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The Challenge of Predicting Financial Crises: Modelling and Evaluating Early Warning Systems

by

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Dedication

This work is dedicated to the real hero, MarGerges.

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Abstract

The main purpose of constructing "Early Warning Systems" (EWSs) for financial crises is to provide policy makers with some lead time to take pre-emptive actions that would help avoid, or at least mitigate, the damages of an approaching crisis. Accordingly, this study empirically evaluates and compares the effectiveness of the econometric models developed so far to construct EWSs. In addition, a more accurate (dynamic-recursive) forecasting technique is developed to generate better out-of-sample warning signals for currency, banking, and sovereign debt crises in the different regions of the world.

The empirical analysis shows that the predictive performance of the EWS is significantly improved when using simple pooled models that account for the heterogeneity of the signalling indicators across the different regions. Moreover, including the entire crisis period in the sample outperforms the more common practice of dropping post-crisis-onset periods or using a multinomial specification of the crisis variable. In addition, the findings reveal that our dynamic-recursive technique provides more accurate out-of-sample forecasts for logit models. Finally, the dynamic signal extraction approach is recommended for policy makers who value avoiding financial crises at all costs, while the binomial logit model is more suitable for less conservative policy makers who consider the economic and social costs of false alarms.

Keywords: financial crisis, early warning, binomial logit, multinomial logit, dynamic signal extraction, dynamic-recursive forecasting

Contents

List of Tables

List of Figures

Chapter 1

Introduction

The renowned economist, Frederic Mishkin, noted the following about the anatomy of financial crises:

> "A healthy and vibrant economy requires a financial system that moves funds to economic agents who have the most productive investments opportunities...Financial crises interfere with this process because they can drive the economy away from an equilibrium with high output in which financial markets perform well to one in which output declines sharply because the financial system is unable to channel funds to those with the best investment opportunities." (Mishkin, 1992, p. 115)

The 1990s have witnessed the outbreak of a number of financial crises. Due to the progressively integrated nature of financial markets around the world and global capital flows, most of these crises were not confined to the individual country in which they originated, but spread to other economies, near and far, in a so-called contagion or "domino effect". During this decade, the most salient crises in terms of severity and social and economic repercussions are mainly: the Japanese banking crisis at the start of the decade, the European currency crisis in 1991/93, the collapse of the Mexican peso in 1994, the tsunami-like Asian financial crisis of 1997/98, the Russian "flu" in 1998, the Latin American crisis at the end of 1999, and the twin crisis in Turkey at the start of the new millennium.

1.1 The Stimulus for Early Warning Systems

The costs of a financial crisis can be severe in terms of losses in international reserves, output declining and worsening standards of living, real exchange rate deterioration, credit crunch due to increasing number of non-performing loans, massive capital flight, disruptions in the payments system, and general loss of confidence. For example, the amount of capital flight out of the East Asian region in the aftermath of the 1997 crisis was estimated at $100 billion. During the currency crisis in 1992, the European countries lost a total of $200 billion in international reserves (Bhattacharyay *et al.*, 2009), whereas the Mexican crisis of 1994 cost the economy a 20% loss in its aggregate output (Davis and Karim, 2008b). In addition, Kaminsky (1999) reported that the fiscal costs of resolving banking crises in Chile and Argentina amounted to over 40% of their GDP, and that central banks tend to lose up to 25% of their foreign exchange reserves when resolving twin crises in general.

Therefore, by the second half of the 1990s, great concern arose in most economies regarding the soundness of their financial and real sectors. Furthermore, the International Monetary Fund (IMF) started to encourage both advanced and emerging countries to improve the transparency, frequency and quality of their statistical data to be able to detect the build-up of financial turmoil in their economies. As a result of such stimulus and startled at how detrimental financial crises could be to an individual, regional and even the world economy, several attempts were devoted to the construction of what came to be known as an "Early Warning System" (hereafter EWS). That is, a financial monitoring tool that applies econometric methods to generate predictions of the likelihood of an approaching financial crisis over a given time horizon (Cheang, 2009). This system aims to provide warning signals of underlying financial or real sector weaknesses and fragility that could put an economy on the verge of a probable crisis, with the purpose of giving policy makers a lead time to adopt pre-emptive measures to prevent, or at least mitigate, such damage to the economy.

To the extent that the "Lucas critique" applies to the study of modelling EWSs for financial crises, a reliable set of early warning indicators that were identified empirically may become less effective if policy makers would henceforth change their behaviour in response to such signals than they did in the past; thereby transforming these variables into early warning indicators of corrective policy actions rather than of financial crises. While this feedback effect of the indicators on crisis prevention has not yet impaired the predictive power of EWSs, as there is still no solid and generally agreed upon EWS that is widely used, there is no guarantee that this feedback effect will not be stronger in the future. This possibility requires the continuous evaluation of the efficiency of existing EWSs as new systemic threats emerge. Furthermore, it triggers the need to investigate the economic, social, and political value of the warning signals once they become public. That is, whether and how they affect the behaviour and the decision-making process of (domestic and international) investors, government officials, and policy makers.

Of the earliest and most influential efforts made in this context are those of Frankel and Rose (1996), representing the primary contribution of academics to the construction of EWSs using a probit regression. A couple of years later, the IMF came up with another original approach, when Kaminsky *et al.* (1998) developed a non-parametric method to model EWSs –namely the "Signal Extraction Approach", while Demirguc-Kunt and Detragiache (1998) suggested the estimation of a multivariate logit regression to predict financial crises. Thereafter, several central banks, such as the U.S. Federal Reserve (Kamin *et al.*, 2001) and the Bank of Finland (Komulainen and Lukkarila, 2003), and other academic researchers (Mariano *et al.*, 2002) have also attempted to develop EWSs. These early models were primarily concerned with identifying the most relevant macroeconomic and financial indicators that are likely to provide warning signals of a vulnerable position from a theoretical and empirical point of view.

1.2 The Renewed Challenge

Notwithstanding the collective efforts of researchers and policy institutions in developing a warning system for crises, Davis and Karim (2008a) argued that the current global financial crisis of 2007/08 "came as a surprise not only to most financial market participants but also in some degree to the policy community". None of the financial stability reports of the IMF, the European Central Bank or the Bank for International Settlements for the beginning of 2007 was able to foresee the severity or international span of the crisis that emanated from the U.S. sub-prime market, let alone the outburst of the deepest financial and economic crisis to hit the global economy since the Great Depression of the 1930s. Moreover, Rose and Spiegel (2009) and Candelon *et al.* (2014) demonstrated that the existing EWSs and the commonly used indicators were unable to provide warning signals of the crisis. This was mainly attributed to ignoring the possibility of cross-country contagion and spillover from other domestic markets (e.g. real estate, external debt), and pooling developed and developing countries together.

This crisis that originated in the U.S. mortgage market in 2006, and started to hit the entire U.S. financial system in 2007, reached the rest of the world by the second half of 2008. A report by Kelleher *et al.* (2012) declared that the crisis had a cost tag of $12.8 trillion in terms of output loss in the U.S. alone. In particular, they reported that the actual GDP loss is estimated at $7.6 trillion, calculated as the difference between the potential GDP had the financial crisis not occurred and the actual GDP as reported by the government for the period 2008-2012. The additional $5.2 trillion is labelled as the avoided output loss that was prevented by the immense fiscal and monetary interventions of the U.S. Treasury and the Fed.

Essentially, almost all the industrialised countries were affected, as well as a large number of developing economies, where stock markets have fallen and large financial institutions have either collapsed or been bought out. Therefore, the renewed challenge manifested by the outburst of the 2008 global financial crisis has posed several questions as to the quality and the effectiveness of the EWSs that were developed thus far in predicting the current crisis as well as any future crises. Despite the numerous efforts to find reliable leading indicators and construct a credible model, “the existing EWSs are not accurate enough and should only be used complementary to other vulnerability indicators” (Lang, 2013, p. 4).

In the April 2009 London Summit, the G20 countries called for the establishment of a new Financial Stability Board that is to “collaborate with the IMF to provide early warning of macroeconomic and financial risks and the actions needed to address them”[1]. Accordingly, further efforts are still required to find new macro-prudential indicators and develop improved methods in an attempt to effectively forewarn the build-up of vulnerabilities and give way to undertaking pre-emptive measures that would mitigate (or ideally avoid) the possible damages to the world economy.

1.3 Research Objectives and Key Contributions

As illustrated in detail in Chapter 2, most authors were mainly concerned with developing or improving on a certain type of econometric technique and comparing its early warning performance to the other standard methods. Others focused on applying these methods to different situations and circumstances, whether of a group of countries or a specific economy, by changing the particular crisis definition or the signalling indicators used to predict crises incidents. As a result, several modified econometric methods were recently introduced in the literature, which were found to outperform the traditional techniques in forecasting a specific type of financial crisis or crises in a specific type of economy.

However, thus far no study has attempted to cross-check the modified statistical methods or to evaluate their performance in forewarning each of the three major types of financial crises (currency, banking, sovereign debt) in the different country regions of the

[1] http://www.g20.utoronto.ca/2009/2009communique0402.html (visited in April 2014)

world. Only Lestano *et al.* (2003) investigated the construction of EWSs for each of the three types of crises in East Asia using a binomial logit regression.

Furthermore, studies attempted to model EWSs in either developed or emerging countries separately, or to pool them together into one dataset. However, no study investigated the possible differences between the different types of economies in terms of the signalling indicators or the most appropriate method to predict crisis periods. This came as a recommendation of Davis and Karim (2008a) after having pooled both types of economies together and getting zero forecasting results. In fact, Gourinchas and Obstfeld (2012) considered a separate model for each type of economy when investigating banking and currency crises, but they examined a limited number of explanatory variables, used annual data, and estimated only binomial logit regressions.

Consequently, this study attempts to close these gaps in the literature. In particular, the contribution to the literature of constructing EWSs for financial crises is three-fold. First, this research investigates the possibility of signalling indicator differences between developed and developing countries, given their inherent distinctiveness with respect to the structure of the economy, vulnerability to shocks, extent of integration into the global financial system, degree of dependence on other economies, institutional effectiveness and policy responses. Furthermore, the investigation goes even deeper to identify the most significant determinants of each type of financial crisis (currency, banking, sovereign debt) in the different country regions[1].

The second contribution entails evaluating and comparing the effectiveness of the recently developed econometric methods to construct EWSs for financial crises in predicting the current global financial crisis, as well as any future crisis. This objective extends to cross-checking the different techniques developed and tested on a particular type of crises or a particular type of economy on the other types. More specifically, the research examines the performance of binary vs. multinomial logit regression models in predicting

[1]Regional models are only considered by Kamin *et al.* (2001), Burkarta and Coudert (2002) and Candelon *et al.* (2012) in the case of currency crises. They found some parameter heterogeneity across the different subsets of the emerging market countries.

currency, banking, and sovereign debt crises in both developed and developing country regions. The use of multinomial logit models was originally suggested by Bussiere and Fratzscher (2006), who examined their predictive performance on currency crises in emerging markets only. Furthermore, our research evaluates the effectiveness of the EWS developed by Casu *et al.* (2012), who proposed a dynamic signal extraction approach (the indicators' thresholds are determined on a dynamic basis as opposed to the traditional static method that depends on the sample distribution) to generate forewarning signals of banking crises in developed countries.

Finally, a more powerful forecasting technique (the dynamic-recursive technique) is proposed, developed and tested to generate more accurate out-of-sample warning signals for currency, banking, and sovereign debt crises in the different country regions of the world. The predictive performance of all econometric and forecasting techniques are compared using a number of evaluation criteria that are applied for both the in-sample as well as the less frequently reported, though more important and policy-relevant, out-of-sample periods. In addition, we utilise two more commonly used model evaluation criteria, namely the quadratic probability score and the area under the receiver operating characteristic (ROC) curve.

