547	0.01781
% Deviation Unemployment Rate - Trend HP	Local	5	23	27	25	85	28	28	25	0.04539	0.03348	0.03602	0.0331	0.04504	0.02591	0.02442	0.02176
House price index	Local	29	28	26	34	34	34	34	34	0.06349	0.06065	0.05434	0.05235	0.05514	0.05725	0.05692	0.05502
% Deviation House Prices from Trend	Local	75	99	99	99	99	99	99	99	0.01261	0.00204	0.00207	0.00209	0.00218	0.00226	0.00232	0.00237
% Deviation Credit to GDP from trend	Local	80	83	77	83	77	77	76	75	0.0478	0.03519	0.03562	0.02909	0.03214	0.03588	0.03708	0.04458
Standardised Credit to GDP Ratio	Local	15	15	15	15	15	15	91	91	0.06345	0.06413	0.0603	0.05867	0.05603	0.05206	0.05016	0.04739
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	16	15	54	54	54	54	54	54	0.07083	0.05217	0.05399	0.05229	0.04995	0.04144	0.04352	0.03979

TABLE 8. Univariate Signals - Noise To Signal Ratio (NTSR)

This table shows the NTSR results achieved for each of the 20 raw input variables examined. NTSR scores <1 contain more signal than noise and are preferred. The lower the NTSR value reported the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding NTSR results depicted. In this instance of the EWS  $\omega$  was set to 0.5 meaning the policy maker is indifferent between false and missed signals. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. A minimum crisis-anticipation accuracy of 25% is required for results to be reported, a criterion which S&P 500 losses only fails to achieve. The best signal is generated by the CLIFS index variable as this has the lowest NTSR score.

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Noise-to-Signal Ratio							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Household credit growth	Local	8	8	8	8	78	8	8	8	0.99099	0.98181	0.97848	0.97103	0.95477	0.95914	0.94886	0.94676
Inflation	Local	2	2	2	2	10	2	2	2	0.99601	0.98984	0.98572	0.98154	0.97151	0.96728	0.96111	0.95913
National GDP growth rate	Local	2	2	2	2	32	2	2	2	1.00613	1.01243	1.0141	1.01581	1.00401	1.01215	1.00716	1.00333
Real Interest Rate (short-term)	Local	2	2	2	2	39	2	2	2	0.99809	0.99731	0.99793	0.99856	0.97717	0.99775	0.99733	0.99691
Credit to GDP Ratio	Local	2	2	2	2	42	2	2	2	0.99543	0.99112	0.98674	0.98231	0.95319	0.9713	0.967	0.96264
External claims growth rate	Local	7	6	6	7	81	6	7	7	0.99544	0.97976	0.97839	0.97033	0.95939	0.96102	0.95387	0.95004
CLIFS Index	Local	2	2	2	2	4	2	2	2	0.98616	0.97537	0.96441	0.95328	0.9438	0.93422	0.92369	0.913
S&P 500 Index	Global	7	7	8	8	29	7	7	7	1.00599	1.01214	1.02101	1.02961	0.96049	1.0349	1.03624	1.04279
Losses only S&P 500 Index	Global	2	2	2	2	.	2	2	2	.	.	.	.	.	.	.	.
Global GDP Growth rate (4-bloc average)	Global	6	6	6	4	26	4	6	6	1.00235	1.00081	0.99658	0.9909	0.95647	0.99104	1.00378	1.01016
% Deviation National GDP from trend	Local	15	15	15	15	78	16	16	17	0.99678	0.99505	0.98856	0.99309	0.99155	1.00059	1.0065	1.00384
% Deviation Global GDP from trend	Global	31	31	31	31	98	31	30	29	1.00146	1.0016	1.00449	1.00326	0.97456	0.9999	1.00699	1.00603
% Deviation Household credit from trend	Local	8	8	8	8	17	8	9	9	0.99835	0.99521	0.99643	1.00067	0.9715	1.00252	0.98874	0.9885
Unemployment Rate	Local	2	2	2	2	6	2	2	2	0.99932	0.99862	0.99676	0.99602	0.99423	0.99554	0.99409	0.99383
% Deviation Unemployment Rate - Trend HP	Local	4	4	4	4	24	4	4	4	1.00118	0.99862	0.99601	0.99846	0.97189	0.99741	0.99422	0.99364
House price index	Local	2	2	2	2	73	2	2	2	1.00269	1.00544	1.00826	1.01116	0.96989	1.0154	1.01759	1.01984
% Deviation House Prices from Trend	Local	40	48	56	56	88	56	55	52	1.001	1.00696	1.01735	1.02221	1.0086	1.03638	1.0442	1.04304
% Deviation Credit to GDP from trend	Local	37	37	36	32	83	28	27	27	1.0038	1.00769	1.01185	1.00885	0.98045	1.00202	0.99923	0.99344
Standardised Credit to GDP Ratio	Local	13	13	13	13	91	13	13	13	0.99286	0.98558	0.98003	0.97436	0.96524	0.96391	0.96141	0.95692
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	15	15	16	16	58	18	18	18	0.99109	0.98569	0.98947	0.98522	0.97703	0.98392	0.97803	0.98709
Logit prediction - local variables only	Local	2	2	2	2	53	2	2	2	1.00053	0.99995	1.00049	1.0022	0.97904	1.0034	1.00462	1.00708
Logit prediction - global variables only	Global	2	2	2	2	73	2	2	2	0.99397	0.98867	0.98595	0.9811	0.951	0.96616	0.95717	0.9484
Logit prediction - combination local and global	Combi	2	2	2	2	20	2	2	2	0.98632	0.9724	0.95823	0.94622	0.91636	0.92088	0.90786	0.8946
Logit prediction - recursive combination local and global	Combi	2	2	2	2	58	2	2	2	0.98679	0.97335	0.96022	0.94883	0.80799	0.92478	0.91243	0.89984

