EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Jan Hannes Lang

Cross-country linkages and spill-overs in early warning models for financial crises

No 2160 / June 2018

Abstract

This paper uses data on bilateral foreign exposures of domestic banking systems in order to construct early warning models for financial crises that take into account cross-country spill-overs of vulnerabilities. The empirical results show that incorporating cross-country financial linkages can improve the signalling performance of early warning models. The relative usefulness increases from 65% to 87% and the AUROC from 0.89 to 0.97 when weighted foreign variables are added to domestic variables in a multivariate logit early warning model. The findings of the paper also suggest that global variables still play a role in predicting financial crises, even when foreign variables are controlled for, which could suggest that both cross-country spill-overs and contagion are important factors for driving financial crises. A parsimonious model with nine variables that combines domestic, foreign and global variables yields an out-of-sample relative usefulness of 0.82 with Type I and Type II errors of 0.11 and 0.07.

Keywords: Early Warning Models, Financial Crises, Financial Linkages

JEL classification: G01, G17, F37, F65

Non-Technical Summary

The global financial crisis that started in August 2007 has renewed the academic and policy interest in understanding the factors that make countries vulnerable to financial crises. One of the main analytical avenues that has been pursued to answer this question is the construction of so-called early warning models. These models aim to predict underlying vulnerabilities for financial crises with a sufficient lead time by using various macro-financial indicators, such as domestic credit or asset price variables. Recent contributions to this line of research, such as Alessi and Detken (2011), Lo Duca and Peltonen (2013) or Behn et al. (2013) have shown that global variables help to improve the predictive power of early warning models. These global variables are usually constructed as a GDP-weighted average of the respective country variables and therefore take on the same values for every country. This leaves open the question to what extent such global variables may simply be a proxy for other underlying factors such as cross-country financial linkages. For example, even though Germany showed little signs of domestic financial vulnerabilities prior to the recent financial crisis, its banking sector experienced stress at least partly because of losses from exposures to foreign assets.

With this background in mind, the aim of this paper is to study the role of cross-country financial linkages and spill-overs in the context of early warning models for financial crises. The basic idea is to use data on bilateral exposures of each domestic banking system to other countries in order to construct early warning models that take into account domestic vulnerabilities as well as cross-country spill-overs of vulnerabilities that arise due to foreign links of the domestic financial system. The approach proposed in this paper therefore combines to some extent the cross-sectional and time-dimension of systemic risk in the prediction of financial vulnerabilities. The analysis is complementary to the early warning literature that has focused on the role of global variables and contributes to our understanding of the determinants of financial vulnerabilities in a highly interconnected world.

The empirical approach taken in this paper is to employ logit models to map domestic, global and weighted foreign vulnerability indicators into a probability that a financial crisis will materialise within the next 1.5 to 4 years. By minimising the loss function of a policy maker with a given preference between missing crises and issuing false crisis alarms, an optimal signalling threshold is then derived that transforms the probabilities from the logit model into binary crisis signals. Foreign vulnerability indicators are defined as the weighted average of the respective variable across all foreign countries from the point of view of the country at hand. The weights for constructing foreign variables are country-specific and time-varying and they are based on the direct asset-side exposure of each national banking system to other foreign countries as a share of the country's GDP.

The empirical results of this paper show that incorporating cross-country financial linkages can indeed improve the signalling performance of early warning models. The relative usefulness, which is a measure of how much benefit the model would yield to a policy maker compared to not using the model, increases from 65% to 87% when foreign variables are added to domestic variables in a multivariate early warning model. Similarly, the fit of the model to the data doubles, as represented by an increase in the pseudo-R^2 from 0.32 to 0.65. The findings of the paper also suggest that global variables still play a role in predicting financial crises, even when foreign variables are included in the model, which could suggest that both cross-country spill-overs and contagion are important factors for driving financial crises.

In summary, the results of this paper suggest that the build-up of foreign and global imbalances can be just as important as the build-up of domestic imbalances for making countries susceptible to financial crises. This finding seems particularly relevant in the context of the EU, where strong financial links exist and cross-country spill-overs could be of particular importance.

1 Introduction

The global financial crisis that started in August 2007 has renewed the academic and policy interest in understanding the factors that make countries vulnerable to financial crises. One of the main analytical avenues that has been pursued to answer this question is the construction of so-called early warning models. These models aim to predict underlying vulnerabilities for financial crises with a sufficient lead time by using various macro-financial indicators, such as domestic credit or asset price variables. Recent contributions to this line of research, such as Alessi and Detken (2011), Lo Duca and Peltonen (2013) or Behn et al. (2013) have shown that global variables, like for example the global private credit gap, help to improve the predictive power of early warning models. These global variables are usually constructed as GDP weighted averages of the respective country variables and therefore take on the same values for all countries.

The importance of global variables in early warning models suggests that contagion can be at play when it comes to financial crises, as within this modelling approach all countries irrespective of their trade or financial links are affected by global development. While contagion might well play a role for financial crises, it is equally plausible that cross-country spill-overs due to financial links with other countries are an important determinant for whether a country's banking sector runs into problems. For example, even though Germany showed little signs of domestic financial vulnerabilities prior to the recent financial crisis, its banking sector experienced stress at least partly because of losses from exposures to foreign assets.

With this discussion in mind, the aim of this paper is to study the role of cross-country financial linkages and spill-overs in the context of early warning models for financial crises. The basic idea is to use data on bilateral exposures of each domestic banking system to other countries in order to construct early warning models that take into account domestic vulnerabilities as well as cross-country spill-overs of vulnerabilities that arise due to foreign links of the domestic financial system. The approach proposed in this paper therefore combines to some extent the cross-sectional and time-dimension in the prediction of financial vulnerabilities. The analysis is complementary to the early warning literature that has focused on the role of global variables and should help to sharpen our understanding of the determinants of financial vulnerabilities in a highly interconnected world.

Important contributions to the early warning literature that this paper relates to are Frankel and Rose (1996), Kaminsky et al. (1998), Demirgüc-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999) and Borio and Lowe (2002). More recent contributions that show a role for global variables in predicting financial vulnerabilities include Alessi and Detken (2011), Lo Duca and Peltonen (2013) or Behn et al. (2013). Even though some attempts have been made to incorporate foreign financial exposures into early warning models, see e.g. Rose and Spiegel (2010), Borio and Drehmann (2009) or Minoiu et al. (2013), there has not been a systematic exploration of this issue within discrete choice models where financial links are interacted with foreign vulnerabilities. Moreover, while the first paper finds no strong evidence for the role of cross-country financial linkages, the latter papers present results that would support a role for cross-border financial linkages in predicting vulnerabilities to financial crises. The way that this paper introduces cross-country financial linkages within the early warning model is similar in spirit to the way that the Global Vector Auto Regression (GVAR) literature models cross-country linkages (See e.g. Pesaran et al. (2004), Galesi and Sgherri (2009), Chudik and Fratzscher (2011) or Sun et al. (2013)).

The empirical approach taken in this paper is to employ logit models to map domestic, global and weighted foreign vulnerability indicators into a probability that a financial crisis will materialise within the next 1.5 to 4 years. By minimising the loss function of a policy maker with a given preference between missing crises (Type I error) and issuing false crisis alarms (Type II error), an optimal signalling threshold for financial crises is derived that transforms the probabilities from the logit model into binary crisis signals. Compared to the existing literature the main innovation of this paper is to consider not only domestic and global indicators as potential risk drivers, but also weighted foreign indicators that capture vulnerabilities in foreign countries to which the banking sector of a given country is linked via direct exposures. A foreign variable is defined by the weighted average of the respective variable across all foreign countries from the point of view of the country at hand. The weights for constructing foreign variables are country-specific and time-varying and they are based on the direct asset-side exposure of each national banking system to other foreign countries as a share of the country's GDP.