It is important to note, that our research follows the suggestion of Frankel and Saravelos (2012) to overcome the problem of indicators' selection bias. They questioned the usefulness of the 'forewarning' indicators that are selected after the crisis has occurred, thus having the benefit of hindsight into its causes and symptoms. Therefore, they chose their variables based on underlying economic reasoning, and complemented that with a broad review of the empirical literature to specify the indicators that were consistently found to be statistically significant over time, country and crisis. On that account, this research applies the same line of criteria to select the candidate indicators for each type of financial crises.

Research Plan: The remainder of the study is organised as follows: Chapter 2 surveys the previous studies that attempted to construct EWSs before and after the current global financial crisis. It details the way they quantified crisis episodes, the methods they applied, and the findings of their studies. The methodologies applied to construct an EWS for the various types of financial crises, as well as the criteria used to compare and evaluate their performance, are outlined in Chapter 3. Then, the sample data, crisis definitions and the results of the constructed EWSs for currency crises are presented in Chapter 4, while Chapter 5 is dedicated to investigating banking crises, and Chapter 6 focuses on sovereign debt crisis incidents. Finally, the summary of results and the concluding remarks are given in Chapter 7.

Chapter 2

Literature Review

It is well noted in the literature that the construction of EWSs undergoes three main steps. First, it is important to find a proper and precise definition of a financial crisis. That is, to distinguish between what is considered as a crisis and what could be labelled under "usual fluctuations". The second step entails identifying the probable causes of the crisis (from both the theory and the empirics), and thus extracting the financial, economic or any other variables that can act as signalling indicators for an upcoming crisis. Finally, deciding on the statistical method to be used to estimate the probability of an impending crisis and to test the statistical and economic significance of the proposed models on both in-sample and out-of-sample data is a crucial matter.

As unpretentious and straightforward as the first two steps may seem, there are nearly as many differences among the researchers regarding these issues as there are with respect to the proposed methods used in prediction. Most importantly, Casu *et al.* (2012) partly attributed the inability of the pre-2008-crisis EWSs to raise an alarm as to the devastation of the crisis to the misspecification of the crisis definition and the warning indicators used (*i.e.* their response and explanatory variables).

Consequently, this chapter is devoted to surveying the paths undertaken by the different previous studies, theoretical and empirical, in tackling the issue of constructing an effective EWS.

2.1 Interdependencies and Sequencing of Financial Crises

In the context of financial crises, three varieties can be distinguished: currency crises, banking crises, and sovereign debt crises. Each of these crises may occur independently of the others; however, recent analyses have evidenced their interconnection and the causality or complementarity that may arise between them.

In particular, Kaminsky and Reinhart (1999) detected that a banking-currency twin crisis has occurred more frequently in the aftermath of the liberalisation of financial markets in several emerging economies in the late 1980s. Their paper evidenced that *"knowing that a banking crisis was underway helps predict a future currency crisis . . . the collapse of the currency deepens the banking crisis, activating a vicious spiral"*. Consequently, more recent studies tend to include a dummy for banking crises as an explanatory variable when analysing currency crises, such as Komulainen and Lukkarila (2003), or at least use a variable like bank deposits as a proxy for the possibility of bank runs (for example refer to Bussiere and Fratzscher, 2006; Lin *et al.*, 2008).

A variety of theoretical models attempted to explain this phenomenon of currency-banking twin crises. For example, Velasco (1987) and Calvo (1998) stressed that when central banks print money to bailout distressed financial institutions, a currency collapse can be triggered by excessive money creation according to the traditional model of currency crises (discussed below). On the other hand, Stoker (1995) pointed to the opposite causal direction, where foreign exchange market problems give rise to banking crisis. He developed a model in which an increase in foreign interest rates, while the monetary authority is committed to a fixed parity, results in the loss of foreign reserves, as the central bank is forced to sell foreign for domestic currency to increase the domestic interest rates. If this is not sterilised by an increase in the money supply, the high interest rate will lead to a credit crunch, increased bankruptcies, and eventually a banking crisis. Moreover, Mishkin (1996), and later Goldstein (2005), referred to the mismatch between banks' foreign liabilities and domestic assets, which makes the banking sector exposed to exchange rate risks. That is, a speculative attack that puts pressure to devalue the domestic currency weakens the position of banks if a large share of their liabilities is denominated in a foreign currency. This induces foreign creditors to withdraw their money and possibly induce a run on the banks. Foreign currency withdrawals indirectly reduce the amount of reserves held by the government, making it even more difficult to defend the domestic currency. This yields a vicious cycle between the two types of crises.

A third family of models assert that currency and banking crises can have common causes. An example of these can be found in McKinnon and Pill (1996), who model an initial economic boom that is fuelled by a marked cumulative appreciation of the real exchange rate. If the increase in the demand for imports is financed by borrowing abroad, the current account deficit worsens and triggers an attack on the domestic currency. Since the boom is usually financed by an expansion in bank credit using foreign borrowings, the capital outflows caused by the speculative attack leads to the collapse of the banking system as well.

With respect to banking-debt twin crises, Babecky *et al.* (2014) and Balteanu and Erce (2014) maintained that the rescue plans (bailout money, government deposits, liquidity injections by the central bank) initiated to support a failing banking sector may impair the sustainability of government debt, especially if the authorities decide to offer explicit deposit insurance to prevent bank runs. Furthermore, the credit crunch that usually accompanies a banking crisis can deepen the recession and lead to further falls in public revenues, which increases the probability of sovereign defaults. On the other hand, the reverse loop running from debt to banking crises can also be triggered as governments, in the face of an external debt problem, default on their bank-held bonds, which in turn may lead to large capital losses and threaten the solvency of banks. Therefore, it is not straightforward to put the bi-directional relationship between banking and debt crises in the context of causality.

Finally, currency-debt twin crises may occur because currency crashes could lead to a sovereign debt crisis if public debt is mostly denominated in foreign currency, as they compromise the ability of public authorities to service and repay their obligations (Babecky *et al.*, 2014). On the other hand, sovereign defaults tend to trigger capital outflows, which can put serious pressure on the domestic currency and induce speculative attacks (Balteanu and Erce, 2014).

Despite these arguments and findings, Lang (2013) cited that no research thus far has considered the possibility of constructing an EWS for "triple crises" by analysing the interdependencies between currency, banking, and sovereign debt crises. Therefore, we attempt to address this issue by including relevant variables from both the fiscal and the banking sectors (*i.e.* crisis dummies and variables that reflect sector vulnerability), as well as indicators of external competitiveness, as explanatory variables in the EWS of each of the three types of financial crises.

2.2 Defining Financial Crises

The first pivotal step in designing an EWS for any type of financial crisis is, ordinarily, to define what is meant by a crisis event. Since crises are a state of economy rather than a variable with a universally agreed-on measure, it is essential to find a quantitative means of measurement of what can be defined as a state of financial crisis before we can hope to construct a model to forecast such events.

2.2.1 Currency Crisis

With respect to currency crises, most studies concurred on a common quantitative definition that accounts for the build-up of pressure on the domestic currency, namely the "Exchange Market Pressure" index (hereafter EMP). This index, which is originally developed in a series of papers by Eichengreen, Rose and Wyplosz in the 1990s (as cited in Edison, 2003), is calculated as a weighted average of the percentage change in each of the exchange rate, the interest rate, and the international reserves. The intuition behind these three index components is to capture both successful (currency devalued) and unsuccessful (currency defended by running down foreign reserves or increasing the interest rate to attract foreign capital) attacks on the domestic currency (Fratzscher, 2003; Su *et al.*, 2010). Accordingly, a crisis episode is identified when this index crosses a pre-specified threshold level.

However, despite agreeing on this common definition, several differences are still noticeable among the various researchers that employed this index as their currency crisis variable. For example, some authors used the real exchange rate and the real interest rate to account for the differences in inflation rates across countries and over time (Bussiere and Fratzscher, 2006; Ari and Dagtekin, 2007), while others used the nominal rates or the changes in the spread between the country's interest rate and that of the U.S. (Lin *et al.*, 2008). Furthermore, Kaminsky and Reinhart (1999), Heun and Schlink (2004) and Arias and Erlandsson (2005) dropped the interest rate differentials from the EMP index altogether due to data availability issues. In addition, the time frequency considered for the data was also subject to differences. Edison (2003), Bussiere and Fratzscher (2006) and Ari and Dagtekin (2007) used monthly intervals, while Andreou *et al.* (2009) and Wong *et al.* (2010) used quarterly periods, and Frankel and Saravelos (2012) and Kamin *et al.* (2001) used annual data.

To the extent that the full version of the EMP index captures both successful and unsuccessful attacks on the domestic currency, some authors argued that only the successful attacks should be considered as a currency crisis. Therefore, they used a different dependent variable in their forecasting models. An example would be Frankel and Rose (1996) and Lestano *et al.* (2003) who defined another variable, the "currency crash" index, which signifies a crisis event as a nominal depreciation of the domestic currency by more than 25% that is accompanied by at least a 10% increase in the rate of depreciation.

Another definition was suggested by Zhang (2001). He argued that the main flaw in using the EMP index is that, to the extent that a currency devaluation was anticipated, domestic interest rates will rise in the period leading up to the devaluation to compensate domestic-currency bond holders for the impending devaluation. Immediately following the devaluation, however, domestic interest rates will fall back to foreign levels. Reserves, which flowed out of the domestic country before the crisis due to reduced money demand, will flow back to satisfy increased money demand. Consequently, the changes in international reserves and interest rates may cancel out some of the change in the exchange rate, resulting in the generation of no signal for a crisis that is actually taking place. Therefore, Zhang suggested the decomposition of the EMP index into its individual components, so that a crisis signal would be generated if any of the three EMP components crossed their pre-determined threshold levels.

However, when Candelon *et al.* (2012) compared the performance of the EMP index to that of the index suggested by Zhang, they concluded that both tend to generate quite similar results (*i.e.* crisis dates). Furthermore, Lestano *et al.* (2003) experimented with four different dating schemes for currency crises and found that the definitions of Eichengreen, Rose and Wyplosz, and Kaminsky and Reinhart are superior to those of Frankel and Rose, and Zhang in terms of the in-sample forecasts.

Another area of discrepancy lies in the specification of the threshold level for the crisis index. A common practice is to define a binary variable that would assume the value of unity if the EMP index is above its country average by a certain multiple of standard deviations, and is zero otherwise. However, significant differences can be found in the specification of the multiple of standard deviations, where several studies used two standard deviations (Komulainen and Lukkarila, 2003; Krznar, 2004; Bussiere and Fratzscher, 2006; Ari and Dagtekin, 2007), while others used 1.5 (Su *et al.*, 2010; Lang, 2013), 2.5 (Edison, 2003), three (Kaminsky *et al.*, 1998; Zhang, 2001; Lin *et al.*, 2008), or even a peculiar 1.75 (Kamin *et al.*, 2001) and 0.75 (Andreou *et al.*, 2009). The choice of the threshold level is mostly arbitrary, while in some cases the authors attempted different thresholds and ended up with the one that fitted best.

2.2.2 Banking Crisis

Although the early study conducted by Kaminsky and Reinhart (1999) identified 26 currency crises and only 3 banking crises during the 1970s, Davis and Karim (2008b) showed that after the financial liberalisation undertaken by a large set of developing countries during the 1980s and the early 1990s and the development of securitised financial markets in more advanced economies, the number of banking crises has more than quadrupled after the start of the new millennium. Nevertheless, until very recently, less attention is given to the investigation and prediction of banking crises than of currency crises. One possible reason for this paradox could be that it is very difficult to find an unambiguous definition for a banking crisis. In fact, it is the most debatable definition of all three types of financial crises.

Davis and Karim (2008b) mention that a banking crisis can be defined as "the occurrence of severely impaired ability of banks to perform their intermediary role". However, this definition is too general as it may include bank runs, closure or mergers of major financial institutions, bank failures that amount to a considerable percent of the country's GDP, increases in non-performing assets, *etc.* Therefore, researchers usually adopted a number of proxies to signal the solvency condition of banks and their general soundness. For example, Casu *et al.* (2012) identified a banking crisis situation if the capitalisation of the banking sector decreased by some base points, or if the net income of the banks as a percentage of their average balance sheet fell below some threshold.