TABLE 9. Univariate Signals - Weighted Noise To Signal Ratio (WNTSR)

This table shows the weighted WNTSR results achieved for each of the 20 raw input variables examined, plus the four fitted crisis probabilities generated by the EWS. WNTSR scores < 1 contain more signal than noise and are preferred. The lower the WNTSR reported the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding WNTSR results depicted. In this instance of the EWS,  $\omega$  was set to 0.45. The policy maker is 45% comfortable with a missed signal and 55% comfortable with a false signal. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. No minimum crisis-anticipation accuracy is required.

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Weighted Noise-to-Signal Ratio							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Household credit growth	Local	2	2	2	2	2	2	2	2	0.9707	0.9564	0.9527	0.9366	0.9429	0.9472	0.9413	0.9397
Inflation	Local	2	2	2	2	2	2	2	2	0.5913	0.5791	0.5750	0.5698	0.5622	0.5529	0.5463	0.5432
National GDP growth rate	Local	2	2	2	2	2	2	2	2	0.8778	0.8740	0.8530	0.8398	0.8235	0.8082	0.7912	0.7785
Real Interest Rate (short-term)	Local	2	2	2	2	2	2	2	2	0.6619	0.6561	0.6543	0.6507	0.6445	0.6385	0.6325	0.6267
Credit to GDP Ratio	Local	2	2	2	2	2	2	2	2	0.5793	0.5733	0.5672	0.5612	0.5530	0.5476	0.5421	0.5365
External claims growth rate	Local	2	2	2	2	2	2	2	2	0.9577	0.9428	0.9194	0.9061	0.8980	0.8939	0.8929	0.8874
CLIFS Index	Local	2	2	99	99	99	99	99	99	0.7869	0.7768	0.8048	0.8078	0.7460	0.7476	0.7487	0.7496
S&P 500 Index	Global	2	2	2	2	2	2	2	2	0.9372	0.9403	0.9488	0.9486	0.9351	0.9136	0.9104	0.9028
Losses only S&P 500 Index	Global	2	2	2	2	2	2	2	2	0.5438	0.5380	0.5323	0.5265	0.5209	0.5153	0.5097	0.5041
Global GDP Growth rate (4-bloc average)	Global	2	2	2	2	2	2	2	2	0.9614	0.9375	0.9305	0.9164	0.9150	0.9097	0.9099	0.9144
% Deviation National GDP from trend	Local	2	2	2	2	2	2	2	2	0.9834	0.9787	0.9739	0.9615	0.9644	0.9663	0.9677	0.9688
% Deviation Global GDP from trend	Global	3	2	2	2	2	2	2	2	0.9827	0.9831	0.9701	0.9721	0.9732	0.9740	0.9746	0.9750
% Deviation Household credit from trend	Local	2	2	2	2	2	2	2	2	0.9820	0.9637	0.9696	0.9726	0.9658	0.9346	0.9290	0.9232
Unemployment Rate	Local	2	2	2	2	2	2	2	2	0.7336	0.7276	0.7175	0.7126	0.7085	0.7039	0.6970	0.6922
% Deviation Unemployment Rate - Trend HP	Local	2	2	2	2	2	2	2	2	0.9854	0.9739	0.9597	0.9599	0.9537	0.9429	0.9329	0.9233
House price index	Local	2	2	2	2	2	2	2	2	0.7224	0.7171	0.7118	0.7066	0.6999	0.6936	0.6877	0.6819
% Deviation House Prices from Trend	Local	2	2	2	2	2	2	2	2	0.9838	0.9795	0.9752	0.9708	0.9664	0.9621	0.9577	0.9534
% Deviation Credit to GDP from trend	Local	5	5	5	5	2	2	2	2	0.9850	0.9818	0.9857	0.9877	0.9788	0.9694	0.9603	0.9515
Standardised Credit to GDP Ratio	Local	2	2	2	3	3	3	3	3	0.9519	0.9494	0.9511	0.8979	0.8931	0.8919	0.8939	0.8948
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	2	3	2	2	2	2	2	2	0.9809	0.9574	0.9776	0.9592	0.9519	0.9539	0.9553	0.9563
Logit prediction - local variables only	Local	2	2	2	2	2	2	2	2	0.7812	0.7694	0.7658	0.7644	0.7604	0.7536	0.7492	0.7464
Logit prediction - global variables only	Global	2	2	2	2	2	2	2	2	0.5676	0.5615	0.5596	0.5555	0.5436	0.5397	0.5316	0.5228
Logit prediction - combination local and global	Combi	99	99	99	99	99	99	99	99	0.7563	0.7682	0.6582	0.6611	0.7752	0.6640	0.6649	0.6655
Logit prediction - recursive combination local and global	Combi	99	99	99	99	99	99	99	99	0.5520	0.5697	0.5442	0.4352	0.5505	0.5520	0.4414	0.4425

TABLE 10. Univariate Signals - Usefulness

This table shows the usefulness results achieved for each of the 20 raw input variables examined. Scores >0 contain more signal than noise and are preferred. The greater the usefulness the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding usefulness results depicted. In this instance of the EWS,  $\omega$  was set to 0.5. The policy maker is indifferent between the costs associated with a missed signal as with a false signal. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. A minimum crisis-anticipation accuracy of 25% is required, a criterion which National GDP fails to achieve within these parameters (up to 6 quarter forecast horizon).