The empirical results of this paper show that incorporating cross-country financial linkages can indeed improve the signalling performance of early warning models. The relative usefulness, which is a loss function based performance measure of early warning models[1], increases from 65% to 87% and the AUROC[2] from 0.89 to 0.97

[1]See for example Alessi and Detken (2011) or Betz et al. (2013)

[2]The AUROC is a global performance measure to evaluate early warning models. The AUROC measures the area underneath the Receiver Operating Characteristic (ROC) curve, which plots

when foreign variables are added to domestic variables in a multivariate early warning model, while the pseudo-R^2 doubles from 0.32 to 0.65. The findings of the paper also suggest that global variables still play a role in predicting financial crises, even when foreign variables are included in the model, which could suggest that both cross-country spill-overs and contagion are important factors for driving financial crises.[3] A parsimonious model with nine variables that combines domestic, foreign and global variables yields an in-sample AUROC of 0.98 and an out-of-sample relative usefulness of 82%, corresponding to out-of-sample Type I and Type II errors of 0.11 and 0.07.[4] The results suggest that the build-up of foreign and global imbalances can be just as important as the build-up of domestic imbalances for making countries susceptible to financial crises. This finding seems particularly relevant in the context of the EU, where strong financial links exist and cross-country spill-overs could be of particular importance.

The remainder of the paper is structured as follows. First the modelling framework is outlined, followed by a description of the data sources and variable definitions. The third part of the paper presents the estimation results, while a concluding part is provided at the end of the paper.

2 Overview of the Modelling Framework

The early warning model developed in this paper can be thought of as a five-step process, which is illustrated in figure 1. The starting point consists of a country-level dataset that contains information on banking crises, macro-financial variables and bilateral banking sector asset-side exposures.[5] In the second step, a logit model is used to map domestic, global and weighted foreign vulnerability indicators into a crisis probability over a pre-specified time horizon. In the third step, an optimal signalling threshold is derived that transforms the probabilities from the logit model into a binary crisis signal, by minimising the loss function of a policy maker with a given preference between missing crises (Type I error) and issuing false crisis alarms (Type II error). The fourth step in the process consists of evaluating the in-sample and out-of-sample performance of the model, while in the final step the estimated

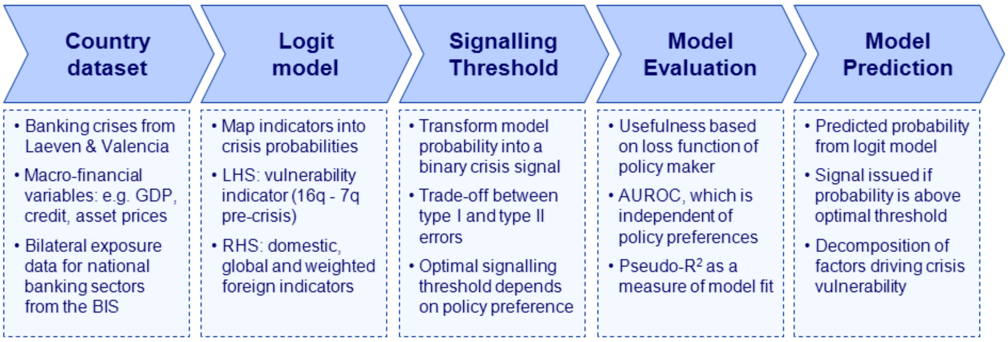
the false positive rate against the true positive rate for every possible threshold. See section 2 for details.

[3]This conclusion regarding the relative role of spill-overs and contagion is tentative at this stage.

[4]Out-of-sample results are based on a recursive 1-quarter-ahead forecasting exercise between 2000q1 and 2012q1.

[5]Details of the data sources and variable definitions can be found in section 3.

Figure 1: The five-step process of the early warning model



Notes: LHS means Left-Hand-Side variable. RHS means Right-Hand-Side variable. Type I errors refer to the share of missed crises. Type II errors refer to the share of false crisis alarms. AUROC refers to the Area Under the Receiver Operating Characteristic Curve.

model is used to make predictions about current vulnerabilities for the countries of interest.

2.1 Mapping Indicators Into Crisis Probabilities

There are two approaches in the early warning literature to generate binary crisis predictions. The first approach is known as the signalling approach which has been pioneered by Kaminsky et al. (1998) and Kaminsky and Reinhart (1999) and further refined by Borio and Lowe (2002), Borio and Drehmann (2009) and Alessi and Detken (2011) to a multivariate setting. In the signalling approach a crisis signal is issued whenever one or more indicators exceed a certain threshold value, which is derived by optimising a particular in-sample criterion such as the Noise-to-Signal ratio or a policy maker's loss function. The second approach to generate binary crisis predictions employs a multivariate logit/probit model to first map indicators into crisis probabilities and then transforms these crisis probabilities into binary crisis predictions by using the univariate signalling approach. This multivariate logit/probit approach has been pioneered by Demirgüc-Kunt and Detragiache (1998) and Berg and Pattillo (1999) and has been extensively used in recent years (See e.g. Berg et al. (2005), Lo Duca and Peltonen (2013), Behn et al. (2013) or Minoiu et al. (2013)). While the two approaches are similar in spirit, the multivariate signalling approach can become computationally very intense if more than three indicators are considered in a given model, while the multivariate logit approach can easily handle models that contain many variables.

Given that the research question posed in this paper requires the inclusion of various domestic, foreign and global indicators in an early warning model, the pooled multivariate logit approach is the modelling framework of choice. Compared to the existing literature the main innovation of this paper is to consider not only domestic and global indicators as potential risk drivers, but also weighted foreign indicators that capture vulnerabilities in foreign countries to which the banking sector of a given country is linked via direct exposures. Formally, the approach can be represented by making the crisis probability $P(C_{i,t} = 1)$ of a given country i at time t a function of past domestic variables $\mathbf{x^d_{i,t-1}}$, foreign variables $\mathbf{x^f_{i,t-1}}$ and global variables $\mathbf{x^g_{t-1}}$:

$$P(C_{i,t} = 1) = f(\mathbf{x^d_{i,t-1}}, \mathbf{x^f_{i,t-1}}, \mathbf{x^g_{t-1}}) = \frac{e^{(\boldsymbol{\beta}'\mathbf{x_{i,t-1}})}}{1 + e^{(\boldsymbol{\beta}'\mathbf{x_{i,t-1}})}} \tag{1}$$

where $\mathbf{x^d_{i,t-1}}$, $\mathbf{x^f_{i,t-1}}$, $\mathbf{x^g_{t-1}}$ and $\boldsymbol{\beta}$ are column vectors of dimension k^d, k^f, k^g and $(1+k^d+k^f+k^g)$ respectively and $\mathbf{x_{i,t-1}} \equiv [1; \mathbf{x^d_{i,t-1}}; \mathbf{x^f_{i,t-1}}; \mathbf{x^g_{t-1}}]$ is a stacked column vector of domestic, foreign and global variables. A foreign variable is defined as the weighted average of the respective variable across all foreign countries from the point of view of the country at hand. The weights for constructing foreign variables are country-specific and time-varying and they are based on the direct asset-side exposure of each national banking system to other foreign countries as a share of the country's GDP. The choice of using banking sector asset-side exposure as a proxy for cross-country financial linkages appears reasonable given the dominant role that banks usually play in the financial system, which is especially true for EU countries. Moreover, credit risk, which should to some extent be captured by asset side exposures of banks, often increases during financial crises. Formally, a foreign variable k^f for country i at time t can be represented as follows:

$$k^f_{i,t} = \sum_{j \neq i} \omega^i_{j,t} k^d_{j,t} = \sum_{j \neq i} \frac{a^i_{j,t}}{y^d_{i,t}} k^d_{j,t} \tag{2}$$

where $a^i_{j,t}$ is the asset side exposure of the banking sector located in country i towards country j at time t and $y^d_{i,t}$ is nominal GDP of country i at time t. The basic intuition behind constructing foreign variables in this way is that if a banking sector is highly exposed to foreign countries, compared to the size of the domestic economy, then vulnerabilities that build up abroad might be relevant for the probability that the domestic banking sector runs into problems. For example, during the recent financial crisis the German banking sector experienced stress at least partly because of losses from exposures to foreign assets. The global variables are constructed in the same way as in Alessi and Detken (2011), Lo Duca and Peltonen (2013) or Behn et al. (2013), namely as a GDP weighted average of the indicator across all countries. Formally, a global variable k^g at time t can be represented as follows:

$$k_t^g = \frac{1}{\sum_j y_{j,t}^d} \sum_j y_{j,t}^d k_{j,t}^d \tag{3}$$

While foreign and global indicators might appear similar in their construction, their spirit is distinct. Foreign indicators imply that direct exposure to other countries matters for the build-up of vulnerabilities. In other words, foreign variables imply that spill-overs across countries with direct links are important in the propagation of financial crises. In contrast, global indicators imply that the global macro-financial environment per se matters for the build-up of vulnerabilities. Global variables affect all countries in the same way, no matter what their international links look like. The interpretation of global variables is therefore akin to contagion of financial crises across countries.