On different grounds, when Simpson (2010) studied the 2008 global financial crisis, he used the variance of a country's banking sector stock price index to capture the vulnerability of its banking system relative to the regional or the world indices. Another recent paper by Singh (2011) criticised the use of event-based crisis dating as it can lead to delayed identification of a crisis, and it fails to account for the severity of the crisis. Instead, the author proposed the construction of a "bank fragility index", which does not require *a priori* knowledge of banking system events and has the advantage of using monthly time series in preference to the usual annual, or at best quarterly, basis related to event timings. This index is defined as the weighted average of six variables related to liquidity risk, credit risk and interest rate risk, and was adopted to study banking crisis in India.

Alternatively, two distinct papers by Lestano *et al.* (2003) and by Davis and Karim (2008b) cited a number of studies with respect to their definition of a banking crisis episode, and summarised these definitions in the following events: substantial decrease in bank capital; considerable decrease in bank deposits signifying bank runs; closures, mergers or takeovers of large banks or financial institutions; massive government intervention in the banking sector; increase in the ratio of non-performing loans to total bank assets; large scale bank nationalisation. They also observed that the introduction of deposit insurance schemes in recent years has significantly decreased the contribution of bank liabilities to the episode of banking crises, as it became very difficult to track the occurrence of bank runs. Therefore, the focus of interest has recently shifted to the assets side of banks' balance sheets to date a banking crisis, where special attention is given to the percentage of non-performing bank assets or to changes in real estate prices (which affects banks engaging in mortgage loans).

However, a more recent study by Barrell *et al.* (2010) criticised this line of thought in defining a banking crisis on the basis that it is unable to identify the true start and end dates of the crisis, as the criteria variables used may take a while after the crisis breaks out or ends to start revealing its onset or termination, respectively. On this ground, they relied on the IMF financial crisis episodes database to extract the timing of systemic banking crises, whereas for the non-systemic crises they used the World Bank database of banking crises (discussed in more detail in 5.2).

Finally, before turning to the definition of the third type of financial crises, it is noteworthy to shed some light on how the literature defined a joint dependent variable for a twin crisis. In this respect, Ari and Dagtekin (2007) defined a composite twin crisis indicator in an attempt to model an EWS for the 2000/2001 Turkish financial crisis. This indicator consists of two parts, where the first is more or less a usual EMP index, with its real exchange rate, real interest rate and international reserves components. The second part is set out to measure the vulnerability of the banking system, which also comprises three components, namely the amount of bank credit extended to the private sector, the total foreign exchange liabilities and the total amount of deposits held by the domestic banking system.

2.2.3 Sovereign Debt Crisis

In contrast to the efforts dedicated to the construction of forewarning systems for both currency and banking crises, very little work was devoted to the prediction of sovereign debt crises. Therefore, the debate on the possible definition of a debt crisis is almost absent. One of the most prominent papers that addressed this type of financial turmoil is that of Manasse *et al.* (2003), who considered a definition for debt crises that captures both actual and potential defaults on sovereign debt. In particular, according to their definition, a country is said to be facing a debt crisis either if it is rated by Standard & Poor's as being in default (*i.e.* is failing to meet its external obligations on the principal or interest payments) or if it receives a loan from the IMF Finance Department in excess of 100% of its quota as an extensive financial rescue scheme.

The exact same definition is later applied by Fioramanti (2008), Manasse and Roubini (2009), Savona and Vezzoli (2015) and Jedidi (2013), while Ciarlone and Trebeschi (2005) extended the definition further to include other events as well. In addition to the ones mentioned above, they defined a country to be in crisis if the amount of overdue interest or principal payments is more than 5% of its outstanding external debt, or if it engaged into some sort of debt restructuring or rescheduling schemes. On the other hand, Lestano *et al.* (2003) and Lausev *et al.* (2011) restricted the debt crisis scenario to the event that a country requests the rescheduling of its sovereign debt, or if it engages into debt-equity swaps or voluntary buybacks. Another suggestion was made by Pescatori and Sy (2007) to take into account the turbulence in sovereign bond markets in order to capture possible debt-servicing difficulties. They argued that as more and more emerging economies gained access to sovereign bond markets, they tend to rely less on bank loan debts. Therefore, their debt crisis event was defined as either the usual Standard & Poor's sovereign default rating or a sovereign bond spread of more than 1000 basis points above the U.S. Treasury bill.

2.3 Crises Causes and Leading Indicators

Defining the dependent variable that is intended to capture the incidents of financial crises is the first step in modelling an EWS for each type of crisis. The following step entails identifying the indicators that could be used to generate warning signals of such crises. These are mainly drawn from financial economic theory and the empirics regarding the probable causes of financial turmoil. Because different types of crises can have many different sorts of causes across the various countries of the world and over decades of time, a wide range of economic and financial variables should be considered (Frankel and Saravelos, 2012). Accordingly, this section traces the pioneering and path-breaking theoretical literature that attempted to present explanations for the occurrence of financial crises. In addition, it outlines the variety of signalling indicators applied and tested by previous empirical studies and their findings with respect to the most statistically significant ones. A summary of the most commonly used indicators is provided in Table 2.1 on page 33.

2.3.1 Currency Crisis Indicators

The theoretical literature identifies three generations of models that explain the causes and determinants of currency crises. Each of these models emphasises a set of economic and financial variables that can be used as leading indicators of approaching currency crises. The different theoretical models, and hence the suggested indicators, provide a comprehensive view of the various possible threats on the domestic currency.

First-Generation Models

Initially, the earliest traditional approach focused on the role of the weak economic fundamentals in explaining currency crises. The seminal work by Krugman (1979), later refined by Flood and Garber (1984)[1], shows that, under a fixed exchange-rate regime[2], expansionary monetary policy (*i.e.* expansion of money supply in excess of the demand for the domestic currency) to finance persistent fiscal budget deficits will result in a gradual loss of international reserves, as market participants sell the excess liquidity and buy foreign currency. To maintain the peg, the central bank sells its foreign reserves, which gradually deplete at a rate equal to the growth of the money supply. As the reserves reach a critical level, a speculative attack is induced on the currency, which exhausts the remaining foreign reserves and forces the authorities to abandon the parity, resulting in currency devaluation.

A number of papers extended Krugman's basic model in various directions, considering other factors that may force the government to abandon the peg. For example, Agenor *et al.* (1992) suggested that a direct result of the expansionary policies is a deterioration of the trade and current account balances due to increased import demand. Moreover, since the expansionary policies lead to increased aggregate demand, an indirect result would be a rise in the price levels. All these would lead to the overvaluation of the real exchange rate, and eventually to a speculative attack. On different grounds, Ozkan and Sutherland (1995) argued that the authorities tend to trade off between internal (preserving a target level of output) and external (fixed exchange rate) policy objectives. Therefore, an increase in the foreign interest rate that puts an upward pressure on the domestic one, will raise the cost of keeping the peg, as it negatively affects the output level (due to reduced investments). Once the cost of keeping the exchange rate fixed surpasses the benefits, the authorities will abandon the peg.

[1] Flood and Garber (1984) constructed a linear model that simplified Krugman's account and extended it to a stochastic environment.

[2] The model was later extended to the cases of crawling pegs and currency bands (as cited in Lang, 2013).

Accordingly, the first-generation models highlight a variety of variables that could be useful for predicting currency crises, namely growing fiscal budget and current account deficits, money supply growth, exchange rate overvaluation, depletion of the foreign reserves, inflation, movements in the level of output, as well as the evolution of domestic and foreign interest rates. These and a set of more economic fundamentals were tested empirically to assess their predictive power in real situations.

Starting with the earliest studies in this field, Kaminsky *et al.* (1998) (depicted in Table 2.1 under KLR98) categorised the variables they applied into six broad groups which cover every aspect of the economy. Specifically, they examined 15 possible indicators to construct their EWS for currency crises in 15 developing and five developed countries over the period 1970-1995. These variables ranged from the financial sector, the real macroeconomy, and the external sector (including current account and capital account variables) to the public finances, some political indicators, and several institutional variables. Their findings signified the importance of a decelerating growth rate, a sharp decrease in exports, a positive deviation of the real exchange rate from its trend, the depletion of international reserves, and a rapid increase in the ratio of domestic credit to GDP (denouncing a lending boom) as possible stimulus for currency crises. On average, these indicators were able to correctly predict 70% of the currency crisis episodes using their proposed signal approach. The same indicators were later used by Edison (2003), who replicated their method but extended the time period to 1998.

Comparable results were depicted by Frankel and Rose (1996) (FR96) who applied a probit regression model on 105 emerging economies over the period 1971-1992. They further highlighted the contribution of foreign direct investment (FDI) outflows in increasing the probability of currency crises in developing countries. In fact, they identified that a decrease in FDI inflows by 1% raises the probability of crises by 0.3%. On different grounds, when examining the causes of the Asian financial crisis in 1997, Dodd (2000) argued that financial derivatives, in the form of foreign exchange forwards and swaps, have played a major role in the formation, spread, and severity of the crisis. The use of derivatives tends to increase the risk-to-capital ratios through leveraging and by dodging prudential regulatory safeguards, thus making the economy more vulnerable to a financial crisis. Furthermore, once the crisis was approaching, they helped quicken and deepen the financial distress.

A very recent and extensive review of the possible currency crisis indicators was conducted by Frankel and Saravelos (2012), who surveyed more than 80 articles that studied crisis episodes from the 1950s to the beginning of the millennium using a variety of estimation techniques, crisis definitions, and country coverage. By summarising the number of times a particular indicator was found to be statistically significant in these articles, they were able to rank the most important signalling indicators. The results of their meta-analysis manifested the prominence of international reserves, real exchange rate, credit growth, GDP growth, and the current account balance. In addition, their own examination of the 2008 financial crisis evidenced the significance of bank liquidity and the level of short-term external debt, which signifies the possibility of spillover from a weak banking sector and sovereign debt distress.

Returning to the signal approach, Andreou *et al.* (2009) investigated the performance of eight forewarning indicators in six individual countries. They were able to identify the most important indicator for each country separately. However, on average, they signified the role of real exchange rate and commercial bank deposits, while the performance of the money supply (as measured by M2) was found to be unsatisfactory. In contrast to these result, a more recent study by El-Shazly (2011), using logit and probit regression analyses to investigate currency crisis incidents in Egypt, showed that the ratio of M2 to international reserves is the most significant leading indicator, followed by the domestic real interest rate and the percentage change in the stock price index. Similar results also were found by Komulainen and Lukkarila (2003) (KL03), who examined 31 emerging markets during the period 1980-2001 using a probit model. In particular, the probability of currency crises was detected to be greatly affected by the M2 to reserves ratio, domestic credit growth, inflation rate, and changes in the stock price index. They also verified the significant effect of public debt and banking sector indicators on the crisis probability, which confirms the findings of Frankel and Saravelos (2012).

Second-Generation Models

The first-generation models, which focused on weak macroeconomic fundamentals and policies as explanatory variables for financial crises, were insufficient in explaining the European Monetary System crisis in 1991-1993. The countries in Western Europe had sound fundamentals in terms of adequate foreign reserves, manageable money growth, and non-monetised fiscal deficits. This motivated a new strand of literature, the so called second-generation models, which added the features of self-fulfilling attacks and the role of investors' expectations in explaining currency crises.

Second-generation models were developed by Obstfeld (1994, 1996) on the basis that government policies are not predetermined, but they respond to changes in the economy, while investors base their expectations about the state of the economy on the behaviour of the policy makers. This circularity between policies and investors' expectations may give rise to multiple equilibria and generate self-fulfilling crises. The term "multiple equilibria" refers to the fact that the economy can move from one equilibrium state to another without noticeable changes in the fundamentals, but rather due to abrupt shifts in investors' confidence. Thus, the economy may be initially in a state of equilibrium consistent with a fixed exchange-rate regime but a sudden worsening of economic prospects may lead to changes in policies that result in abandoning the peg, thereby validating investors' expectations. Calvo (1998) explained the latter case as follows: "If investors deem you unworthy, no funds will be forthcoming and, thus, unworthy you will be".