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Usefulness							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Household credit growth	Local	57	58	58	58	58	58	58	58	0.09835	0.08796	0.07759	0.07615	0.07965	0.07526	0.07227	0.07017
Inflation	Local	27	27	50	17	17	17	17	17	0.08057	0.06128	0.0489	0.04534	0.04546	0.04806	0.04807	0.04821
National GDP growth rate	Local	0	0	0	0	0	0	33	33	0	0	0	0	0	0	0.00172	0.0047
Real Interest Rate (short-term)	Local	44	41	40	39	39	34	27	25	0.1086	0.09766	0.08539	0.071	0.05535	0.04266	0.03528	0.03101
Credit to GDP Ratio	Local	44	44	43	43	42	41	41	41	0.11884	0.12011	0.11657	0.11098	0.11373	0.11434	0.11251	0.10959
External claims growth rate	Local	61	80	82	80	81	81	81	79	0.06467	0.0763	0.06219	0.06424	0.06434	0.06	0.05494	0.05234
CLIFS Index	Local	7	2	2	2	2	4	4	2	0.1037	0.09805	0.09911	0.10019	0.09694	0.09784	0.09882	0.09881
S&P 500 Index	Global	26	29	29	29	29	29	17	17	0.04517	0.05166	0.05448	0.05279	0.05457	0.05834	0.05755	0.05935
Losses only S&P 500 Index	Global	84	84	84	84	84	84	84	99	0.06247	0.05642	0.05024	0.04049	0.02137	0.01066	0.00284	0.00125
Global GDP Growth rate (4-bloc average)	Global	42	42	20	26	26	26	26	26	0.06722	0.06122	0.05939	0.05087	0.05338	0.05058	0.05277	0.05098
% Deviation National GDP from trend	Local	8	82	71	80	78	70	70	0	0.03914	0.02924	0.03621	0.02253	0.01788	0.00393	0.00146	0
% Deviation Global GDP from trend	Global	98	98	98	92	92	92	92	81	0.03361	0.02053	0.01623	0.02329	0.0323	0.03625	0.03926	0.04671
% Deviation Household credit from trend	Local	18	18	18	18	17	17	17	17	0.06301	0.06368	0.06437	0.06507	0.06808	0.06341	0.06017	0.05602
Unemployment Rate	Local	37	27	3	3	6	52	52	50	0.01655	0.01448	0.0157	0.01473	0.01382	0.01354	0.01547	0.01781
% Deviation Unemployment Rate - Trend HP	Local	5	23	27	25	85	28	28	25	0.04539	0.03348	0.03602	0.0331	0.04504	0.02591	0.02442	0.02176
House price index	Local	29	28	26	34	34	34	34	34	0.06349	0.06065	0.05434	0.05235	0.05514	0.05725	0.05692	0.05502
% Deviation House Prices from Trend	Local	75	99	99	99	99	99	99	99	0.01261	0.00204	0.00207	0.00209	0.00218	0.00226	0.00232	0.00237
% Deviation Credit to GDP from trend	Local	80	83	77	83	77	77	76	75	0.0478	0.03519	0.03562	0.02909	0.03214	0.03588	0.03708	0.04458
Standardised Credit to GDP Ratio	Local	15	15	15	15	15	15	91	91	0.06345	0.06413	0.0603	0.05867	0.05603	0.05206	0.05016	0.04739
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	16	15	54	54	54	54	54	54	0.07083	0.05217	0.05399	0.05229	0.04995	0.04144	0.04352	0.03979
Logit prediction - local variables only	Local	79	78	77	75	74	25	30	34	0.06706	0.07196	0.06792	0.0589	0.04921	0.04456	0.05255	0.05039
Logit prediction - global variables only	Global	80	67	48	55	58	59	62	55	0.0954	0.1153	0.11384	0.10137	0.09417	0.09675	0.08427	0.08179
Logit prediction - combination local and global	Combi	9	9	9	19	18	21	23	7	0.0821	0.08298	0.08387	0.08182	0.08188	0.0828	0.08351	0.08008
Logit prediction - recursive combination local and global	Combi	62	51	48	45	44	41	39	37	0.11954	0.11294	0.11174	0.10723	0.10665	0.10442	0.10344	0.1026