2.2 Deriving Optimal Signalling Thresholds

Once a logit model is estimated, the probabilities that the model produces need to be transformed into a binary signal by setting a probability threshold above which all model probabilities are classified as a crisis signal. For a given threshold the signals that are produced from the model can be compared to the actual incidence of crises and classified into one of the categories displayed in table 1. In order to decide which particular threshold should be used to produce crisis signals from the model, a criterion is needed to rank the classifications that are produced by each threshold. In line with the paper by Alessi and Detken (2011) a loss function approach is chosen, where the optimal signalling threshold minimises a weighted average between Type I (T_1) and Type II (T_2) errors:

$$L(\mu) = \mu \cdot T_1 + (1 - \mu) \cdot T_2 \tag{4}$$

The policy preference parameter μ reflects the relative concern assigned to missing crises (T_1) versus issuing false crisis alarms (T_2).[6] All baseline results in this paper are derived under the assumption of balanced preferences between Type I and Type II errors, i.e. that $\mu = 0.5$.

[6]Formally, Type I and Type II errors are defined as follows: $T_1 = \frac{FN}{TP+FN}$ and $T_2 = \frac{FP}{TN+FP}$.

Table 1: Classification table for signals and crises

	Crisis	**No Crisis**
Signal	True Positive (TP)	False Positive (FP)
No Signal	False Negative (FN)	True Negative (TN)

2.3 Evaluation Criteria for the Models

Once a logit model has been estimated and an optimal signalling threshold has been derived, the signalling performance and fit of the early warning model need to be evaluated. One of the advantages of the loss function approach for deriving the optimal signalling threshold is that it allows for the evaluation of the early warning model in terms of the relative usefulness of the model for the policy maker as proposed by Sarlin (2013):

$$U_r(\mu) = \frac{\min[\mu, 1-\mu] - L(\mu)}{\min[\mu, 1-\mu]} \tag{5}$$

The relative usefulness measure represents the difference in the loss that the policy maker would get by using the model compared to ignoring the model, expressed as a share of the maximum achievable difference.[7] The measure therefore gives an idea of how close the early warning model is to a perfect model of crisis prediction for a policy maker with preferences represented by μ. However, relative usefulness depends on the preferences of the policy maker and it is therefore desirable to look at global measures of signalling performance in addition to relative usefulness.

The AUROC is such a global performance measure to evaluate early warning models.[8] The AUROC measures the area underneath the Receiver Operating Characteristic (ROC) curve, which plots the false positive rate against the true positive rate for every possible threshold. Both the false positive rate and the true positive rate are decreasing (weakly) monotonely with a rise in the signalling threshold. Intuitively, the higher the threshold, the less signals are issued and the less crises are signalled correctly, while fewer false alarms are called at the same time. A perfect indicator has an AUROC of 1, while an uninformative indicator has an AUROC of

[7]It is always possible to never signal a crisis or signal a crisis all the time. In the first case Type II errors would be equal to zero and Type I errors equal to one, while in the latter case the reverse would be true. Hence, a policy maker can always achieve a loss of $\min[\mu, 1-\mu]$ without a model.

[8]The AUROC is used as an evaluation criterion by e.g. Schularick and Taylor (2012), Behn et al. (2013) and Detken et al. (2014).

0.5.

Finally, in addition to the AUROC and relative usefulness the pseudo-R^2 proposed by McFadden (1974) is also used to evaluate the model fit for the logit model. These three evaluation criteria combined should give a fairly robust picture of the performance of the early warning model.

3 Data Sources and Variable Definitions

The dataset used in this paper has three main building blocks. First, information on the incidence of banking crises is needed at the country level. Second, information on national macro-financial variables such as GDP, credit and house prices is required to construct indicators that signal the build-up of imbalances. Third, asset-side exposure information to foreign countries is needed for each national banking sector, in order to be able to capture vulnerabilities that emerge due to non-domestic imbalances. The following subsections describe each of these building blocks in greater detail.

3.1 The Binary Vulnerability Indicator

Before we can start to build an early warning model for financial crises, it is necessary to define the type of events that the early warning model is supposed to forecast. The approach taken in this paper follows much of the recent early warning literature, which tries to forecast vulnerable states rather than actual crisis events.[9] For the baseline model specification the binary vulnerability indicator is set equal to one for 16 to 7 quarters before the start of a banking crisis and zero otherwise. The 6 quarters that precede the start of a banking crisis are excluded from the estimation, in order to allow a sufficiently long lead time for the early warning signals. In addition, all crisis quarters and quarters following within one year after the resolution of a banking crisis are excluded from the estimation, in order to alleviate any potential crisis and post-crisis bias (See Bussiere and Fratzscher (2006)). The underlying banking crisis events that are used to construct the binary vulnerability indicator are taken from Laeven and Valencia (2012), which covers all systemic banking crises across the world between 1970 - 2011.[10]

[9] See for example Borio and Drehmann (2009), Alessi and Detken (2011), Lo Duca and Peltonen (2013), Behn et al. (2013) or Detken et al. (2014).

[10] The crisis database used is an update of Laeven and Valencia (2008).

3.2 Macro-Financial Variables

Various macro-financial indicators that have been found to be useful in the context of early warning models for financial crises were collected for a large set of advanced and emerging market economies. These variables include total credit to the non-financial private sector, residential real-estate prices, equity prices, gross domestic product (GDP), the real effective exchange rate (REER), the net international investment position (NIIP) and the current account balance. For these variables various ratios and transformations are considered, such as annual growth rates and differences, as well as gap measures as proposed in Borio and Lowe (2002), Borio and Drehmann (2009) or Drehmann et al. (2011) for example. All of the gap measures are derived by applying a recursive one-sided HP-filter with a smoothing parameter of 400,000 to the series of interest and taking the resulting cyclical component as the gap measure. For stock prices and real estate prices the relative gap compared to the recursive one-sided trend is used, while for the credit-to-GDP ratio the absolute gap is considered. For the models that are estimated in section 4 all of the variables are lagged by one quarter in order to account for publication lags. Details of the data sources and start dates for data availability by country can be found in table 6 in the appendix.

3.3 Data on Cross-Country Financial Linkages

In order to capture the asset-side exposure of national banking sectors vis-à-vis other countries in the world, the confidential version of the Locational Banking Statistics (LBS) of the Bank for International Settlements (BIS) is used. This dataset contains quarterly asset and liability positions of 44 national banking sectors vis-à-vis virtually all other countries in the world, starting as early as 1977 for the major advanced economies. For the purpose of building the early warning model, a subset of 30 major advanced economies and key emerging markets was selected as the relevant country sample. A summary of data availability for this list of countries can be found in table 6 in the appendix.

4 Estimation Results

In order to study the role of cross-border financial linkages for the build-up of vulnerable states that can lead to banking crises, three separate exercises are performed.

First, a number of univariate early warning models are estimated for indicators that have been found to have good signalling properties in the existing literature. For all of these indicators a domestic, foreign and global version is evaluated and compared. Based on this initial univariate analysis of the relative performance of domestic, foreign and global indicators, a number of pooled multivariate logit early warning models are constructed and estimated that combine all of the variable categories. Finally, a recursive out-of-sample forecasting exercise is performed for the various pooled multivariate models with a particular focus on the added forecasting performance that comes through the inclusion of foreign indicators.

4.1 Univariate Analysis

Table 2 summarises the results for the univariate models, which cover credit, property price and stock price indicators, the Real Effective Exchange Rate (REER), as well as the Net International Investment Position (NIIP) and the current account balance.[11] In order to allow for maximum comparability the domestic, foreign and global versions of each indicator are tested on the same sample.