In this framework, Obstfeld (1994) developed a model where devaluation expectations induce investors to sell their holdings of the domestic currency. This leads to higher interest rates as the monetary authorities attempt to maintain the peg. However, eventually, the higher interest rates might trigger the authorities to abandon the peg out of concern for the increased expenses of servicing public debt. Furthermore, the models suggested by

Velasco (1987) and Obstfeld (1996) indicate that higher interest rates could also weaken the banking sector through moral hazard and adverse selection problems, increasing the probability of banking distress. The authorities, in this case, may prefer to devalue than to suffer the associated fiscal costs of a bailout. On different grounds, Drazen (2000) showed that political factors have a strong impact on the expectations of a country's economic status, where continued political instability leads to prospects of persistent budget deficit, high external debt, an ineffective tax system, and low growth rates. Investors seeking refuge in foreign currency will trigger a self-fulfilling currency crisis.

According to this class of models, leading indicators of currency crises should include such variables that reflect banking problems, political stability, public debt, and investors' expectations. Examples of research in this area include Ari and Dagtekin (2007), Son *et al.* (2009), and Candelon *et al.* (2012) who used variables, such as interest rate spreads, the term spread, and stock market prices, which have a forward-looking dimension as explanatory variables to measure the shifts in investors' expectations and confidence.

Third-Generation Models

The outbreak of the Asian financial crisis in 1997 led to a reorientation of modelling currency crises, since the economic fundamentals of the affected countries were rather sound prior to the crisis and there were no abrupt shifts in investors' confidence. In fact, the crisis was marked by problems in the financial sector following the liberalisation of capital markets under inadequate prudential supervision. Therefore the new third generation of theoretical models highlight the adverse effect of the financial sector's vulnerability and the possibility of contagion –the transmission of crises through different channels from one country to another.

With respect to the dynamic feedback between banking problems and currency crises (originally suggested by Velasco, 1987), Chang and Velasco (2000) and Pesenti and Tille (2000) stress the adverse consequences of moral hazard practises in the banking system under inadequate supervision and explicit or implicit government guarantees, which result in excessive credit expansion and a large share of high-risk loans in bank portfolios. That is, the liberalisation of the capital market usually leads to more competition across banks, which in turn leads some banks to extend riskier loans in the hope of raising their profitability. Furthermore, the anticipation of a government bailout in case of trouble reinforces the engagement of banks in excessively risky projects and heavy dependence on foreign financing. Consequently, even a small shock in the financial assets market may cause significant deterioration in bank portfolios, leading to a liquidity crunch due to lower confidence in the banking system. The authorities are forced to intervene through inflationary policies in order to save the banking sector, which imposes severe burdens on the public sector and may lead to a currency crisis.

As for the other part of this generation of theoretical currency crisis models, Masson (1998) suggested three possible channels for crises to spread from one country to another. First, in the *global shock model*, a common external shock (e.g. fluctuations in world interest rates or changes of oil prices) could trigger crises in different countries. Second, the *spillover model* shows that currency devaluation in one country leads its trading partners to devalue so as to avoid a loss of competitiveness and the deterioration of their trade balance. In addition, crises may also spread due to financial interdependence between countries, where a country with credit exposure or equity stakes in a neighbouring country facing a currency crisis would be adversely affected, causing weakness in its financial sector. Third, *pure contagion* may be caused by shifts in market sentiments and the herding behaviour of investors. Montiel and Reinhart (2001) showed that the resulting sudden stop, and possibly reversal, of capital inflows are more abrupt when they are in the form of portfolio flows or short-term capital movements rather than FDI.

Given the models suggested in the third generation, the growth of domestic credit, changes in assets prices, and crises in neighbouring countries can serve as leading indicators of currency crises. Empirically, a number of articles (e.g. Zhang, 2001; Fratzscher, 2003; Bussiere and Fratzscher, 2006; Wong *et al.*, 2010; Kumar *et al.*, 2003) have considered the possibility of financial contagion and spillover effects through trade links and capital flows among closely integrated countries.

In this respect, a study by Kamin *et al.* (2001) estimated a probit regression on 26 developing countries to investigate whether fixed or flexible exchange-rate regimes are more suitable for emerging economies in terms of making them less vulnerable to currency crises. Their results emphasised that, although domestic factors (such as GDP growth, fiscal deficit and the ratio of M2 to international reserves) may be the main impetus of the underlying vulnerability of an economy, it is in fact the adverse fluctuations of the external factors, including capital and trade flows, terms of trade, U.S. interest rates, and output growth in advanced economies, that tend to push the emerging economies into financial crises. They thus suggested that, in general, a flexible exchange rate may be more appropriate for emerging markets as it can act as a "cushion" against the severe spillover effects of external shocks and imbalances.

2.3.2 Banking Crisis Indicators

Turning to the theory on banking crises, Breuer (2004) showed that it is usually categorised according to four generations. The first-generation models, initially suggested by Mishkin (1978), propose that poor macroeconomic conditions that adversely affect banks' borrowers may result in business failures and consumer defaults, leading to banking problems. The deterioration in the quality of the portfolio of bank assets may trigger a run on the bank, as depositors rush to withdraw their funds before the bank declares bankruptcy. Runs on banks ultimately forces the closure of financial institutions as banks fail to meet all cash withdrawals.

Similar to the currency crisis models, the second generation of banking distress relate crises to self-fulfilling attacks on bank deposits which are not related to downturns in the business cycle or banking conditions, but rather to depositors' expectations regarding policies and future prospects. Diamond and Dybvig (1983) focused on the role of the loss of confidence and arbitrary shifts in depositors' expectations in precipitating runs on banks, regardless their underlying financial position. If depositors believe that other depositors are withdrawing their funds even in the absence of an initial deterioration in the banks' balance sheets, the resulting run on the banks weakens the entire banking system and raises the possibility of a self-fulfilling crisis.

The seminal work by Kiyotaki and Moore (1997) formed the basis for the third generation of banking crisis models, called the "credit cycle model". Within the framework of this boom-bust cycle model of bank lending, banking distress arises on the asset side of the banks' balance sheets due to excessive lending against asset collateral. Particularly, during economic boom times, the value of assets (especially real estates) increases rapidly and banks become more willing to extend larger loans against the increased value of collateral. However, the excess lending and the pervasive exposure of banks to the real estate market makes them more vulnerable when asset bubbles burst. As the bust ensues, the resulting depreciation of collateral value as asset prices fall impedes the banks' lending ability. A credit crunch develops leading to further economic slowdown and making it more likely that borrowers' defaults will increase and a crisis will break out.

Finally, the most recent fourth-generation models consider the institutional factors that cause the build-up of macroeconomic imbalances (refer for example to Hall and Jones, 1999), which in turn increase the likelihood of banking problems. These models emphasise the role of economic and financial regulations, the legal framework, corporate governance, and political variables that may give rise to poor fundamentals, inconsistent government policies, excessive lending, and self-fulfilling attacks. For example, George (as cited in Davis and Karim, 2008b) suggested a model in which high correlations between banks' idiosyncratic risks and counter-party claims between banks via interbank transactions can lead to high systemic risks and widespread failures if one (big) bank fails. Moreover, Demirguc-Kunt and Detragiache (1998) argued that financial liberalisation, which gives rise to higher real interest rates, that is not accompanied by adequate prudential regulations and supervision can lead to increased credit risk, as bank managers compete over borrowers. On the other hand, the model developed by Stiglitz and Weiss (1981) shows that higher interest rates can also give rise to credit rationing, where (high-risk) borrowers are willing to pay the high rate, but lenders are not willing to lend out of concern for adverse selection. This situation can further lead to a credit crunch and thus to recession.

In the light of these models, one could expect pre-crisis periods to be characterised by: rapid domestic credit growth (which captures credit risk), low GDP growth (which captures cyclical downturns), low bank liquidity, profitability and capitalisation (which capture liquidity risk), runs on bank deposits (which capture self-fulfilling attacks), high rates of non-performing loans (which capture deteriorating bank assets quality), high real interest rates (which capture interest rate risk), high inflation rates (which cause higher nominal interest rates), falling asset prices (which capture default risk), fiscal budget and current account imbalances (which capture poor fundamentals), among others.

With respect to the empirical findings and attempts at constructing EWSs for banking crises, Demirguc-Kunt and Detragiache (1998) (DD98), who applied a pooled logit regression to estimate the probability of banking crises in both developed and emerging economies over the period 1980-1994, were able to forecast about 70% of the crisis episodes. Alongside the other usual indicators of international reserves, credit growth, GDP growth rate and inflation rate, they depicted an important positive relation between adopting an explicit deposit insurance scheme and the probability of a banking crisis, which signifies the extent of excessive risk-taking and moral hazard exercised by bank managers as a result of reduced risk of bank runs. Notwithstanding, more recent papers that examined later periods evidenced that the widespread use of such deposit insurance schemes have greatly diminished their role as crisis indicators, as they can no longer distinguish between distressed and healthy banking systems (refer for example to Davis and Karim, 2008a; Barrell *et al.*, 2010).

A more recent study by Wong *et al.* (2010) on 11 Asia-Pacific countries using a probit model highlighted the contribution of credit growth to the build-up of systemic banking problems. They also confirmed the results of Demirguc-Kunt and Detragiache (1998) that banking crises are usually preceded by rapid credit growth within a time-frame of two years. Furthermore, they found evidence for some spillover effects from banking distress in neighbouring economies due to mutual dependencies. For this purpose, they used the sum of neighbouring economies recently suffering a banking crisis as an explanatory variable.

Ari and Dagtekin (2007) (AD07) pointed out the liberalisation of the financial market as a key driver of the Turkish financial crisis in 2000/01, as it creates uncontrollable volatility of massive inflows and sudden withdrawals of capital out of the economy. Furthermore, they highlighted the significance of current account imbalances, the ratios of short-term debt and M2 to international reserves, the rise in domestic credit and public sector borrowing relative to the economy's GDP, and the shortfall of bank reserves to total bank assets to the occurrence of banking crises. On the other hand, focusing on developed countries and using a logit model to construct a warning system for banking crises, Barrell *et al.* (2010) demonstrated the prominence of several bank balance-sheet variables, such as the leverage ratio and the liquidity ratio, in addition to the growth rate of house prices, as determinants of banking crises in OECD countries. They lag all variables by one period, apart from house price growth which has a longer lag to reflect potential lending problems that frequently develop as a consequence of a house price bubble. Prolonged periods of risky mortgage lending by banks are expected to increase the possibility of borrower defaults. This result was later confirmed for low-income countries, as well, by Caggiano *et al.* (2014) who applied a multinomial logit regression on 35 Sub-Sahara African countries.

Another recent study by Casu *et al.* (2012) (CCS12), which applied a modified version of the signal approach to study banking crises in 30 OECD countries over the period 1980-2009, reported the significance of several other variables. Specifically, they used the growth in pension funds as a proxy for liquidity bubbles, arguing that pension funds are large liquidity providers; therefore the growth of their assets could result in more funds poured into the stock markets and real estate, which may contribute to crises by bubble development. Furthermore, they used the reduction in equity market dividends as an indicator of corporate ability to service their debts, since firms usually distribute dividends from their free cash flows after paying their obligations to creditors. They also found a positive relation between the growth in the banking sector assets, the formation of house price bubbles, and the reduction in the liquidity of banks on one side and the vulnerability of the economy to banking crises on the other side.

On different grounds, instead of using aggregated data for the whole banking system, a study by Bongini *et al.* (2002) investigated the probability of distress for more than 200 individual banks in South-East Asia. They investigated the predictive power of several micro-level variables, including 5 different accounting ratios, agents credit rating and the cost of deposit insurance. Using some ad hoc assessment to identify crisis timings for the individual banks, they found that none of the micro-level variables are significant once the macroeconomic indicators are controlled for.