TABLE 11. Robustness Test - Real Short-term Interest Rates

Robustness Analysis Type:	Logit Regression		
Variable of interest:	<b>Real short-term interest rates</b>		
Outcome variable:	<b>Crisis</b>	Number of observations	702
Possible control terms:	<b>19</b>	Mean R-squared	0.23
Number of models:	<b>524,288</b>	Multicollinearity	0.63
Model Robustness Statistics:		Significance Testing:	
Mean(b)	76.2623	Sign Stability	100%
Sampling SE	10.4146	Significance rate	100%
Modeling SE	9.0746		
Total SE	13.8135	Positive	100%
		Positive and Sig	100%
Robustness Ratio:	5.5209	Negative	0%
		Negative and Sig	0%
<b>Model Influence:</b>			
Marginal Effect			
of Variable Inclusion	from Mean(b)	Percent Change	
Losses only S&P 500 Index	8.802	11.50%	
Global GDP Growth Rate	8.7656	11.50%	
S&P 500 Index	6.6923	8.80%	
Inflation	4.0036	5.20%	
% Deviation Unemployment Rate from Trend	-3.8184	-5.00%	
CLIFS Index	1.7585	2.30%	
% Deviation Global GDP from Trend	1.3858	1.80%	
% Deviation House Price Index from Trend	1.2272	1.60%	
External claims growth rate	-0.9661	-1.30%	
Household credit growth rate	-0.7896	-1.00%	
Local GDP Growth Rate	0.7669	1.00%	
Unemployment	0.4564	0.60%	
Credit-to-GDP ratio	0.4063	0.50%	
House Price Index	-0.3823	-0.50%	
Standardised Credit-to-GDP ratio	0.3788	0.50%	
Loan Elasticity	0.2833	0.40%	
% Deviation Credit to GDP Ratio from Trend	0.1528	0.20%	
% Deviation Local GDP Growth from Trend	0.1441	0.20%	
% Deviation Household Credit Growth from Trend	0.123	0.20%	
Constant	61.5672		
R-squared	0.7261		
This analysis took 968 minutes (16.1 hours) to complete.			

TABLE 12. Robustness Test - S&P 500 Index

Robustness Analysis Type:	Logit Regression		
Variable of interest:	<b>S&amp;P 500 Index</b>		
Outcome variable:	<b>Crisis</b>	Number of observations	702
Possible control terms:	<b>19</b>	Mean R-squared	0.18
Number of models:	<b>524,288</b>	Multicollinearity	0.75
Model Robustness Statistics:		Significance Testing:	
Mean(b)	0.9299	Sign Stability	50%
Sampling SE	1.3508	Significance rate	46%
Modeling SE	2.2598		
Total SE	2.9832	Positive	50%
		Positive and Sig	46%
Robustness Ratio:	0.3117	Negative	50%
		Negative and Sig	0%
<b>Model Influence:</b>			
Marginal Effect of Variable Inclusion	from Mean(b)	Percent Change	
Losses only S&P 500 Index	-4.9315	-530%	
Real short-term interest rates	1.7979	193%	
CLIFS Index	-0.3732	-40%	
% Deviation Global GDP from Trend	-0.1368	-15%	
Global GDP Growth Rate	0.0957	10%	
External claims growth rate	-0.0859	-9%	
% Deviation Unemployment Rate from Trend	0.0734	8%	
Household credit growth rate	0.0722	8%	
Unemployment	0.0653	7%	
Local GDP Growth Rate	-0.0646	-7%	
House Price Index	-0.0607	-7%	
% Deviation Household Credit Growth from Trend	0.0588	6%	
Credit-to-GDP ratio	0.0298	3%	
Standardised Credit-to-GDP ratio	0.0297	3%	
% Deviation Credit to GDP Ratio from Trend	0.0165	2%	
% Deviation House Price Index from Trend	-0.0145	-2%	
Loan Elasticity	-0.0108	-1%	
Inflation	0.0006	0%	
% Deviation Local GDP Growth from Trend	-0.0003	0%	
Constant	2.6491		
R-squared	0.9808		
This analysis took 493 minutes (8.2 hours) to complete.			

TABLE 13. Model Robustness - Summary

This table presents a summary of the model robustness of each of our EWS input indicators (variables). For each variable there are 19 controls, yielding 2<sup>19</sup> potential models for all combinations of a logit model involving the reference variable and its 19 controls (all possible combinations). A distribution of the beta coefficient for each variable is developed as well as a summary showing the delta Beta impact (i.e. upon the mean value of the variables Beta coefficient) from the inclusion of each other variable in the model. Variables which have a greater than 10% impact upon the reference variable are highlighted in the table below. Also shown is a model robustness coefficient which is analogous to the t-stat of the significance of a variable in a regression. Thus a variable with a robustness ratio of 2 (or greater) or -2 (or less) are considered as robust variables and we make the tentative assumption that they should form part of the EWS. Other considerations are the consistent reporting of the sign of the coefficient and the percentage of models where the sign is statistically significant. There are no guidelines presented in Young and Holsteen (2017) as to what constitutes a make-or-break threshold for model inclusion. So we additionally prefer a variable to be significant in 50% of the models estimated.