The first result that emerges from the univariate analysis is that foreign and global indicators often have similar or even better signalling properties than the corresponding domestic indicator.[12] For example, the foreign and global property-price gap attain AUROC values of 0.82 and 0.81 and a pseudo-R^2 of 0.17 and 0.18, whereas the domestic property-price gap has an AUROC of 0.63 and a pseudo-R^2 of 0.03. For the credit-to-GDP gap, which is one of the most prominent signalling variables used in the early warning literature, the foreign variable is slightly better than the domestic counterpart and considerably better than the global variable, with AUROCs of 0.75, 0.71 and 0.56 respectively.

All in all, for seven out of the ten indicators that were tested, the foreign version has a higher AUROC than the corresponding domestic or global variable. When pseudo-R^2 and relative usefulness are used as the evaluation criterion, then six and four of the foreign indicators perform better than the domestic or global counterparts. Among the domestic variables only the stock-price gap and the REER have a higher AUROC and pseudo-R^2 than the corresponding foreign and global variables, while for the property price gap and the NIIP the global version achieves the highest

[11] Both the NIIP and current account are measured as a share of GDP.

[12] The good signalling properties of global variables has been pointed out by many recent contributions to the early warning literature like Alessi and Detken (2011), Lo Duca and Peltonen (2013) or Behn et al. (2013), while the focus on foreign variables is the key innovation of this paper.

Table 2: Results for the univariate models

Indicator	**U_r**	**AUROC**	**pseudo-R^2**	**Type I**	**Type II**	**Coeff**	**Obs**
Credit-to-GDP gap (D)	0.34	0.71	0.067	0.24	0.42	0.071***	2,030
Credit-to-GDP gap (F)	0.43	0.75	0.072	0.27	0.30	0.191***	2,030
Credit-to-GDP gap (G)	0.31	0.56	0.005	0.22	0.47	-0.059	2,030
Credit growth (D)	0.10	0.53	0.002	0.75	0.15	-0.018	2,030
Credit growth (F)	0.22	0.67	0.046	0.16	0.62	0.112***	2,030
Credit growth (G)	0.24	0.61	0.021	0.30	0.47	-0.153**	2,030
Δ Credit-to-GDP (D)	0.16	0.60	0.020	0.28	0.55	0.082**	2,030
Δ Credit-to-GDP (F)	0.30	0.69	0.040	0.43	0.27	0.179***	2,030
Δ Credit-to-GDP (G)	0.23	0.61	0.013	0.23	0.54	-0.162**	2,030
Property-price gap (D)	0.28	0.63	0.034	0.46	0.26	0.038***	1,892
Property-price gap (F)	0.51	0.82	0.172	0.30	0.19	0.155***	1,892
Property-price gap (G)	0.57	0.81	0.181	0.25	0.18	0.318***	1,892
Property-price growth (D)	0.18	0.59	0.009	0.45	0.38	0.029*	1,911
Property-price growth (F)	0.36	0.73	0.070	0.48	0.16	0.152***	1,911
Property-price growth (G)	0.54	0.70	0.026	0.11	0.36	0.131***	1,911
Stock-price gap (D)	0.35	0.69	0.050	0.36	0.29	-0.023*	2,110
Stock-price gap (F)	0.34	0.67	0.045	0.51	0.15	-0.050***	2,110
Stock-price gap (G)	0.38	0.68	0.045	0.09	0.52	0.031***	2,110
Stock-price growth (D)	0.27	0.63	0.012	0.27	0.46	0.011***	2,110
Stock-price growth (F)	0.40	0.75	0.088	0.31	0.29	0.067***	2,110
Stock-price growth (G)	0.37	0.65	0.036	0.12	0.52	0.033***	2,110
NIIP (D)	0.16	0.54	0.002	0.47	0.37	-0.004	1,854
NIIP (F)	0.18	0.58	0.000	0.66	0.17	-0.001	1,854
NIIP (G)	0.56	0.72	0.088	0.21	0.23	-0.373***	1,854
Current account (D)	0.12	0.50	0.001	0.67	0.21	0.017	2,008
Current account (F)	0.32	0.66	0.019	0.43	0.26	0.517	2,008
Current account (G)	0.24	0.50	0.000	0.04	0.72	-0.088	2,008
REER (D)	0.32	0.69	0.083	0.18	0.51	0.059***	1,932
REER (F)	0.26	0.65	0.035	0.48	0.26	0.007**	1,932
REER (G)	0.48	0.66	0.000	0.24	0.28	-0.001	1,932

Notes: (D), (F) and (G) refer to domestic, foreign and global variables respectively. U_r stands for relative usefulness, pseudo-R^2 is the Pseudo-R-Squared proposed by McFadden (1974), Coeff is the estimated coefficient from the logit model and Obs refers to the number of observations. Usefulness, Type I and Type II errors are derived for balanced preferences, i.e. $\mu = 0.5$. Growth rates and differences are computed in year-on-year terms. All gap measures are calculated using a recursive one-sided HP-filter with a smoothing parameter of 400,000. NIIP is the Net International Investment Position measured as a share of GDP. The Current Account balance is also measured as a share of GDP. REER is the Real Effective Exchange Rate. Significance of the coefficients is based on robust standard errors, clustered at the country level: *** p<0.01, ** p<0.05, * p<0.1.

relative usefulness and pseudo-R^2.

In most cases, the estimated coefficient from the univariate logit model has the expected sign based on economic intuition. For example, property-price variables and stock price growth consistently display positive coefficients, which is in line with a narrative that large asset price increases or bubbles are often associated with subsequent financial problems or crises. There are however a couple of notable exceptions, where the estimated coefficient has a counterintuitive sign. For example, the global credit variables all have negative coefficients, as do the domestic credit growth variable and the domestic and foreign stock-price gap. Of course, due to the univariate nature of the models, omitted variables bias is potentially an issue and the coefficients should not be interpreted as a causal effect. However, this caveat should not be a major concern, given that the focus of this paper is on studying the signalling properties of different variables, rather than on identifying their true causal effect.

The univariate results suggest that foreign variables can indeed have useful signalling properties for financial crises. However, even though in some cases one of the domestic, foreign or global version of the variable appears clearly better than the others, there are some cases where it is not self-evident which of the transformations is best. All of these results suggest that it could be promising to combine domestic, foreign and global variables within a multivariate early warning model framework. In addition to possibly improving the signalling performance, the inclusion of domestic, foreign and global variables within a multivariate model also allows for a better assessment of the relative importance of each variable category.

4.2 Multivariate Analysis

Based on the univariate results a domestic, foreign and global variable block was created and various combinations of these variable blocks were tested in a pooled multivariate logit framework. The combination of indicators in each of the variable blocks was chosen so as to yield good signalling properties with a fairly parsimonious model. The individual indicators that are contained in the three variable blocks therefore differ somewhat. As can be seen from the first three colums of table 3, all of the variable blocks have reasonable signalling properties with AUROCs above 0.80 and relative usefulness above 65%. In terms of pseudo-R^2, the foreign variable block achieves the highest value with 0.36, while the domestic variable block has the highest AUROC with 0.89, and the global variable block the highest usefulness

Table 3: Results for the multivariate models I

	Domestic	**Foreign**	**Global**	**Domestic Foreign**
Credit-to-GDP gap (D)	0.0798***			0.150***
Property-price gap (D)	0.0268			0.0357*
Stock-price gap (D)	-0.0602***			-0.0369*
Stock-price growth (D)	0.0675***			0.0484***
REER (D)	0.0505**			0.120***
Credit-to-GDP gap (F)		-0.597***		-1.070***
Property-price gap (F)		0.985***		1.228***
Property-price growth (F)		-0.942***		-0.903*
Stock-price growth (F)		0.130**		0.116
Credit growth (G)			-0.247**	
Property-price gap (G)			0.278***	
Stock-price growth (G)			0.0416***	
NIIP (G)			-0.179*	
Constant	-8.623***	-2.787***	-2.152**	-16.79***
Pseudo R2	0.318	0.360	0.279	0.646
AUROC	0.894	0.865	0.823	0.972
Relative Usefulness	0.651	0.681	0.693	0.870
Noise-2-Signal Ratio	0.128	0.120	0.073	0.107
Type I Error	0.254	0.226	0.253	0.027
Type II Error	0.095	0.093	0.054	0.104
Signalling Threshold	0.166	0.095	0.334	0.082
Conditional Probability	0.425	0.451	0.575	0.529
Unconditional Probability	0.086	0.090	0.090	0.107
Probability Difference	0.338	0.361	0.485	0.422
True Positives	141	147	142	184
False Positives	191	179	105	164
True Negatives	1812	1753	1827	1413
False Negatives	48	43	48	5
Observations	2,192	2,122	2,122	1,766