With respect to the signalling indicators for twin crises, studies by Kaminsky (1999), Kaminsky and Reinhart (1999) (KR99), and later by Ahec-Sonje (2002) pointed out the key role played by bank deposits, current account indicators, international reserves, the ratio of M2 to international reserves, domestic and foreign real interest rates, and the rate of inflation in explaining the twin occurrence of banking and currency crises. The same results were found by Ari and Dagtekin (2007) when considering the sole case of the Turkish twin crisis in 2000/2001, but they also stressed the significance of portfolio investment, bank liquidity and short-term external debt in explaining this twin crisis episode.

Another distinguished paper by Lestano *et al.* (2003) (LJK03) was set out to study the causes of all three types of financial crisis using a panel of six Asian countries over the period of 30 years from 1970-2001. Applying a logit regression model, they concluded that crises in general are related to the growth rates of money aggregates, per capita output, and national savings. Some additional variables are related to the incidence of currency crises, namely growth of international reserves, domestic real interest rate, and the rate of inflation. Variables that are more closely linked to banking crises include the ratio of M2 to international reserves and current account indicators. Finally, they associated the commercial bank deposits, the interest rates in the U.S., and the output growth in OECD countries with the incidence of sovereign debt crises.

2.3.3 Sovereign Debt Crisis Indicators

The theoretical literature highlights a variety of factors that can lead to debt crises and sovereign defaults. Basically, two main approaches are introduced in the literature that attempt to explain the occurrence of debt crises. On the one hand, the "willingness-to-pay" approach, pioneered by Eaton and Gersovitz (1981) and Eaton *et al.* (1986), models defaults as an event where a sovereign chooses to repudiate its debt based on the optimisation of some loss function. That is, if the perceived costs of defaulting (in terms of sanctions, penalties, being excluded from the credit market, *etc.*) are less than the benefits, a country willingly refuses to service its debt. According to this approach, Hernandez-Trillo (1995) argued that factors like trade openness (which increases the costs of default), measures of macroeconomic stability (e.g. low inflation and money growth) that reflect policy credibility and predictability and thus influence investors' risk attitudes toward a country, as well as sound political and institutional environments can positively affect the country's willingness to repay its debts.

On the other hand, the "ability-to-pay" approach, represented by McFadden and Hajivassiliou (as cited in Peter, 2002), models debt crises as a situation where the sovereign is unable to repay its debt due to being insolvent or illiquid. Consequently, measures of solvency such as public and external debt relative to the country's capacity to pay, measures of liquidity such as short-term debt and debt service to foreign reserves, and several macroeconomic variables that affect the government's ability to pay (e.g. real GDP growth, terms of trade, fiscal deficit, current account balance) are important determinants of debt crises. Furthermore, Uribe (2006) showed that certain monetary-fiscal arrangements can lead to government insolvency. In particular, if the government is running a persistent fiscal deficit in the midst of a prolonged recession while the central bank is targeting inflation or pegging the nominal exchange rate, the government is unable to inflate away the real value of its nominal public liabilities, making default on public debt inevitable. This situation was the reason behind Argentine's debt crisis in 2001.

Another area of research that attempts to explain the factors that can make a sovereign unable to repay its debts was initiated by Calvo (1988), who considered the issue of "confidence crisis" in some sovereign's bonds. He analysed the case where a government uses new loans to service its existing debt (*i.e.* debt roll-over). The model shows that, if the government uses inflation to repudiate some portion of the debt in real terms, investors may lose confidence in sovereign bonds. The resulting liquidity crunch induced by the inability to roll-over the debt can push the government into a debt crisis. Cole and Kehoe (2000) extended this model to include the possibility of self-fulfilling crises with the aim of explaining the Mexican crisis of 1994. According to their model, once investors think that other creditors will not purchase a sovereign's new issues of bonds, they will either refrain from purchasing or demand higher interest rates, leading to a self-confirming default. It is important to note that the model of credit rationing, developed by Stiglitz and Weiss (1981), can also be used to explain the stop of roll-over of debt by investors. If the demand for new loans to service existing debt exceeds the supply at the upper ceiling interest rate at which creditors are willing to lend, the country is unable to fully refinance itself and may have to default. Finally, the survey conducted by Reinhart (2002) on about 60 countries over a period of 20 years (1979-1999) conveyed that 84% of the sampled debt crises were preceded by a currency crisis. Hence, variables that are well-suited for predicting currency crisis should also have some explanatory power in the EWSs for sovereign defaults, especially the overvaluation of the exchange rate.

There is only a limited number of empirical studies that focused on developing an EWS of sovereign debt crises, the most prominent of which include Manasse *et al.* (2003) (MRS03), Ciarlone and Trebeschi (2005), Fuertes and Kalotychou (2007), Fioramanti

(2008), Manasse and Roubini (2009), and finally Jedidi (2013) and Savona and Vezzoli (2015). Chakrabarti and Zeaiter (2014) have recently carried out a comprehensive review[1] of the previous findings with respect to the significant factors and their observed effect on the probability of default.

The previous studies applied different statistical techniques to model a warning system, ranging from logit regressions and binary recursive tree analyses to the more complicated Artificial Neural Networks. However, they seemed to agree on a number of significant indicators that could act as explanatory variables for debt crises. Particularly, they emphasised the role of external debt ratios (short-term debt to reserves, debt service to reserves or to exports, and total debt to GDP) that measure the solvency and the debt sustainability of an economy, the growth in international reserves and export earnings which reflect the ability to service debt, the current account deficit plus short-term debt as a measure of illiquidity risk, and some macroeconomic indicators, namely real GDP growth, FDI flows, volatility of export growth, and inflation rate. Finally, the interest rate on U.S. treasury bills and the degree of financial market openness or trade openness also seem to play a significant role.

2.4 Statistical Methods

In the context of modelling EWSs for financial crises, there are basically two distinct approaches in the literature, namely the "Signal Extraction Approach", a non-parametric method originally developed by Kaminsky *et al.* (1998) and Kaminsky (1999), and the "Discrete-dependent-variable Approach", a parametric approach proposed by Frankel and Rose (1996) which uses either logit or probit regression models to estimate the probability of an approaching crisis. Apart from these two approaches, several researchers have attempted the utilisation of other statistical techniques, but these are not as popular in the literature. Consequently, this section highlights the proposed methods in the literature

[1] Refer to Table 1 in Chakrabarti and Zeaiter (2014).

Table 2.1: Review of Financial Crises Signalling Indicators

Indicator	FR96	KLR98	KL03	DD98	AD07	CCS12	MRS03	KR99	LJK03
Real Exchange Rate	✓	✓	✓	✗				✓	
Growth of Exports		✓	✓		✗			✗	
Growth of Imports		✗			✗			✗	
Terms of Trade		✗		✗	✓			✗	
CA / GDP	✗			✗		✗		✓	✓
M2 / Reserves		✓	✓	✓	✓			✓	✓
Growth of Reserves	✓	✗		✓			✓	✓	✓
Domestic Credit / GDP	✓	✓	✓	✗	✓			✓	
Domestic Real Interest Rate		✗		✓				✓	✓
U.S. Interest Rate	✓	✗	✓				✓	✓	✓
Commercial Bank Deposits		✗	✗					✓	✓
Bank Reserves / Bank Assets			✗		✓				
Fiscal Deficit / GDP	✗		✗	✗	✗		✓	✓	
Public Debt / GDP	✗		✓		✓		✗		
Industrial Countries Output	✗		✗						✓
Stock Price Changes		✓	✓	✓	✗	✓		✓	
Inflation Rate			✓	✓			✓	✓	✓
Real GDP Growth Rate	✓	✓		✓		✓	✓		✓
FDI / GDP	✓		✓				✓		
External Debt / Reserves					✓	✗	✓		
Time Period	1971-1992	1970-1995	1980-2001	1980-1994	1987-2004	1980-2009	1970-2002	1970-1995	1970-2001
Statistical Method	PR	SA	PR	LR	LR	SA	LR	SA	LR
Country Coverage	105	20	31	45	Turkey	30	47	20	6
Type of Crisis	CC	CC	CC	BC	BC	BC	DC	TC	TC+DC

Source: Author survey, adapting design from Lestano *et al.* (2003)
Notes: A (✓) sign indicates a significant indicator, a (✗) sign indicates an insignificant indicator, while empty cells imply that the variable was not considered in the study.
SA = Signal Approach, LR = Logit Regression, PR = Probit Regression,
CC, BC, DC, and TC denote currency crisis, banking crisis, debt crisis, and twin crisis respectively.

and the various modifications suggested to each method to improve its performance in generating warning signals for financial crises.

2.4.1 Signal Extraction Approach

This approach involves identifying and monitoring certain macroeconomic and financial market variables that tend to behave in an unusual manner in the run-up to financial or economic distress. The model would, thus, signal an alarm of an impending crisis when these indicators exceed a certain threshold value (calculated as a specific percentile of the indicator's distribution over the sample). In this respect, Davis and Karim (2008b) stated that some researchers prefer to select a relatively low threshold so as to minimise the probability of missed crises, arguing that policy makers ought to make sure that a crisis is avoided at all costs. On the other hand, scholars that bear in mind the huge bailout costs that the governments must incur to avoid or mitigate the effects of a crisis, prefer choosing a relatively high threshold that would minimise the percentage of false alarms. In general, though, most studies attempt to balance between both types of errors by minimising the ratio of bad signals to good signals when choosing the appropriate threshold [1].

On a different ground, Ari and Dagtekin (2007) criticised the idea of setting a certain threshold level for each indicator, arguing that once an indicator passes the specified threshold, it is not possible to observe its behaviour thereafter, *i.e.* whether it just crosses the threshold by a little or if it deteriorated greatly. Furthermore, even though an indicator might be behaving in an unusual manner or is deviating much from its trend, this method will not generate any signal as long as the indicator value remains below the specified threshold. To address these issues, Kaminsky (1999) and Lin *et al.* (2008) attempted to construct EWSs that specify two different threshold levels for each indicator. Accordingly, each variable is assigned a mild threshold value, which captures the relatively moderate deviations from the usual trend, and a drastic threshold value, which reflects

[1] For more details on the conception and the calculation, refer to Kaminsky *et al.* (1998).

strong deviations. However, the choice of the threshold levels, where the drastic is twice as high as the mild, was rather arbitrary.

Furthermore, a recent paper by Casu *et al.* (2012) proposed a more dynamic choice of the threshold, so that a warning signal is issued if an indicator fluctuates beyond a certain multiple of standard deviations away from its long-run mean. Focusing on the volatility of the indicators instead of choosing a threshold level that is specific to the sample data, they were able to reduce the percentage of missed crises from 30-40% (refer for example to Kaminsky and Reinhart, 1999; Ahec-Sonje, 2002; Berg *et al.*, 2005; Andreou *et al.*, 2009) to a mere 3%.

2.4.2 Discrete-Dependent-Variable Models

The parametric approach considers the same indicator variables as the signal approach, but uses them as explanatory variables in either a logit or a probit regression. Ari and Dagtekin (2007) argued that the advantage of this model over the signal approach lies in the possibility of applying statistical tests on the estimated coefficients. However, the model they applied was able to predict correctly only 40% of the crisis episodes, but was able to foresee the absence of a crisis in 97% of the cases (*i.e.* false alarm rate was 3%). Slightly better results were found by other papers that used either logit or probit regressions. For example, using a logit model, Barrell *et al.* (2010) correctly identified 66% of crisis episodes, while generating 29% of false alarms. Furthermore, the results depicted by Manasse *et al.* (2003) and by Ciarlone and Trebeschi (2005) show around 70% of correct crisis hits and around 35% of false alarm signals.

On the other hand, estimating a probit regression, Komulainen and Lukkarila (2003) reported 56% of correctly called crisis and 92% of correctly called tranquil periods; while the percentage of correct crisis hits estimated by Berg *et al.* (2005) ranged from 58% to 84%, and from 53% to 80% for tranquil periods. Compared to the probit model, Manasse *et al.* (2003) proclaimed that the logit model tends to perform better when the dependent variable is not evenly distributed between the two outcomes, that is, crisis and no-crisis, which is usually the case since crisis events ought to be the exception-to-the-rule case.