	H/hold Credit Growth	Infln.	Local GDP Growth	Real s.t. int. Rates	Credit GDP Ratio	Ext. Claims Growth	Fin. Stability Index	S&P 500 Index	Losses S&P 500 Index	Global GDP Growth	% Devn. Loc. GDP Trend	% Devn. Glo. GDP Trend	% Devn. H/hold credit Trend	Unemp. Rate	% Devn. Unemp. Trend	House Price Index	% Devn. House Price Trend	% Devn. Credit-GDP Trend	Std. Credit GDP	Loan Elasticity
H/hold Credit Growth	#N/A	-0.184	0.35	-0.005	0.125	-0.166	-0.042	0.075	0.036	0.242	0.439	-1.005	-0.036	0.008	-0.102	-0.039	0.047	0.012	0.115	0.273
Inflation	-0.09	#N/A	0.478	0.029	0.104	-0.01	0.022	0.003	0.007	0.236	0.021	0.022	-0.002	-0.117	0.011	0.003	0.016	-0.03	0.099	0.03
Local GDP Growth	0.04	0.255	#N/A	0.013	0.255	-0.021	-0.03	-0.071	0.008	0.154	-0.032	-0.028	-0.026	-0.09	0.01	-0.021	0.176	-0.164	0.262	-0.008
Real s.t. Int. Rates	-0.534	-4.467	2.03	#N/A	-0.872	-0.358	0.098	1.956	0.254	4.666	0.682	-0.091	0.064	-2.349	-0.552	-0.096	0.62	-0.21	-0.904	0.681
Credit-GDP Ratio	0.075	0.508	-2.692	0.02	#N/A	-0.011	-0.021	0.033	0.002	-0.088	0.029	-0.024	-0.001	-0.008	0.01	0.18	0.167	0.135	1.99	0.016
Ext. Claims Growth	-0.054	-0.024	0.165	0	-0.04	#N/A	-0.065	-0.094	0.016	0.21	-0.144	-0.343	0.016	-0.043	-0.031	-0.018	0.073	-0.155	-0.049	-0.037
Fin. Stability Index	-0.033	0.251	0.36	0.006	-0.685	-0.083	#N/A	-0.403	-0.078	-0.36	-0.176	0.733	-0.015	-0.202	0.142	0.087	0.741	0.057	-0.677	0.106
S&P 500 Index	0.164	0.608	0.945	0.068	0.047	-0.028	-0.206	#N/A	0.173	-0.16	-0.08	-0.624	-0.024	0.042	0.097	-0.071	0.026	-0.04	0.063	-0.115
Losses S&P 500 index	0.203	0.76	2.563	0.065	0.102	0.064	-0.627	-5.376	#N/A	-0.707	-0.482	-1.626	-0.18	0.087	0.333	-0.243	0.08	-0.354	0.1	-0.563
Global GDP Growth	0.408	-0.226	-0.488	0.035	0.003	0.003	-0.018	0.102	0.035	#N/A	0.225	-0.536	-0.004	-0.038	0.033	-0.075	-0.08	0.295	0.006	0.096
%Devn. Loc. GDP Trend	0.031	0.003	0.009	0.001	-0.002	-0.004	0	-0.001	-0.003	0.003	#N/A	0.002	0	0.009	0.006	-0.007	-0.007	-0.005	0.008	1.055
%Devn. Glo. GDP Trend	-0.286	-0.124	-1.212	0.093	-0.057	-0.049	0.07	-0.148	-0.003	-0.378	0.045	#N/A	0.021	-0.014	-0.01	-0.042	0.016	0.116	-0.046	0.104
%Devn. H/hold Credit - Trend	-0.103	-0.128	0.541	0.007	-0.015	0.013	-0.008	0.062	-0.013	-0.006	0.025	0.148	#N/A	-0.048	0.05	-0.007	-0.077	-0.016	-0.029	0.019
Unemployment	0.017	-0.133	0.044	0.083	0.106	-0.019	-0.015	0.07	0.008	0.169	0.027	-0.013	-0.002	#N/A	-0.057	-0.042	0.231	0.042	0.106	0.074
%Devn. Unemp. Rate - Trend	-0.238	-0.761	0.493	-0.014	0.568	-0.05	0.202	0.082	0.086	0.76	0.081	-0.163	0.109	-1.152	#N/A	-0.377	-0.091	-1.018	0.58	0.357
House Price Index	-0.068	-0.358	0.643	0.031	0.976	-0.038	0.077	-0.061	-0.037	-1.119	-0.098	-0.188	0.001	-0.339	-0.239	#N/A	0.253	-0.299	1.012	-0.163
%Devn. House Prices - Trend	0.133	-0.235	-2.192	0.05	0.5	0.022	0.195	-0.019	0.008	-0.431	-0.038	0.033	-0.037	0.328	-0.019	0.076	#N/A	0.144	0.484	-0.027
%Devn. Credit-GDP Ratio - Trend	-0.011	-0.011	0.02	0.005	0.139	-0.025	0.004	0.022	-0.002	0.27	0.078	0.061	0	0.031	-0.031	-0.025	0.06	#N/A	0.134	0.006
Std. Credit-GDP Ratio	0.003	0.243	-0.923	0.029	2.006	-0.012	-0.023	0.027	0.001	-0.092	0.019	-0.022	-0.001	0	0.011	0.186	0.176	0.134	#N/A	0.013
Loan Elasticity	0.032	0.006	0.063	0.002	0.048	-0.006	0.017	-0.008	-0.007	0.002	2.335	0.055	0.003	0.012	0.027	-0.011	-0.009	-0.018	0.021	#N/A
Robustness Ratio	-1.685	0.0627	0.3399	5.5249	0.3921	1.6353	-1.615	0.3073	-3.196	0.3412	-0.256	0.4837	-1.685	-0.549	-1.854	1.7034	0.8937	-0.598	-0.394	-0.459
Distribution Shape	Normal	Bi-modal	Normal	Uni-Skewed L	Uni-Skewed R	Bi-modal	Normal	Multi-modal	Bi-modal	Bi-modal	Bi-modal	Normal	Normal	Multi-modal	Normal	Multi-modal	Normal	Normal	Uni-Skewed L	Uni-Skewed L
Positive Coefficient	99%	51%	65%	100%	68%	100%	0%	50%	0%	58%	37%	75%	0%	33%	0%	100%	92%	11%	25%	6%
Positive and Significant	27%	15%	10%	100%	2%	42%	0%	46%	0%	34%	0%	14%	0%	0%	0%	60%	10%	0%	1%	0%
Negative Coefficient	1%	49%	35%	0%	32%	0%	100%	50%	100%	42%	63%	25%	100%	67%	100%	0%	8%	89%	75%	94%
Negative and Significant	0%	7%	0%	0%	1%	0%	53%	0%	100%	9%	0%	0%	20%	21%	72%	0%	0%	72%	2%	0%
No. Models	52,523	52,523	52,407	52,129	52,129	52,377	52,494	52,377	52,377	52,077	52,407	52,407	52,509	52,439	52,494	52,111	52,129	52,494	52,499	52,523