Notes: (D), (F) and (G) refer to domestic, foreign and global variables respectively. Growth rates are in year-on-year terms. All gap measures are calculated using a recursive one-sided HP-filter with a smoothing parameter of 400,000. Usefulness, Type I and Type II errors are derived for balanced preferences, i.e. $\mu = 0.5$. Significance of the coefficients is based on robust standard errors, clustered at the country level: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Results for the multivariate models II

	Domestic Global	**Foreign Global**	**All**	**Select**
Credit-to-GDP gap (D)	0.103***		0.164***	0.161***
Property-price gap (D)	-0.0418**		0.00371	0.0290
Stock-price gap (D)	-0.00954		-0.00288	
Stock-price growth (D)	0.0208		0.0233	0.0191
REER (D)	0.120***		0.188***	0.173***
Credit-to-GDP gap (F)		-0.451***	-0.892***	-0.921***
Property-price gap (F)		0.666***	0.817***	1.044***
Property-price growth (F)		-0.594**	-0.493	-0.764**
Stock-price growth (F)		0.0826*	0.0554	
Credit growth (G)	-0.181	-0.197	-0.262	
Property-price gap (G)	0.363***	0.141**	0.270**	
Stock-price growth (G)	0.0649***	0.0202***	0.0433*	0.0644***
NIIP (G)	-0.670***	-0.0597	-0.542**	-0.818***
Constant	-17.57***	-1.814	-24.23***	-24.84***
Pseudo R2	0.570	0.400	0.715	0.676
AUROC	0.962	0.853	0.985	0.981
Relative Usefulness	0.796	0.702	0.889	0.877
Noise-2-Signal Ratio	0.130	0.061	0.061	0.099
Type I Error	0.085	0.253	0.053	0.027
Type II Error	0.119	0.046	0.058	0.096
Signalling Threshold	0.069	0.219	0.152	0.089
Conditional Probability	0.420	0.617	0.663	0.548
Unconditional Probability	0.086	0.090	0.107	0.107
Probability Difference	0.334	0.528	0.556	0.441
True Positives	173	142	179	184
False Positives	239	88	91	152
True Negatives	1764	1844	1486	1425
False Negatives	16	48	10	5
Observations	2,192	2,122	1,766	1,766

Notes: (D), (F) and (G) refer to domestic, foreign and global variables respectively. Growth rates are in year-on-year terms. All gap measures are calculated using a recursive one-sided HP-filter with a smoothing parameter of 400,000. Usefulness, Type I and Type II errors are derived for balanced preferences, i.e. $\mu = 0.5$. Significance of the coefficients is based on robust standard errors, clustered at the country level: *** p<0.01, ** p<0.05, * p<0.1.

with 0.69.

When these variable blocks are combined among each other, some interesting observations emerge. First, combining domestic and foreign variables leads to considerable increases in the signalling performance. The relative usefulness increases from 65% to 87% and the AUROC from 0.89 to 0.97 when foreign variables are added to the domestic variable block, while the pseudo-R^2 doubles from 0.32 to 0.65, as shown in table 3. Second, combining domestic and global variables also leads to good improvements in the signalling performance, although the increase in terms of relative usefulness and pseudo-R^2 is somewhat lower than for the combination of domestic and foreign variables (See tables 3 and 4). Interestingly, when foreign and global variables are combined the signalling performance does not improve a lot compared to the model with only the foreign variable block.

Combining domestic, foreign and global variables in a model leads to the best overall signalling performance, although the improvements compared to a model with only domestic and foreign variables are modest, as shown in table 4. The AUROC increases from 0.972 to 0.985, the pseudo-R^2 from 0.646 to 0.715, and the relative usefulness from 87% to 89%. These performance measures are extremely high in comparison to most early warning models that have been proposed in the literature. In-sample overfitting is of course always an issue in this context and adding more variables to a model might not always be a good idea. For example, the number of variables increases from 9 to 13 when adding global variables to the domestic and foreign model, which might appear excessive given the modest increase in signalling performance that goes along with this increase in model complexity. The final column of table 4 therefore presents a parsimonious model with only 9 variables that covers domestic, foreign and global indicators, while having a similar signalling performance to the model with 13 variables. Reassuringly, all of the models have good out-of-sample signalling properties as shown in section 4.3.

In many cases, the estimated coefficients from the multivariate logit models have the expected sign based on economic intuition and are relatively stable across the different model specifications. For example, the domestic credit-to-GDP gap and the domestic real effective exchange rate always have positive and significant coefficients. Domestic and foreign stock price growth also display positive coefficients throughout, albeit not always statistically significant. Moreover, the foreign and global property price gap and global stock price growth always have significant positive coefficients. Nevertheless, similar to the univariate case, there are again a few instances where the estimated coefficients have counterintuitive signs. For example, the domestic stock price gap, the foreign credit-to-GDP gap, foreign property-price growth and global credit growth all have negative estimated coefficients across the specifications. While the coefficients for the domestic stock-price gap and global credit growth are also negative in the univariate case (see table 2), multicollinearity could in principle be an issue for the foreign variables, where the credit-gap and property-price growth switch sign between the univariate and multivariate models.

While collinearity is present to some extent, its magnitude does not appear to definitely require excluding some of the variables. For example, the correlations between the foreign property-price gap and the foreign credit-gap and foreign property-price growth are 0.75 and 0.76 respectively, while the variance inflation factors for these three variables are 4.96, 2.69 and 3.07 respectively. Although these numbers are not trivial they are not as high as to unambiguously suggest that multicollinearity is an issue. Moreover, the signalling performance of the foreign model block increases when the foreign credit-gap and foreign property-price growth are added to the property-price gap.[13]

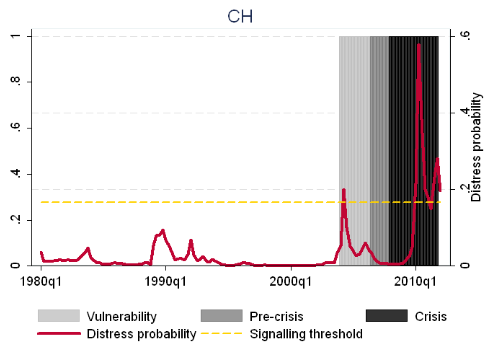
A negative coefficient for property-price growth, conditional on the property-price gap could even be theoretically justified: if we assume that the property-price gap already measures some form of deviation from fundamentals, then a high growth rate could capture part of a high fundamental growth trend. Moreover, Schudel (2013) has shown that property prices already peak many quarters before a financial crisis materialises so that the negative foreign property-price growth coefficient could be picking up part of these dynamics. Even though this is just a conjecture, it shows that coefficient signs are sometimes not unambiguously determined by economic reasoning. Given that the focus of this paper is more on the added value of foreign variables for signalling purposes, rather than on identifying the causal effect (or true parameter) for different variables, some counterintuitive coefficient signs do not appear to be a major issue at this point.

In order to gain more intuition on how foreign variables help to signal financial crises figures 2 and 3 plot the crisis predictions for Switzerland, the US, Canada and Spain for a number of different models. These four countries illustrate cases where foreign vulnerabilities played a major role (Switzerland), mainly domestic vulnerabilities played a role (US), no major vulnerabilities were present (Canada), and where both domestic and foreign vulnerabilities existed (Spain).