Nonetheless, an important criticism directed at the results of both the binomial logit/probit models is the one entitled by Bussiere and Fratzscher (2006) as the "post-crisis bias". They claimed that instead of comparing the behaviour of the indicators during tranquil times with their behaviour on the verge of a crisis, using binomial regressions, the model is actually combining the observations of tranquil times with those of post-crisis periods into one group. This procedure can lead to some sort of bias, because the indicators are reasonably expected to behave differently during tranquil times than during post-crisis periods when the economy is undergoing an adjustment process to recover from a crisis. Caggiano *et al.* (2014) also explained that including observations after the onset of a crisis can further lead to an endogeneity problem, where the behaviour of the indicator variables is affected by the crisis itself and the policy responses. They defined this effect as the "crisis duration bias".

While some authors[1] simply dropped all the post-crisis observations from their sample to avoid this pitfall, thus suffering the loss of considerable potentially valuable information, Bussiere and Fratzscher (2006) proposed the use of multinomial models, where the discrete dependent variable has more than two outcomes to account for all three states of the economy (tranquil periods, pre-crisis periods, and crisis and post-crisis periods). They investigated this model on currency crises in emerging markets and evidenced a reduction in the percentage of false alarms from about 65% to nearly 58%, and a rise in the percentage of correct hits from 57% to 66%. Furthermore, Ciarlone and Trebeschi (2005), who relied on an earlier version of Bussiere and Fratzscher work in 2002, investigated its performance in predicting debt crisis episodes, again only in the case of emerging economies. They reported that the binomial logit EWS was able to signal only two out of the five (40%) out-of-sample crisis episodes, whereas the multinomial signalled four (80%) without generating more false alarms. A very recent paper by Caggiano *et al.* (2014) also

[1] Refer to Demirguc-Kunt and Detragiache (1998); Fuertes and Kalotychou (2007); Candelon *et al.* (2014); Wong *et al.* (2010); Lang (2013).

manifested the usefulness of the multinomial regression model in predicting banking crisis episodes in Sub-Saharan Africa, as it was able to detect more crisis incidents and generate fewer false alarms than the binomial model.

Another profound study was conducted by Fuertes and Kalotychou (2006), who aimed to identify the most accurate parametrisation of a logit regression model. For this purpose they compared nine different specifications, ranging from a pooled model that imposes full homogeneity, and a fixed country- and/or time-specific effects, to a very complex random effects model that allows for time-varying country heterogeneity in both the intercept and the slopes.

When examining the goodness-of-fit and the forecasting ability of all these models in the case of sovereign debt crises in developing countries, they found that the more complex models that control for unobserved heterogeneity across countries and time describe the data better. Nonetheless, they showed that the parsimonious pooled logit model with full country and time homogeneity fitted separately to each region tends to significantly outperform the more complex specifications in terms of out-of-sample predictions, where the latter usually underperformed even the naïve benchmarks. The authors, hence, suggested that heterogeneity seems to be regional rather than country- or time-specific.

On different grounds, when Davis and Karim (2008b) compared between the forecasting ability of the logit model and the signal approach, they found that logit models can be more suitable for the construction of global EWSs while the signal approach is better at predicting country-specific crisis episodes. Nonetheless, the results obtained by Berg *et al.* (2005), after examining the forecasts of the signal approach, a probit model, a logit model, and three other non-model analyst ratings, emphasised that forewarning systems are not accurate enough to be relied on to forecast financial crises. They, thus, suggested that the construction of an effective EWS still requires further investigation.

2.4.3 Other Methods

Several other less common methods were proposed to construct an EWS for financial crisis. For example, Son *et al.* (2009) used *Machine Learning Algorithms* in order to forecast the behaviour of global institutional investors in the Asian local markets. These investors tend to play a key role in destabilising the stock markets and causing severe financial turmoil via massive selling of their stock holdings. Another attempt was undertaken by Fuertes and Kalotychou (2007) who used the *K-means clustering* approach, which entails assigning every observation to the cluster with the nearest mean vector so as to maximise within cluster similarity and between-cluster discrepancy. Yet, comparing the forecasts of their suggested algorithm to that of a usual logit model, they found that the latter outperforms in out-of-sample.

On different grounds, Rose and Spiegel (2009) used a *Multiple Indicator Multiple Cause* model to design an EWS for the 2008 financial crisis. Their results, however, failed to find a significant relation between most of the causes they investigated and the crisis indicator. They were thus doubtful of the usefulness of this technique to model an EWS. A rather more successful, and more recent, attempt was made by Savona and Vezzoli (2015), which involved a new algorithm for regression tree models that accounts for country specificities. Basically, this so-called "CRAGGING" algorithm entails the estimation of a number of regression trees by removing one country at a time and obtaining their predicted probabilities. The following step is to calculate the average predictions of all the estimated regression trees and fit a single final tree using the prediction averages instead of the original dependent variable. Comparing the forecasts of this algorithm with the traditional approaches, the results indicated their superiority over the signal approach and similarity to the logit model. In the out-of-sample period, they were able to forecast 88% of the defaults but only 64% of the tranquil periods.

On the other hand, some studies resorted to *Markov Regime Switching* models. For example, Mariano *et al.* (2002), Abiad (2003) and Arias and Erlandsson (2005) defined the tranquil regime as periods with low volatility in the nominal exchange rate, while the crisis regime corresponds to periods with high volatility. Focusing on countries from South-East Asia, and using a country-by-country approach, they reported relatively low in-sample predictive power, as the percentage of correctly predicted crises was around 65-75% with a false alarm rate of about 10%. Furthermore, when Candelon *et al.* (2012) compared the forecasting performance of Markov models to logit regressions, the latter consistently outperformed in all countries under investigation. A probable explanation for this relatively poor performance is provided by Engel (1994), who argued that Markov switching models tend to perform well if there are long swings in the time series of the underlying variable. That is, any particular regime/state should persist for some time before switching to another state, giving the Markov model the ability to detect the change in the direction or the behaviour of the underlying variables. Financial crises, on the other hand, are sudden and rare events that do not persist for a long time relative to the tranquil periods. Their construction is, therefore, not very fit for EWSs of financial crises.

The most recent endeavour to the construction of EWSs is the use of complex *Data Mining Classifiers*. In this respect, a paper by Kim *et al.* (2004) was set out to compare the performance of five different classifiers in forecasting the Korean 1997 financial crisis. Their findings showed that the Artificial Neural Network model was able to predict almost all crisis and tranquil period episodes. Furthermore, Fioramanti (2008) evidenced that the Artificial Neural Network model outperforms the probit regression, as it was able to predict correctly 96% of the debt crises, while the probit model had a hit rate of only 77%. However, the author noted that despite its better ability to predict crises, the Neural Network model does not give any marginal-effects interpretation of the individual signalling indicators, and thus argued that it may be better in forecasting crises than probit estimation, but it is less useful as a policy tool.

Next Chapter: After this detailed discussion about the literature of constructing EWSs for financial crises, it is important next to outline the different methodologies that are applied in this research to construct EWSs for each type of financial crisis. For this purpose, several criteria are also discussed to evaluate the proposed methods and to identify the model with the best fit and the most accurate in-sample and out-of-sample forecasts.

Chapter 3

Econometric Methods and Evaluation Criteria

This chapter illustrates the different econometric techniques used throughout this research to model a forewarning system of each of the three types of financial crises (currency, banking, sovereign debt). We focus on the recently developed econometric methods to construct EWSs in an attempt to evaluate their effectiveness vis-a-vis the traditional techniques and with respect to each other. Therefore, this chapter also outlines three criteria that will be used in the next chapters to assess the predictive performance of the individual estimated models.

Before attempting to build an EWS, it is useful to get a visual impression of the data. Therefore, in each of the following chapters that discuss the three different financial crisis types, a quantitative analysis is first conducted on every potential signalling indicator. This preliminary analysis entails applying a t-test on the differences in the means of the explanatory variables across crisis and non-crisis periods. This could give a basic idea about how the behaviour of the chosen variables changes around the time of crises as compared to tranquil periods. In addition, a graphical representation of this behavioural change is illustrated as a form of event study, where the mean of each variable is plotted over the four different phases of economic states: normal times, pre-crisis period, crisis onset, and the post-crisis phase.

The remainder of the chapter is structured as follows: the first three sections are dedicated to outline the procedures of the dynamic signal approach, the binary logit and the multinomial logit techniques respectively. The last section illustrates the various criteria used to compare the results of the estimated models in order to identify the most accurate method to construct an EWS.

3.1 Dynamic Signal Extraction Approach

The essence of the signal approach is to transform each indicator into a binary variable by setting critical thresholds. That is, if an indicator exceeds its specified threshold, the binary variable takes the value of unity, and thus the indicator is said to signal an imminent crisis, or is zero otherwise. The dynamic threshold, as suggested by Casu *et al.* (2012), is measured in terms of a certain multiple of standard deviations away from the variable's long-run mean. In this way, the volatility of the variables could be captured. Compared to absolute values or static percentile or quantile thresholds that depend on the sample distribution of the variables, the dynamic threshold has the advantage of making the model design usable in different time periods and different states of the world. Therefore, it is expected to provide more accurate out-of-sample warning signals.

The main advantage of this approach is that it allows for the evaluation of each indicator's individual predictive power, and thus its contribution to the effectiveness of the constructed EWS. However, it does not account for the possible interactions among the variables, which may obscure the real causes of crises (Komulainen and Lukkarila, 2003). Another drawback of the signal method is that, by converting the explanatory variables into a binary form, it is not possible to examine the severity of the signal, that is, to distinguish whether a particular variable barely or greatly exceeds the specified threshold.

By checking this generated binary series against the actual crises events defined by the dependent variable, the following contingency table can be constructed with four possible scenarios:

	Crisis	No Crisis
Signal	A	B
No Signal	C	D

If a signal (no signal) is actually followed by a crisis (no-crisis) during the following h forecasting periods (called the "crisis window"), it is viewed as a "good" signal; otherwise it is referred to as "noise". Hence, outcomes A and D are considered good crisis and tranquil signals, respectively. On the other hand, outcome C signifies a Type I error of "missed crisis" (*i.e.* failure to predict an actual crisis), while outcome B denotes a Type II error of "false alarm" (*i.e.* sending warning signals of a crisis that did not occur within the specified crisis window). The *sensitivity* or the *hit rate* of the forecasts is calculated as $1 - Type\ I\ Error$, while the *specificity* is calculated as $1 - Type\ II\ Error$.

Clearly, choosing a relatively low threshold causes the indicator variables to generate too many signals, which would significantly increase the probability of committing Type II error. Likewise, choosing a relatively high threshold will increase the probability of missing actual crises. In practice, Fuertes and Kalotychou (2007) argued that Type II errors are less important to policy makers than Type I errors, since the actual costs of adopting pre-emptive policies are usually less severe than the grave economic and social losses of missed crises [1]. Furthermore, Lang (2013) noted that false alarms are not always 'mistakes' caused by the predictive failure of the EWS, but could simply be the result of undertaking suitable policy actions that were successful in mitigating or avoiding the otherwise crisis hit. One more important reason for giving more weight to Type I error than Type II is the fact that, due to the way the model is designed, a signal issued 'too

[1] Nevertheless, Savona and Vezzoli (2015) warned against trivialising the costs associated with false alarms, because they tend to trigger negative market sentiments and international reputation.

early' ($i.e.$ outside the crisis window) is also counted as false alarm although it is followed by an actual crisis.