TABLE 14. Univariate Signals - Noise To Signal Ratio (NTSR)

This table shows the NTSR results achieved for each of the 20 raw input variables examined. NTSR scores <1 contain more signal than noise and are preferred. The lower the NTSR value reported the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding NTSR results depicted. In this instance of the EWS $\omega$  was set to 0.5 meaning the policy maker is indifferent between false and missed signals. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. A minimum crisis-anticipation accuracy of 25% is required for results to be reported, a criterion which S&P 500 losses only fails to achieve. The best signal is generated by the CLIFS index variable as this has the lowest NTSR score.

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Noise-to-Signal Ratio							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Household credit growth	Local	8	8	8	8	78	8	8	8	0.99099	0.98181	0.97848	0.97103	0.95477	0.95914	0.94886	0.94676
Inflation	Local	2	2	2	2	10	2	2	2	0.99601	0.98984	0.98572	0.98154	0.97151	0.96728	0.96111	0.95913
National GDP growth rate	Local	2	2	2	2	32	2	2	2	1.00613	1.01243	1.0141	1.01581	1.00401	1.01215	1.00716	1.00333
Real Interest Rate (short-term)	Local	2	2	2	2	39	2	2	2	0.99809	0.99731	0.99793	0.99856	0.97717	0.99775	0.99733	0.99691
Credit to GDP Ratio	Local	2	2	2	2	42	2	2	2	0.99543	0.99112	0.98674	0.98231	0.95319	0.9713	0.967	0.96264
External claims growth rate	Local	7	6	6	7	81	6	7	7	0.99544	0.97976	0.97839	0.97033	0.95939	0.96102	0.95387	0.95004
CLIFS Index	Local	2	2	2	2	4	2	2	2	0.98616	0.97537	0.96441	0.95328	0.9438	0.93422	0.92369	0.913
S&P 500 Index	Global	7	7	8	8	29	7	7	7	1.00599	1.01214	1.02101	1.02961	0.96049	1.0349	1.03624	1.04279
Losses only S&P 500 Index	Global	2	2	2	2	.	2	2	2	.	.	.	.	.	.	.	.
Global GDP Growth rate (4-bloc average)	Global	6	6	6	4	26	4	6	6	1.00235	1.00081	0.99658	0.9909	0.95647	0.99104	1.00378	1.01016
% Deviation National GDP from trend	Local	15	15	15	15	78	16	16	17	0.99678	0.99505	0.98856	0.99309	0.99155	1.00059	1.0065	1.00384
% Deviation Global GDP from trend	Global	31	31	31	31	98	31	30	29	1.00146	1.0016	1.00449	1.00326	0.97456	0.9999	1.00699	1.00603
% Deviation Household credit from trend	Local	8	8	8	8	17	8	9	9	0.99835	0.99521	0.99643	1.00067	0.9715	1.00252	0.98874	0.9885
Unemployment Rate	Local	2	2	2	2	6	2	2	2	0.99932	0.99862	0.99676	0.99602	0.99423	0.99554	0.99409	0.99383
% Deviation Unemployment Rate - Trend HP	Local	4	4	4	4	24	4	4	4	1.00118	0.99862	0.99601	0.99846	0.97189	0.99741	0.99422	0.99364
House price index	Local	2	2	2	2	73	2	2	2	1.00269	1.00544	1.00826	1.01116	0.96989	1.0154	1.01759	1.01984
% Deviation House Prices from Trend	Local	40	48	56	56	88	56	55	52	1.001	1.00696	1.01735	1.02221	1.0086	1.03638	1.0442	1.04304
% Deviation Credit to GDP from trend	Local	37	37	36	32	83	28	27	27	1.0038	1.00769	1.01185	1.00885	0.98045	1.00202	0.99923	0.99344
Standardised Credit to GDP Ratio	Local	13	13	13	13	91	13	13	13	0.99286	0.98558	0.98003	0.97436	0.96524	0.96391	0.96141	0.95692
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	15	15	16	16	58	18	18	18	0.99109	0.98569	0.98947	0.98522	0.97703	0.98392	0.97803	0.98709
Logit prediction - local variables only	Local	2	2	2	2	53	2	2	2	1.00053	0.99995	1.00049	1.0022	0.97904	1.0034	1.00462	1.00708
Logit prediction - global variables only	Global	2	2	2	2	73	2	2	2	0.99397	0.98867	0.98595	0.9811	0.951	0.96616	0.95717	0.9484
Logit prediction - combination local and global	Combi	2	2	2	2	20	2	2	2	0.98632	0.9724	0.95823	0.94622	0.91636	0.92088	0.90786	0.8946
Logit prediction - recursive combination local and global	Combi	2	2	2	2	58	2	2	2	0.98679	0.97335	0.96022	0.94883	0.80799	0.92478	0.91243	0.89984
Logit prediction - combination local and global (robust)	Combi	83	80	77	73	71	68	69	60	0.89598	0.82442	0.78122	0.75163	0.71528	0.69674	0.63357	0.6865
Logit prediction - recursive combination local and global (robust)	Combi	93	91	89	82	78	68	64	56	0.67189	0.46872	0.40545	0.51643	0.50418	0.61994	0.61161	0.63245



TABLE 15. Univariate Signals - Weighted Noise To Signal Ratio (WNTSR)

This table shows the weighted WNTSR results achieved for each of the 20 raw input variables examined, plus the four fitted crisis probabilities generated by the EWS. WNTSR scores < 1 contain more signal than noise and are preferred. The lower the WNTSR reported the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding WNTSR results depicted. In this instance of the EWS,  $\omega$  was set to 0.45. The policy maker is 45% comfortable with a missed signal and 55% comfortable with a false signal. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. No minimum crisis-anticipation accuracy is required.