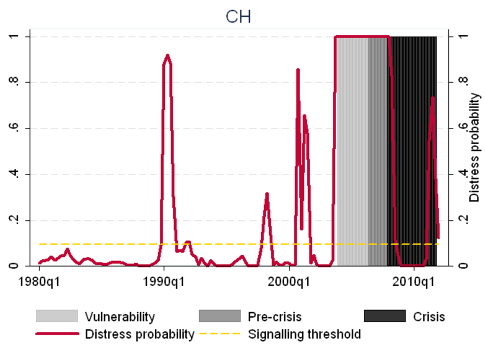
[13] The in-sample relative usefulness increases from 0.51 to 0.68 and the out-of-sample usefulness from 0.43 to 0.56 (See section 4.3).

Figure 2: Crisis predictions of selected models for Switzerland and the US

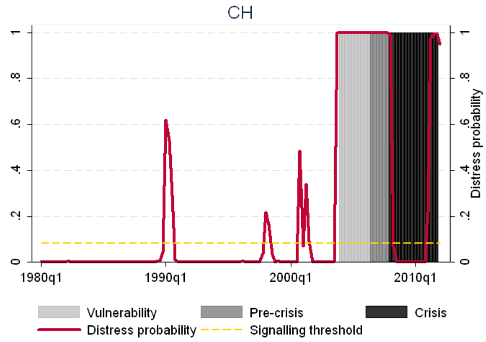
(a) Domestic Model



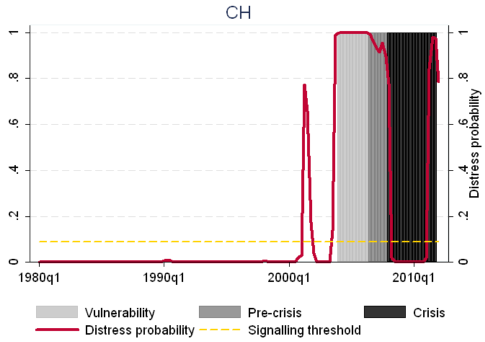
(b) Foreign Model



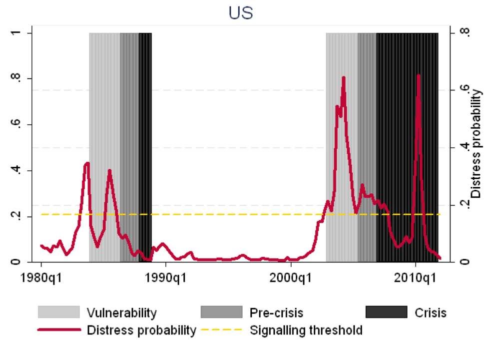
(c) Domestic + Foreign



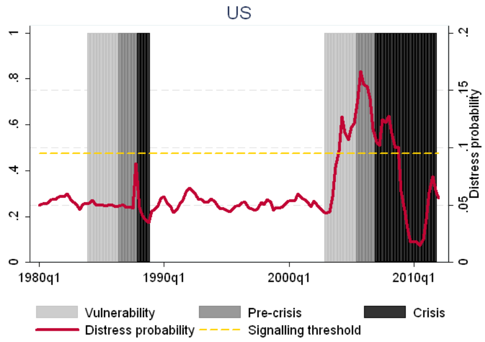
(d) Select Model



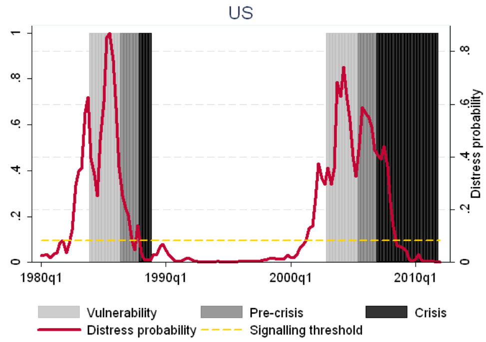
(e) Domestic Model



(f) Foreign Model



(g) Domestic + Foreign



(h) Select Model

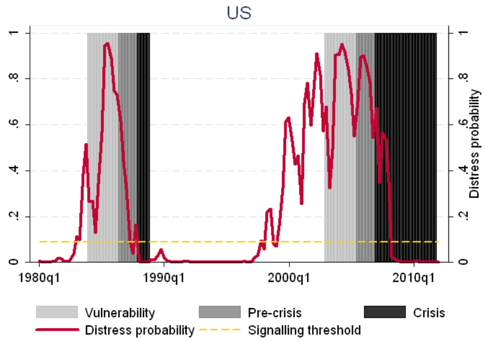
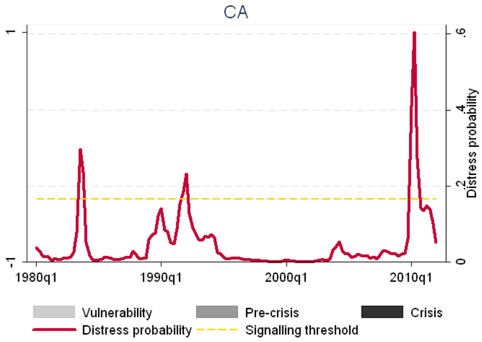
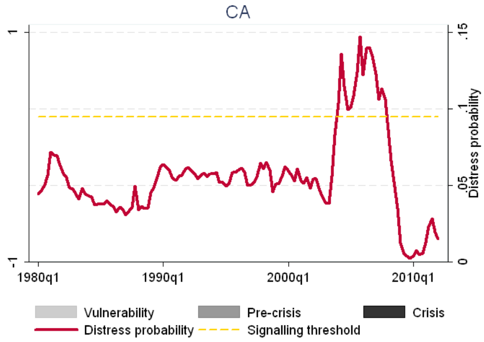