Nevertheless, in an attempt to strike a balance between both types of errors, the most commonly used practice in the literature to choose the optimal threshold for each variable is to minimise a joint error measure, namely the in-sample "noise-to-signal ratio" (hereafter $NTSR$). This index was originally suggested by Kaminsky (1999), and it can be defined using the following hypothesis test:

$$H_0: \ \textit{crisis occurs} \ (i.e. \ A \cup C) \quad \text{vs.} \quad H_1: \ \textit{no crisis occurs} \ (i.e. \ B \cup D)$$

Thus, a Type I error is the probability of rejecting H_0 when it is true $P(C|A \cup C)$, whereas a Type II error is the probability of accepting H_0 when it is false $P(B|B \cup D)$. The $NTSR$ is then calculated as the ratio of bad to good signals:

$$NTSR = \frac{Type\ II\ Error}{1 - Type\ I\ Error} = \frac{P\left(B|B \cup D\right)}{1 - P\left(C|A \cup C\right)} = \frac{P\left(B|B \cup D\right)}{P\left(A|A \cup C\right)} \tag{3.1}$$

Candelon *et al.* (2012) suggested another way to identify the optimal cut-off point by maximising Youden's J-statistic, which is defined as the hit rate ($HR = 1 - Type\ I\ error$) minus the false alarm rate ($FAR = Type\ II\ error$). Savona and Vezzoli (2015) argued that, compared to $NTSR$, the J-statistic is quite robust to the extreme Type I and Type II errors, since $NTSR$ could lead to acute thresholds causing close-to-zero false alarms but also negligible hit rates.

$$J = HR - FAR = 1 - P(C|A \cup C) - P(B|B \cup D) \tag{3.2}$$

Taking these findings into consideration, we choose the optimal dynamic threshold for each explanatory variable by applying a grid search over seven different multiples of standard deviations and five various types of long-run means so as to identify the threshold that simultaneously minimises the $NTSR$ and maximises the J-statistic. Hence, the equation used to calculate the thresholds can be written as follows:

$$Threshold = \mu \pm s\,\sigma \tag{3.3}$$

where:

μ: in-sample / rolling mean over 2 years, 3 years, 5 years, or 10 years

$\pm$: threshold is placed above or below the mean depending on whether the variable increases or decreases the probability of crises

s: 0.5 / 0.75 / 1 / 1.5 / 2 / 2.5 / 3

After identifying the optimal thresholds, the indicators are evaluated and ranked according to four different criteria:

1. the percentage of crises correctly called (to get 100% the indicator must issue at least 1 signal before every crisis onset)
2. the optimal $NTSR$ (*i.e.* the least $NTSR$ that maximises J-statistic)
3. the signals average lead time (*i.e.* how early the first warning signal is usually issued; the average number of periods in advance of the crisis when the first signal occurs)
4. the signal persistence (*i.e.* how frequent/persistent the signals are before crises compared to during tranquil periods[1])

To use this information about the individual indicators to build an EWS, the next step entails constructing a composite index that summarises the signals generated by the different indicators into a single crisis monitor. It is quite common in the literature[2] to construct this index by weighting the signals of each variable by the inverse of its in-sample $NTSR$, thereby giving more weight to the signals generated by the more reliable indicators (with low $NTSR$).

$$I_{rt} = \sum_{j=1}^{n} \frac{S^{j}_{rt-h}}{NTSR_{rj}} \tag{3.4}$$

[1]Signal persistence can also be calculated as the inverse of the optimal $NTSR$, that is, the signal-to-noise ratio.

[2]Refer to El-Shazly (2002); Pasternak (2003); Krznar (2004); Davis and Karim (2008b); Lin *et al.* (2008); Andreou *et al.* (2009).

where $S^{j}_{rt-h} = 1$ if indicator j sent out a signal during the previous h periods (*i.e.* the crisis window), n denotes the number of individual indicators considered, and r stands for the country region (or is dropped when studying the global sample). Originally, the criterion used by Kaminsky (1999) and Goldstein *et al.* (2000) for including indicators in the composite index was to have $NTSR$ less than one, which implies that the variable is sending out at least as many good signals as noise. However, we prefer to follow the suggestion of Davis and Karim (2008b) to use a stronger criterion by including the indicators that can generate at least twice as many good signals (*i.e.* have $NTSR_r < 0.5$).

Finally, the conditional probability of an approaching crisis in each country i can be calculated as the ratio between the number of times I_{rt} falls within certain bounds, I_{rL} (lower bound) and I_{rU} (upper bound), and a crisis did occur over the crisis window (h) and the total number of periods it falls within this interval. The bounds are exogenously determined over the in-sample period for each country region r separately according to the values of its specific composite indicator I_{rt}.

$$P\left(C_{it,t+h}|I_{rL} < I_{rt} < I_{rU}\right) = \frac{\sum t \textit{ with } I_{rL} < I_{rt} < I_{rU} \textit{ given crisis occurs within } h}{\sum t \textit{ with } I_{rL} < I_{rt} < I_{rU}} \tag{3.5}$$

These predicted probabilities can then be compared to the actual crisis incidents using the contingency table explained above to determine the overall predictive ability of the EWS. For this purpose, we choose the cut-off probability that maximises the J-statistic.

3.2 Binary Logit Model

In contrast to the non-parametric signal approach that transforms each indicator into a binary variable and does not allow for interaction between the different indicators, the logit regression uses all information incorporated in the data to estimate the overall simultaneous effect of the explanatory variables on the probability of an approaching crisis. In addition, being a parametric model, it provides insight into the magnitude of the effect of each indicator on the probability of a crisis (given the specification of the other variables), and gives room for conducting standard statistical tests. However, it cannot measure the precise predictive ability of each individual variable. A variable is either statistically significant or not. The signal approach, on the other hand, can show the exact contribution of each variable to the crisis prediction.

In particular, the logit model estimates the probability of a crisis in a country i at time period t using a logistic distribution function:

$$Pr\left(Y_{it}=1\right)=F\left(X_{it-h}\beta\right)=\frac{e^{X_{it-h}\beta}}{1+e^{X_{it-h}\beta}} \tag{3.6}$$

where $F(\cdot)$ is the cumulative logistic distribution, X_{it-h} is the vector of h-periods lagged explanatory variables[1], and β denotes the vector of coefficients that measure the effect of a change in the indicators on the probability of a crisis relative to tranquil periods. The number of lags, h, may vary from one variable to another in accordance with the logical reasoning and the empirical evidence with respect to the influence of each particular variable on the state of the economy.

The maximum likelihood estimation method is then utilised to obtain the actual parameter estimates, where the log-likelihood function is written as follows:

$$\log\mathcal{L}=\sum_{i=1}^{N}\sum_{t=1}^{T}\left[Y_{it}\ln F(X_{it}\beta)+(1-Y_{it})\ln\left(1-F\left(X_{it}\beta\right)\right)\right] \tag{3.7}$$

Whereas the estimated signs of the coefficients can be directly interpreted as the directional effect of the corresponding indicators on the crisis probability, their values however do not represent the marginal effects[2]. Rather, the value of any β_j denotes the effect of indicator X_j given that all other explanatory variables are held at their in-sample mean

[1] Henceforth, the lags will be suppressed for simplicity of presentation, but they are implied in all the following equations.

[2] The marginal effect of an indicator on the probability of an approaching crisis is defined as: $\partial Pr(Y_{it}=1)/\partial X_{it}$

values. In other words, β_j gives the relative change in the odds of a crisis (Ω) due to a small change in X_j, where the crisis odds refers to the ratio of the probability that a crisis occurs divided by the probability that it does not occur:

$$\Omega(Y_{it} = 1|X_{it}) = \frac{Pr\left(Y_{it} = 1\right)}{Pr\left(Y_{it} = 0\right)} = e^{X_{it}\beta} \tag{3.8}$$

Thus, dividing the crisis odds for two different realisations of X_j (e.g. X_{j1} and X_{j2}) gives the effect of a change in the indicator on the odds of observing $Y_{it} = 1$, *i.e.* the so-called "odds ratio":

$$\frac{\Omega\left(Y_{it} = 1|X_2\right)}{\Omega\left(Y_{it} = 1|X_1\right)} = e^{(X_2 - X_1)\beta} \tag{3.9}$$

Taking logs on both sides of (3.9) and given a small change in X_j, it can easily be shown that β_j measures the percentage change in the odds of a crisis due to a small percentage change in X_j.

That being the case, and in order to provide a meaningful presentation of the effect of the individual indicators on the probability of an approaching crisis, the marginal effects – rather than the raw beta coefficients are calculated and reported in all the results tables in the following chapters. In other words, the reported figures give the percentage change in the predicted probabilities (rather than the log of odds) for a unit change in the respective indicator variable. Furthermore, we use the Huber-White robust variance estimator of the covariates to account for country-specific variances in all our regression models (refer to Manasse *et al.*, 2003, p. 19).

The estimation of the models proceeds along three steps:

(i) running an exploratory bivariate regression of the crisis episodes on the lagged values (to avoid endogeneity) of each indicator separately to extract the variables with negligible significance. In addition, a quantitative analysis and a graphical event study is conducted to get a sense of how each variable changes around crisis periods.

(ii) putting together the "best performers" from the first stage into a multivariate model and retesting their significance. The indicators that do not contribute to the model's predictive power are then dropped.

(iii) excluding the variables that are found to be highly multi-collinear and adding back some of the excluded variables in steps 1 or 2 that were found to be significant in the event study or generally in the literature[1].

Finally, to evaluate the performance of the chosen model, one would ideally want to compare the actual probability of a crisis with the predicted probability obtained from the logit EWS. However, because we can only observe the actual occurrence of crises and not its probability, we need to convert the estimated/predicted probabilities into warning signals by choosing a cut-off probability. If the estimated probability at any time period exceeds the cut-off, the model is said to issue a signal of a forthcoming crisis. As noted in section 3.1, choosing the cut-off probability requires balancing between Type I and Type II errors. Therefore, as illustrated in the previous section and recommended by Savona and Vezzoli (2015), the optimal cut-off is calculated as the one that maximises Youden's J-statistic defined in (3.2).

3.3 Multinomial Logit Model

Whereas the binary logit regression estimates the effect of a set of explanatory variables on a binary response variable with only two states (crisis and no-crisis), the multinomial logit regression extends this estimation to study their effect on a response variable which allows for three states. In particular, the procedure for conducting a multinomial logit regression can be summarised as follows.

The first step entails transforming the binary dependent variable into a three-state variable that assumes the value of 1 for the crisis entry period(s), the value of 2 during

[1]This is necessary to avoid falling into an omitted variable bias by dropping a potentially important variable that belongs to the true model.

the post-crisis periods (*i.e.* the periods following the crisis onset till returning to the normal state), and is zero during tranquil periods:

$$Y_{it} = \begin{cases} 0 & with\ probability\ Pr(Y=0)\ if\ C_{it}=0 \\ 1 & with\ probability\ Pr(Y=1)\ if\ C_{it-k}=1\ for\ k=0...p \\ 2 & with\ probability\ Pr(Y=2)\ otherwise \end{cases} \tag{3.10}$$

where Y_{it} is the three-state dependent variable, and C_{it} denotes the binary response variable for each of the different types of crises (currency CC_{it}, banking BC_{it}, and sovereign debt DC_{it}). The exact specification of p (*i.e.* the duration of the crisis state) differs from one crisis type to another, and are therefore discussed in their respective chapters.

The next step is to specify the logit model that estimates the probability of each economic state using a logistic distribution function:

$$\begin{aligned} Pr\left(Y_{it}=0\right) &= F\left(X_{it}\beta\right) = \frac{1}{1+e^{X_{it}\beta^1}+e^{X_{it}\beta^2}} \\ Pr\left(Y_{it}=1\right) &= F\left(X_{it}\beta\right) = \frac{e^{X_{it}\beta^1}}{1+e^{X_{it}\beta^1}+e^{X_{it}\beta^2}} \\ Pr\left(Y_{it}=2\right) &= F\left(X_{it}\beta\right) = \frac{e^{X_{it}\beta^2}}{1+e^{X_{it}\beta^1}+e^{X_{it}\beta^2}} \end{aligned} \tag{3.11}$$

where $F(\cdot)$ is again the cumulative logistic distribution, X_{it} is the vector of (lagged) explanatory variables, and β denotes the vector of coefficients. This model implies that β^1 measures the effect of a change in the indicators on the probability of entering into a crisis relative to being in a tranquil period (the base state), while β^2 measures the effect of a change in the indicators on the probability of being in the post-crisis/recovery period relative to being in a tranquil period.