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Weighted Noise-to-Signal Ratio							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Household credit growth	Local	2	2	2	2	2	2	2	2	0.9707	0.9564	0.9527	0.9366	0.9429	0.9472	0.9413	0.9397
Inflation	Local	2	2	2	2	2	2	2	2	0.5913	0.5791	0.5750	0.5698	0.5622	0.5529	0.5463	0.5432
National GDP growth rate	Local	2	2	2	2	2	2	2	2	0.8778	0.8740	0.8530	0.8398	0.8235	0.8082	0.7912	0.7785
Real Interest Rate (short-term)	Local	2	2	2	2	2	2	2	2	0.6619	0.6561	0.6543	0.6507	0.6445	0.6385	0.6325	0.6267
Credit to GDP Ratio	Local	2	2	2	2	2	2	2	2	0.5793	0.5733	0.5672	0.5612	0.5530	0.5476	0.5421	0.5365
External claims growth rate	Local	2	2	2	2	2	2	2	2	0.9577	0.9428	0.9194	0.9061	0.8980	0.8939	0.8929	0.8874
CLIFS Index	Local	2	2	99	99	99	99	99	99	0.7869	0.7768	0.8048	0.8078	0.7460	0.7476	0.7487	0.7496
S&P 500 Index	Global	2	2	2	2	2	2	2	2	0.9372	0.9403	0.9488	0.9486	0.9351	0.9136	0.9104	0.9028
Losses only S&P 500 Index	Global	2	2	2	2	2	2	2	2	0.5438	0.5380	0.5323	0.5265	0.5209	0.5153	0.5097	0.5041
Global GDP Growth rate (4-bloc average)	Global	2	2	2	2	2	2	2	2	0.9614	0.9375	0.9305	0.9164	0.9150	0.9097	0.9099	0.9144
% Deviation National GDP from trend	Local	2	2	2	2	2	2	2	2	0.9834	0.9787	0.9739	0.9615	0.9644	0.9663	0.9677	0.9688
% Deviation Global GDP from trend	Global	3	2	2	2	2	2	2	2	0.9827	0.9831	0.9701	0.9721	0.9732	0.9740	0.9746	0.9750
% Deviation Household credit from trend	Local	2	2	2	2	2	2	2	2	0.9820	0.9637	0.9696	0.9726	0.9658	0.9346	0.9290	0.9232
Unemployment Rate	Local	2	2	2	2	2	2	2	2	0.7336	0.7276	0.7175	0.7126	0.7085	0.7039	0.6970	0.6922
% Deviation Unemployment Rate - Trend HP	Local	2	2	2	2	2	2	2	2	0.9854	0.9739	0.9597	0.9599	0.9537	0.9429	0.9329	0.9233
House price index	Local	2	2	2	2	2	2	2	2	0.7224	0.7171	0.7118	0.7066	0.6999	0.6936	0.6877	0.6819
% Deviation House Prices from Trend	Local	2	2	2	2	2	2	2	2	0.9838	0.9795	0.9752	0.9708	0.9664	0.9621	0.9577	0.9534
% Deviation Credit to GDP from trend	Local	5	5	5	5	2	2	2	2	0.9850	0.9818	0.9857	0.9877	0.9788	0.9694	0.9603	0.9515
Standardised Credit to GDP Ratio	Local	2	2	2	3	3	3	3	3	0.9519	0.9494	0.9511	0.8979	0.8931	0.8919	0.8939	0.8948
Loan Elasticity (% hrcgrowth / % gdpgrowth)	Local	2	3	2	2	2	2	2	2	0.9809	0.9574	0.9776	0.9592	0.9519	0.9539	0.9553	0.9563
Logit prediction - local variables only	Local	2	2	2	2	2	2	2	2	0.7812	0.7694	0.7658	0.7644	0.7604	0.7536	0.7492	0.7464
Logit prediction - global variables only	Global	2	2	2	2	2	2	2	2	0.5676	0.5615	0.5596	0.5555	0.5436	0.5397	0.5316	0.5228
Logit prediction - combination local and global	Combi	99	99	99	99	99	99	99	99	0.7563	0.7682	0.6582	0.6611	0.7752	0.6640	0.6649	0.6655
Logit prediction - recursive combination local and global	Combi	99	99	99	99	99	99	99	99	0.5520	0.5697	0.5442	0.4352	0.5505	0.5520	0.4414	0.4425
Logit prediction - combination local and global (robust)	Combi	99	99	99	99	99	99	99	98	0.7146	0.7233	0.5893	0.5915	0.5928	0.5936	0.5942	0.5233
Logit prediction - recursive combination local and global (robust)	Combi	99	99	99	99	99	99	99	99	0.4714	0.4845	0.4888	0.4910	0.4923	0.4931	0.4937	0.4942

TABLE 16. Univariate Signals - Usefulness

This table shows the usefulness results achieved for each of the 20 raw input variables examined. Scores >0 contain more signal than noise and are preferred. The greater the usefulness the stronger the signal. Up to 8 quarters in advance of crises are considered with optimal percentile and corresponding usefulness results depicted. In this instance of the EWS,  $\omega$  was set to 0.5. The policy maker is indifferent between the costs associated with a missed signal as with a false signal. Only data relating to the quarter in which a crisis occurs is retained in the sample although multiple crises per country are permitted so long as they are separated by non-crisis quarters. A minimum crisis-anticipation accuracy of 25% is required, a criterion which National GDP fails to achieve within these parameters (up to 6 quarter forecast horizon).