Figure 3: Crisis predictions of selected models for Canada and Spain

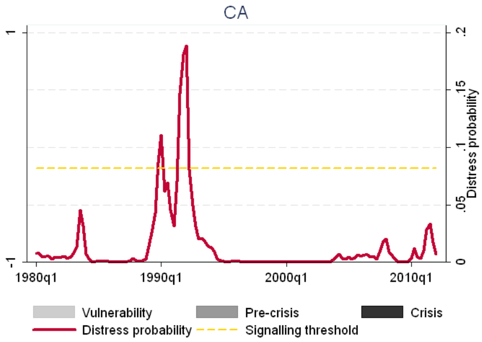
(a) Domestic Model



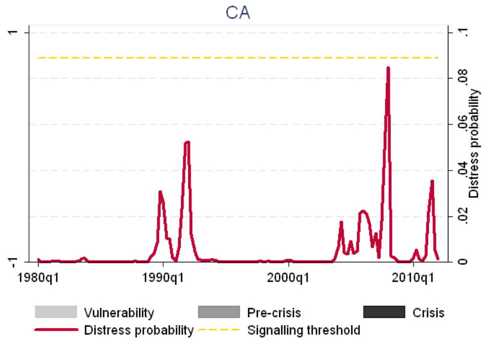
(b) Foreign Model



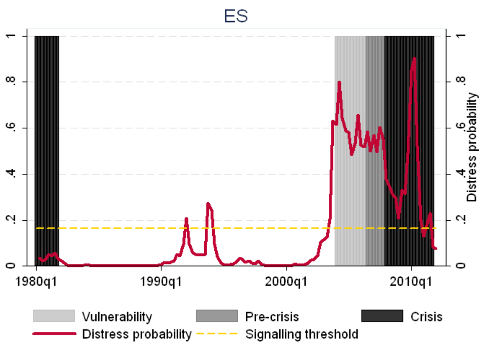
(c) Domestic + Foreign



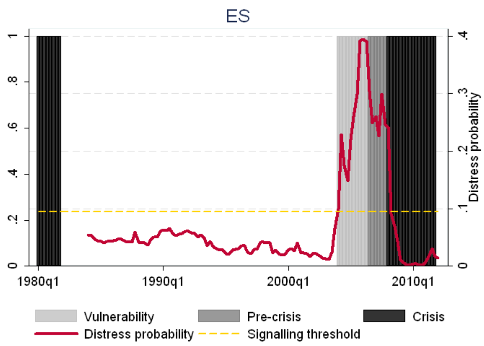
(d) Select Model



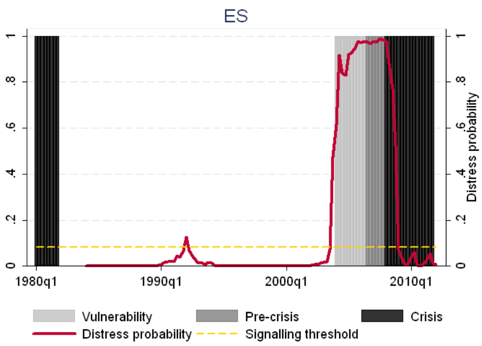
(e) Domestic Model



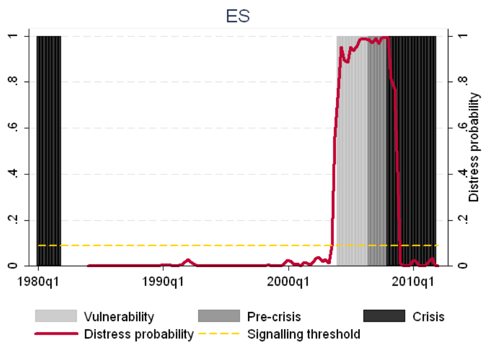
(f) Foreign Model



(g) Domestic + Foreign



(h) Select Model



For the case of Switzerland panels (a) - (d) in figure 2 show that a domestic model did not signal any vulnerabilities ahead of the recent financial crisis, while the foreign model starts to signal heavily as early as 2004. For the US, the opposite is true, which can be seen from panels (e) - (h) in figure 2. For the banking crisis that materialised at the end of the 1980s only domestic vulnerabilities played a role while during the build up to the recent financial crisis domestic factors dominated while foreign factors only signalled marginally and closer to the start of the financial crisis.

For Canada, which did not experience a financial crisis in 2008, domestic vulnerabilities were very low in the run up to the global financial crisis and foreign factors only marginally signalled a crisis, which is illustrated in panels (a) - (b) in figure 3. The model that combines domestic and foreign factors and the parsimonious model that combines domestic, foreign and global factors correctly do not issue any early warning signals for the country over the last 15 years. Finally, as can be seen from panels (e) - (h) of figure 3 domestic as well as foreign vulnerabilities signalled a crisis in Spain as early as 2004. The combined models show crisis probabilities of close to 1 during the run up to the global financial crisis.

4.3 Out-of-Sample Performance

In order to test the robustness of the models over time a recursive out-of-sample forecasting exercise was performed for all of the eight multivariate early warning models, along the lines of the procedure suggested in Betz et al. (2013): Starting at a given point in time, each model is estimated recursively, adding one quarter of new observations at a time and making predictions for the next quarter ahead. This way a large collection of out-of-sample forecasts can be generated for which various performance measures such as the relative usefulness can be computed. This recursive out-of-sample forecasting exercise was performed for the period 2000q1 to 2012q1 with balanced policy maker preferences, the results of which are displayed in table 5.

The domestic, foreign and global models all display good out-of-sample forecasting performance with a relative usefulness in excess of 55%, which is not considerably lower than the in-sample usefulness of around 65%. When domestic variables are combined with foreign or global variables the relative out-of-sample usefulness increases to 74% and 72% respectively. For the models that combine all three variable categories, the parsimonious specification with 9 variables outperforms the more

Table 5: Out-of-Sample forecasting performance of the multivariate models

	Domestic	**Foreign**	**Global**	**Domestic Foreign**	**Domestic Global**	**All**	**Select**
Rel. Usefulness	0.569	0.559	0.677	0.743	0.718	0.795	0.820
Noise-2-Signal	0.185	0.383	0.201	0.104	0.158	0.074	0.074
Type I Error	0.302	0.093	0.153	0.174	0.148	0.141	0.114
Type II Error	0.129	0.347	0.170	0.086	0.135	0.064	0.066
Cond. Prob.	0.601	0.363	0.520	0.759	0.638	0.815	0.815
True Positives	104	136	127	123	127	128	132
False Positives	69	239	117	39	72	29	30
True Negatives	466	449	571	416	463	426	425
False Negatives	45	14	23	26	22	21	17
Robustness							
U_r $(\mu = 0.4)$	0.520	0.453	0.592	0.742	0.687	0.770	0.803
U_r $(\mu = 0.6)$	0.454	0.505	0.584	0.660	0.647	0.737	0.747
U_r $(\mu = 0.7)$	0.285	0.387	0.456	0.561	0.496	0.586	0.676

Notes: The baseline performance measures are based on balanced preferences, i.e. $\mu = 0.5$, and computed for a recursive 1-quarter-ahead forecasting exercise between 2000q1 and 2012q1.

complex one with 13 variables. The best model has an out-of-sample relative usefulness of 82% and Type I and Type II errors of 0.11 and 0.07, which are encouraging numbers. All of these results suggest that a combination of domestic, foreign and possibly global variables in a parsimonious model can have very good in-sample and out-of-sample signalling properties.

The lower part of table 5 shows that the out-of-sample performance results of the models are qualitatively robust for different policy maker preferences between missing crises and issuing false alarms. For preferences parameters of 0.4, 0.6, and 0.7 the result holds that adding foreign variables to domestic variables increases the out-of-sample relative usefulness. Moreover, the combination of domestic, foreign and global variables in a multivariate model further improves the out-of-sample performance. Similar to the results for balanced policy maker preferences, the parsimonious model specification with 9 variables ("Select") outperforms the more complex model with 13 variables ("All"). In quantitative terms, the out-of-sample relative usefulness measures decrease somewhat for the alternative preference specifications, which is in line with expectations, as the relative usefulness is usually maximised when balanced policy preferences are assumed. However, the out-of-sample relative usefulness measures of 68% to 80% attained by the "Select" model with domestic, foreign and global variables for the alternative preference parameters are still fairly high.

5 Conclusion

The empirical results of this paper show that incorporating cross-country financial linkages can indeed improve the signalling performance of early warning models. This conclusion is based on the signalling performance of foreign variables in both univariate and multivariate early warning models. For example, the relative usefulness increases from 65% to 87% and the AUROC from 0.89 to 0.97 when foreign variables are added to domestic variables in a multivariate early warning model, while the pseudo-R^2 doubles from 0.32 to 0.65. The findings of the paper also suggest that global variables still play a role in predicting financial crises, even when foreign variables are included in the model, which could suggest that both cross-country spill-overs and contagion are important factors for driving financial crises.[14] A parsimonious model with nine variables that combines domestic, foreign and global variables yields an in-sample AUROC of 0.98 and an out-of-sample relative usefulness of 82%, corresponding to out-of-sample Type I and Type II errors of 0.11 and 0.07. All in all, the results suggest that the build-up of foreign and global imbalances can be just as important as the build-up of domestic imbalances for making countries susceptible to financial crises. This finding seems particularly relevant in the context of the EU, where strong financial links exist and cross-country spill-overs could be of particular importance.

[14] This conclusion regarding the relative role of spill-overs and contagion is tentative at this stage.