Variable Name	Local/ Global	Optimal Centile (Per Quarters Ahead)								Usefulness							
		1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Household credit growth	Local	57	58	58	58	58	58	58	58	0.09835	0.08796	0.07759	0.07615	0.07965	0.07526	0.07227	0.07017
Inflation	Local	27	27	50	17	17	17	17	17	0.08057	0.06128	0.0489	0.04534	0.04546	0.04806	0.04807	0.04821
National GDP growth rate	Local	0	0	0	0	0	0	33	33	0	0	0	0	0	0	0.00172	0.0047
Real Interest Rate (short-term)	Local	44	41	40	39	39	34	27	25	0.1086	0.09766	0.08539	0.071	0.05535	0.04266	0.03528	0.03101
Credit to GDP Ratio	Local	44	44	43	43	42	41	41	41	0.11884	0.12011	0.11657	0.11098	0.11373	0.11434	0.11251	0.10959
External claims growth rate	Local	61	80	82	80	81	81	81	79	0.06467	0.0763	0.06219	0.06424	0.06434	0.06	0.05494	0.05234
CLIFS Index	Local	7	2	2	2	2	4	4	2	0.1037	0.09805	0.09911	0.10019	0.09694	0.09784	0.09882	0.09881
S&P 500 Index	Global	26	29	29	29	29	29	17	17	0.04517	0.05166	0.05448	0.05279	0.05457	0.05834	0.05755	0.05935
Losses only S&P 500 Index	Global	84	84	84	84	84	84	84	99	0.06247	0.05642	0.05024	0.04049	0.02137	0.01066	0.00284	0.00125
Global GDP Growth rate (4-bloc average)	Global	42	42	20	26	26	26	26	26	0.06722	0.06122	0.05939	0.05087	0.05338	0.05058	0.05277	0.05098
% Deviation National GDP from trend	Local	8	82	71	80	78	70	70	0	0.03914	0.02924	0.03621	0.02253	0.01788	0.00393	0.00146	0
% Deviation Global GDP from trend	Global	98	98	98	92	92	92	92	81	0.03361	0.02053	0.01623	0.02329	0.0323	0.03625	0.03926	0.04671
% Deviation Household credit from trend	Local	18	18	18	18	17	17	17	17	0.06301	0.06368	0.06437	0.06507	0.06808	0.06341	0.06017	0.05602
Unemployment Rate	Local	37	27	3	3	6	52	52	50	0.01655	0.01448	0.0157	0.01473	0.01382	0.01354	0.01547	0.01781
% Deviation Unemployment Rate - Trend HP	Local	5	23	27	25	85	28	28	25	0.04539	0.03348	0.03602	0.0331	0.04504	0.02591	0.02442	0.02176
House price index	Local	29	28	26	34	34	34	34	34	0.06349	0.06065	0.05434	0.05235	0.05514	0.05725	0.05692	0.05502
% Deviation House Prices from Trend	Local	75	99	99	99	99	99	99	99	0.01261	0.00204	0.00207	0.00209	0.00218	0.00226	0.00232	0.00237
% Deviation Credit to GDP from trend	Local	80	83	77	83	77	77	76	75	0.0478	0.03519	0.03562	0.02909	0.03214	0.03588	0.03708	0.04458
Standardised Credit to GDP Ratio	Local	15	15	15	15	15	15	91	91	0.06345	0.06413	0.0603	0.05867	0.05603	0.05206	0.05016	0.04739
Loan Elasticity (% hhcgrowth / % gdpgrowth)	Local	16	15	54	54	54	54	54	54	0.07083	0.05217	0.05399	0.05229	0.04995	0.04144	0.04352	0.03979
Logit prediction - local variables only	Local	79	78	77	75	74	25	30	34	0.06706	0.07196	0.06792	0.0589	0.04921	0.04456	0.05255	0.05039
Logit prediction - global variables only	Global	80	67	48	55	58	59	62	55	0.0954	0.1153	0.11384	0.10137	0.09417	0.09675	0.08427	0.08179
Logit prediction - combination local and global	Combi	9	9	9	19	18	21	23	7	0.0821	0.08298	0.08387	0.08182	0.08188	0.0828	0.08351	0.08008
Logit prediction - recursive combination local and global	Combi	62	51	48	45	44	41	39	37	0.11954	0.11294	0.11174	0.10723	0.10665	0.10442	0.10344	0.1026
Logit prediction - combination local and global (robust)	Combi	74	68	68	60	62	62	69	54	0.12706	0.12406	0.1254	0.12059	0.11592	0.11203	0.11092	0.10871
Logit prediction - recursive combination local and global (robust)	Combi	91	83	58	64	58	40	49	45	0.14084	0.13742	0.13699	0.13207	0.1269	0.12209	0.11871	0.11854