Appendix A: Tables

Table 6: Country sample and start dates of data availability

Country	BIS LBS	Credit data	House prices	Equity prices	GDP	REER	NIIP	Current account
Austria	1977q4	1970q1	2000q1	1970q1	1970q1	1975q1	1980q1	1970q1
Belgium	1977q4	1970q4	1970q1	1970q1	1970q1	1975q1	1981q1	2002q1
Cyprus	2008q4	-	2002q1	-	1995q1	1980q1	2002q1	1976q1
Finland	1983q4	1970q4	1970q1	1970q1	1970q1	1970q1	1985q1	1975q1
France	1977q4	1970q1	1970q1	1970q1	1970q1	1979q4	1980q1	1975q1
Germany	1977q4	1970q1	1970q1	1970q1	1970q1	1975q1	1980q1	1971q1
Greece	2003q4	1970q1	1997q1	1988q1	1970q1	1980q1	1998q1	1976q1
Ireland	1977q4	1971q2	1970q1	1970q1	1970q1	1975q1	2001q1	1974q1
Italy	1977q4	1970q1	1970q1	1970q1	1970q1	1980q1	1972q1	1970q1
Netherlands	1977q4	1970q1	1970q1	1970q1	1970q1	1975q1	1980q1	1970q1
Portugal	1997q4	1970q1	1988q1	1988q1	1970q1	1975q1	1996q1	1975q1
Spain	1983q4	1970q1	1971q1	1970q1	1970q1	1980q1	1981q1	1975q1
Denmark	1977q4	1970q1	1970q1	1970q1	1970q1	1975q1	1991q1	1975q1
Sweden	1977q4	1970q1	1970q1	1970q1	1970q1	1975q1	1982q1	1970q1
UK	1977q4	1970q1	1970q1	1970q1	1970q1	1975q1	1980q1	1970q1
Australia	1997q4	1970q1	1970q1	1970q1	1970q1	1979q4	1986q1	1970q1
USA	1977q4	1970q1	1970q1	1970q1	1970q1	1979q4	1980q1	1970q1
Canada	1977q4	1970q1	1970q1	1970q1	1970q1	1975q1	1970q1	1970q1
Japan	1977q4	1970q1	1970q1	1970q1	1970q1	1980q1	1980q1	1977q1
Switzerland	1977q4	1970q1	1970q1	1970q1	1970q1	1975q1	1983q1	1977q1
Brazil	2002q4	1993q4	2001q2	1995q2	1994q1	1979q4	2001q1	1975q1
Chile	2002q4	-	-	1990q1	1990q1	1979q4	1997q1	1975q1
India	2001q4	1970q1	-	1970q1	1996q2	-	1996q1	1975q1
Indonesia	2010q3	1976q1	2002q1	1988q1	1983q1	-	2001q1	1981q1
Malaysia	2007q4	1970q1	1999q1	1988q1	1991q1	1975q1	1980q1	1974q1
Mexico	2003q4	1980q4	2005q1	1986q3	1970q1	1979q4	2001q1	1979q1
South Africa	2009q3	1970q1	1970q1	1970q1	1970q1	1975q1	1970q1	1970q1
South Korea	2005q1	1970q1	1986q1	1981q1	1970q1	-	2001q1	1976q1
Taiwan	2000q4	-	1993q1	1988q1	1970q1	-	2002q1	2005q1
Turkey	2000q4	1986q1	2010q1	1988q1	1970q1	-	1996q1	1974q1
Source	BIS	BIS	OECD BIS	MSCI OECD	OECD Haver	IMF	IMF	IMF

Notes: BIS LBS refers to the Locational Banking Statistics. REER is the Real Effective Exchange Rate and NIIP the Net International Investment Position.

References

Alessi, Lucia and Carsten Detken, "Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity," *European Journal of Political Economy*, September 2011, *27* (3), 520–533.

Behn, Markus, Carsten Detken, Tuomas A. Peltonen, and Willem Schudel, "Setting Countercyclical Capital Buffers based on Early Warning Models: Would it Work?," Working Paper Series 1604, European Central Bank November 2013.

Berg, Andrew and Catherine Pattillo, "Predicting currency crises:: The indicators approach and an alternative," *Journal of International Money and Finance*, August 1999, *18* (4), 561–586.

_ , Eduardo Borensztein, and Catherine Pattillo, "Assessing Early Warning Systems: How Have They Worked in Practice?," *IMF Staff Papers*, 2005, *52* (3), 462–502.

Betz, Frank, Silviu Oprica, Tuomas A. Peltonen, and Peter Sarlin, "Predicting distress in European banks," *Journal of Banking & Finance*, 2013, (0), –.

Borio, Claudio and Mathias Drehmann, "Assessing the risk of banking crises - revisited," *BIS Quarterly Review*, March 2009, pp. 29–46.

_ and Philip Lowe, "Asset prices, financial and monetary stability: exploring the nexus," BIS Working Papers 114, Bank for International Settlements 2002.

Bussiere, Matthieu and Marcel Fratzscher, "Towards a new early warning system of financial crises," *Journal of International Money and Finance*, October 2006, *25* (6), 953–973.

Chudik, Alexander and Marcel Fratzscher, "Identifying the global transmission of the 2007-2009 financial crisis in a GVAR model," *European Economic Review*, April 2011, *55* (3), 325–339.

Demirgüc-Kunt, Asli and Enrica Detragiache, "The Determinants of Banking Crises in Developing and Developed Countries," *IMF Staff Papers*, March 1998, *45* (1), 81–109.

Detken, Carsten, Olaf Weeken, Lucia Alessi, Diana Bonfim, Miguel M. Boucinha, Christian Castro, Sebastian Frontczak, Gaston Giordana,

Julia Giese, Nadya Jahn, Jan Kakes, Benjamin Klaus, Jan Hannes Lang, Natalia Puzanova, and Peter Welz, "Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options," ESRB Occasional Paper Series No. 5, ESRB 2014.

Drehmann, Mathias, Claudio Borio, and Kostas Tsatsaronis, "Anchoring countercyclical capital buffers: the role of credit aggregates," BIS Working Papers 355, Bank for International Settlements November 2011.

Frankel, Jeffrey A. and Andrew K. Rose, "Currency crashes in emerging markets: An empirical treatment," *Journal of International Economics*, November 1996, *41* (3-4), 351–366.

Galesi, Alessandro and Silvia Sgherri, "Regional Financial Spillovers Across Europe: A Global VAR Analysis," IMF Working Papers 09/23, International Monetary Fund February 2009.

Kaminsky, Graciela L. and Carmen M. Reinhart, "The Twin Crises: The Causes of Banking and Balance-of-Payments Problems," *American Economic Review*, June 1999, *89* (3), 473–500.

Kaminsky, Graciela, Saul Lizondo, and Carmen M. Reinhart, "Leading Indicators of Currency Crises," *IMF Staff Papers*, March 1998, *45* (1), 1–48.

Laeven, Luc and Fabian Valencia, "Systemic Banking Crises: A New Database," IMF Working Papers 08/224, International Monetary Fund September 2008.

_ **and** _ , "Systemic Banking Crises Database: An Update," IMF Working Papers 12/163, International Monetary Fund June 2012.

Lo Duca, Marco and Tuomas A. Peltonen, "Assessing systemic risks and predicting systemic events," *Journal of Banking & Finance*, 2013, *37* (7), 2183 – 2195.

McFadden, D. L., "Conditional logit analysis of qualitative choice behavior," in P. Zarembka, ed., *In Frontiers in Econometrics*, New York: Academic Press, 1974, pp. 105 – 142.

Minoiu, Camelia, Chanhyun Kang, V.S. Subrahmanian, and Anamaria Berea, "Does Financial Connectedness Predict Crises?," IMF Working Papers 13/267, International Monetary Fund December 2013.

Pesaran, Hashem, Til Schuermann, and Scott Weiner, "Modeling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model," *Journal of Business & Economic Statistics*, April 2004, *22*, 129–162.

Rose, Andrew K. and Mark M. Spiegel, "Cross-Country Causes And Consequences Of The 2008 Crisis: International Linkages And American Exposure," *Pacific Economic Review*, 08 2010, *15* (3), 340–363.

Sarlin, Peter, "On policymakers' loss functions and the evaluation of early warning systems," *Economics Letters*, 2013, *119* (1), 1–7.

Schudel, Willem, "Shifting horizons: Assessing macro trends before, during, and following systemic banking crises," Mimeo, European Central Bank 2013.

Schularick, Moritz and Alan M. Taylor, "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008," *American Economic Review*, April 2012, *102* (2), 1029–61.

Sun, Yan, Frigyes F Heinz, and Giang Ho, "Cross-Country Linkages in Europe: A Global VAR Analysis," IMF Working Papers 13/194, International Monetary Fund September 2013.

Acknowledgements

I would like to thank Carsten Detken and Tuomas Peltonen for useful comments and suggestions on earlier drafts of the paper. The views expressed in this paper are those of the author and do not necessarily reflect those of the European Central Bank.

Jan Hannes Lang
European Central Bank, Frankfurt am Main, Germany; email: jan-hannes.lang@ecb.europa.eu

PDF ISBN 978-92-899-3265-3 ISSN 1725-2806 doi:10.2866/528484, QB-AR-18-040-EN-N