To make the reported coefficients comparable to those of the binary logit regressions and to avoid interpreting the effects of the indicators relative to the base state, we calculate and report the marginal effects of the indicators. Accordingly, the coefficients depicted in all the results tables in the following chapters denote for each state of the dependent variable the overall percentage change in the probability of being in that state due to a unit change in the corresponding indicator. Furthermore, we continue to use the Huber-White robust variance estimator as in the case of the binary logit regressions, which allows for country-specific variances.

When interpreting the marginal effects of the post-crisis period, it is important to keep in mind that this state entails two possible developments in the economic stance: either the economic conditions are worsening and causing the crisis to deepen or the economy is recovering from the crisis and is advancing to the normal state. Since we cannot identify in advance which development is going to occur, or the magnitude of each development if both do occur subsequently, there are no pre-determined expectations with respect to the signs of the signalling indicators in the post-crisis state.

The same argument applies when comparing the estimated coefficients of the binary and the multinomial logit regressions. Since the logit coefficients are estimated for all crisis periods (onset and post), while the multinomial coefficients are estimated for each state separately, it is reasonable to expect a change in the signs and/or the statistical significance of the coefficients across both regressions.

After obtaining the predicted probabilities from the estimated multinomial logit models, their performance is evaluated in the same manner as the binary logit and the signal approach so as to make the results comparable across the three econometric techniques. The specific criteria used to evaluate the predictive power of the constructed EWSs are discussed in the next section.

3.4 EWS Evaluation Criteria

In the previous three sections, we discussed the procedures of the various econometric techniques applied to construct an EWS for financial crises and obtain predicted probabilities of approaching crises. Next, we turn to evaluating the predictive performance of these methods and their effectiveness in forecasting future crises. Basically, assessing the performance of EWSs involves comparing the warning signals generated by the model with the actual occurrence of crises. In this respect, three evaluation criteria are used to appraise the predictive ability of the different techniques:

1. *Classification Table:* As described in section 3.1, the HR and FAR ratios can be used to assess the predictive power of the model. In this respect, these could be calculated based on in-sample predictions, but the more policy-relevant evaluation is the one based on the out-of-sample predictions. We calculate two types of out-of-sample predictions, a regular h-step-ahead, which is commonly known in the literature though surprisingly not frequently reported, and we developed a new recursive forecasting technique that allows for dynamic predictions.

   In the regular h-step-ahead forecast, the model is estimated once using a sub-sample of the data while leaving out the most recent observations. The estimated model is then used to generate forecasts for h periods into the future (*i.e.* the holdout period), which are evaluated by comparing the signals generated to the left-out actual crisis incidents.

   On the other hand, the 'dynamic-recursive forecasting' technique estimates the model several times, each time adding 1 further out-of-sample observation (thus recursive) along with the predicted probability of the previous period (thus dynamic[1]), and generating a 1-step-ahead forecast. Thus, for example, if the holdout period was from 2008-2012, then the first round uses data up to 2007 and generates the predicted probability for 2008; the next round adds the 2008 observations and its predicted probability to forecast 2009; and so on.

   We report and compare the HR and FAR ratios for the in-sample, the regular and the dynamic-recursive out-of-sample predictions. Furthermore, since the definition of a crisis episode is different between the binary and the multinomial logit regressions, and to make the results comparable across these methods and the signal approach, we also report the percentage of correct crisis *onsets* (not just the usual HR) for the binary logit models.

[1]For a detailed discussion on why a dynamic model should be more useful, refer to Candelon *et al.* (2014).

2. *Quadratic Probability Score (QPS):* This score (also knows as Brier score) is a measure of the mean squared error of the estimated model. It is calculated as the squared difference between the predicted crisis probability ($\widehat{y}_{it}$) and the real crisis indicator (y_{it}). It takes values between zero and unity, where the zero indicates perfect accuracy. The QPS is defined as:

$$QPS = \frac{2}{T}\sum_{t=1}^{T}\left(\widehat{y}_{it} - y_{it}\right)^2 \tag{3.12}$$

3. *Area under the ROC Curve (AUC):* The ROC curve is a graphic representation of the predictive ability of an EWS. It depicts for every cut-off value [0,1] the trade-off between HR and FAR. In a perfect model, the curve will be strictly monotonically increasing on the y-axis (HR), showing 100% correct crisis predictions and zero false alarms. For a random guess, the curve will be strictly proportionally increasing, that is, it will form a 45° line. Typically, the ROC curve for any reasonable EWS is expected to lie above the diagonal line of the random guess.

   The area below the curve, also known as the ROC statistic, can thus be used to assess the predictive power of the model. The larger is the AUC, which ranges between zero and unity, the more accurate is the model. The AUC statistic is calculated as:

$$AUC = \int_0^1 (HR \times FAR)\, dFAR \tag{3.13}$$

Next Chapters: After illustrating the different econometric techniques applied to construct EWSs for financial crises and their evaluation criteria, the remainder of this research focuses on the empirical investigation of the determinants of the three types of financial crises in both developed countries and emerging economies. Each chapter (currency, banking, and sovereign debt) illustrates the data over the sample period, the definition employed to quantify the crisis episodes, and the results of applying the different proposed methodologies. In addition, an evaluation of the in-sample and out-of-sample forecasts of the estimated EWSs is also presented, along with how they compare against each other and against the previous findings in the literature for every type of crisis.

Chapter 4

Modelling EWSs
The Case of Currency Crises

The main purpose of this chapter is to construct an effective EWS for currency crises. With this target in mind, we begin by illustrating how a currency crisis can be defined and the important signalling indicators in both advanced and emerging economies. The results of the different econometric techniques applied to model the EWS are then outlined in detail, along with a thorough evaluation of their predictive performance.

Accordingly, the chapter is divided into eight sections, where section 4.1 outlines the sample data of country coverage and the time period considered. Then, section 4.2 is concerned with how a currency crisis episode is quantified to construct the dependent variable. The proposed explanatory variables that can act as signalling indicators, how each is measured, and their expected effect on the probability of a currency crisis are detailed in section 4.3. A brief quantitative analysis and a graphical event study is given in section 4.4. Subsequently, the results of the three econometric methods applied to construct an EWS for currency crises are outlined in sections 4.5, 4.6 and 4.7. Finally, section 4.8 evaluates the results of the different methods according to a number of criteria in order to identify the most accurate forewarning model.

4.1 Sample Data

In accordance with the research objectives, the set of countries covered falls into two main categories, namely developed countries and emerging economies. The time dimension of the dataset extends over the period 1994-2012 on a monthly basis. Yet, only the sub-sample from 1994-2008 is used for estimation, while the monthly observations over the four-year period 2009-2012 are held back and used to conduct out-of-sample forecasts. While annual and quarterly data can give access to a larger set of indicators, countries and time periods, we prefer to use monthly data to get a clearer view and a closer monitor of the developments in the foreign exchange market to be able to capture the sudden nature of currency crises (see Goldstein *et al.*, 2000; Ari and Dagtekin, 2007).

As a representative of the advanced economies, a sample of 10 developed countries[1] is selected, which includes: the U.S., Canada, Japan, U.K., Sweden, Denmark, Norway, Iceland, Australia, and New Zealand. On the other hand, a number of emerging economies from South and East Asia, Latin America, Eastern and Central Europe, and the Middle East and Africa are selected to investigate currency crises in developing countries. The sample covers 15 countries from these respective regions, which are divided as follows. From South-East Asia: Indonesia, the Philippines, Thailand and South Korea; from Latin America: Mexico, Brazil, Chile and Argentina; from Eastern and Central Europe: Turkey, Russia, Bulgaria, and the Czech Republic; and from the Middle East and Africa: Egypt, Jordan, and South Africa. The choice of the sampled countries depends primarily on the data availability in the frequency required over the specified sample period.

4.2 Currency Crisis Definition

In light of the literature review discussed in Chapter 2 regarding the various definitions used to quantify a currency crisis, this chapter employs the full version of the EMP

[1] The Eurozone is excluded from the sample, because an attack on the Euro is an attack on all zone countries. Thus, they cannot be treated as separate entities.

index as suggested by Kaminsky *et al.* (1998) and Kaminsky and Reinhart (1999), which captures both successful and unsuccessful speculative attacks on a domestic currency. After comparing different currency crisis definitions, Lestano *et al.* (2003) and Candelon *et al.* (2012) found that their EMP definition performs best as a crisis dating measure, as it captures most well-known episodes in the literature. Our analysis also supports this finding as explained below.

Accordingly, the pressure on the domestic currency of country i at time period t is measured as:

$$EMP_{it} = \omega_e \left(\frac{e_{it} - e_{it-1}}{e_{it-1}} \right) + \omega_r \left(r_{it} - r_{it-1} \right) - \omega_{res} \left(\frac{res_{it} - res_{it-1}}{res_{it-1}} \right) \tag{4.1}$$

That is, the EMP_{it} index is calculated as the weighted average of the relative changes in bilateral exchange rate[1] (e_{it}), domestic interest rate (r_{it}), and international reserves (res_{it}). The weights assigned to each component, denoted by ω, are the inverse of their standard deviations over the *in-sample* period[2], so as to give a larger weight to the variables with lower volatility.

Subsequently, the specific crisis incidents in country i at time t (C_{it}) are identified when its EMP index crosses a certain threshold level. This threshold is calculated as a specific multiple of standard deviations ($\sigma_{EMP_{it}}$) away from the *in-sample* country average ($\mu_{EMP_{it}}$). Accordingly, C_{it} can be defined as:

[1] The bilateral exchange rate is measured as the units of the domestic currency per the IMF's special drawing rights (SDR). For those countries that pegged their currency to the US dollar, the exchange rate vis-a-vis the USD is used instead.

[2] It is quite common in the literature to calculate the EMP index using the weights over the *full* sample period. However, since the main purpose of the EWS is to provide out-of-sample forecasts, the volatility of the index components over the holdout period should not be provided *ex-ante* to the model. In addition, we experimented with other specifications of the EMP index by excluding the interest rate component (refer for example to Kamin *et al.*, 2001; Kaminsky, 2006; Takahashi, 2012; Frankel and Saravelos, 2012; Comelli, 2014), considering each component separately with and without the interest rate (as suggested by Zhang, 2001), and calculating the weights using a rolling standard deviation. We find that the EMP with all three components and calculated using the in-sample weights can best fit the known crisis incidents in the different countries.

$$C_{it} = \begin{cases} 1 & if\ EMP_{it} > \mu_{EMP_i} + s\ \sigma_{EMP_i} \\ 0 & otherwise \end{cases} \tag{4.2}$$

As a benchmark, the multiple of standard deviations is set arbitrarily at two (*i.e.* $s = 2$) to match the major bulk of the literature that applied the same threshold level. However, for robustness we also probe with 1.5 and 3 standard deviations to investigate whether the results are significantly affected by a change in the crisis definition. As a result, three response variables are created corresponding to the three chosen values of s, namely $C1_{it}$, $C2_{it}$ and $C3_{it}$. In addition, we follow the suggestion of Ciarlone and Trebeschi (2005) by turning all the zeros positioned between two ones within a period of up to three months into ones. That is, the non-crisis observations sandwiched between two crashes up to three months apart are considered as a continuation of the same ongoing crisis.

To give a sense of how a crisis is being quantified, Figure 4.1 displays time-series patterns of the pressure index for each country under investigation over the sample period. The three horizontal lines represent the corresponding three threshold levels of 1.5, 2 and 3 standard deviations, above which $C1$, $C2$ and $C3$ would respectively indicate a crisis incident; that is, they change from zero to unity. The corresponding crisis dates for each definition are detailed in Table 4.1, while Figure 4.2 summarises for each country the number of months it suffered a currency crash according to each of these crisis definitions.

Generally, it can be noted that the choice of the multiple of standard deviations causes a significant change in the quantification of crisis episodes. In particular, in developed countries, $C1$ seems to depict too many crisis episodes as compared to those identified in the literature, whereas $C3$ could provide a more reasonable measurement. In emerging markets, there is less discrepancy between the crisis definitions, yet $C1$ is still depicting too many episodes compared to those identified in the literature. However, a formal econometric investigation is required to identify the optimal value for s for each country group.

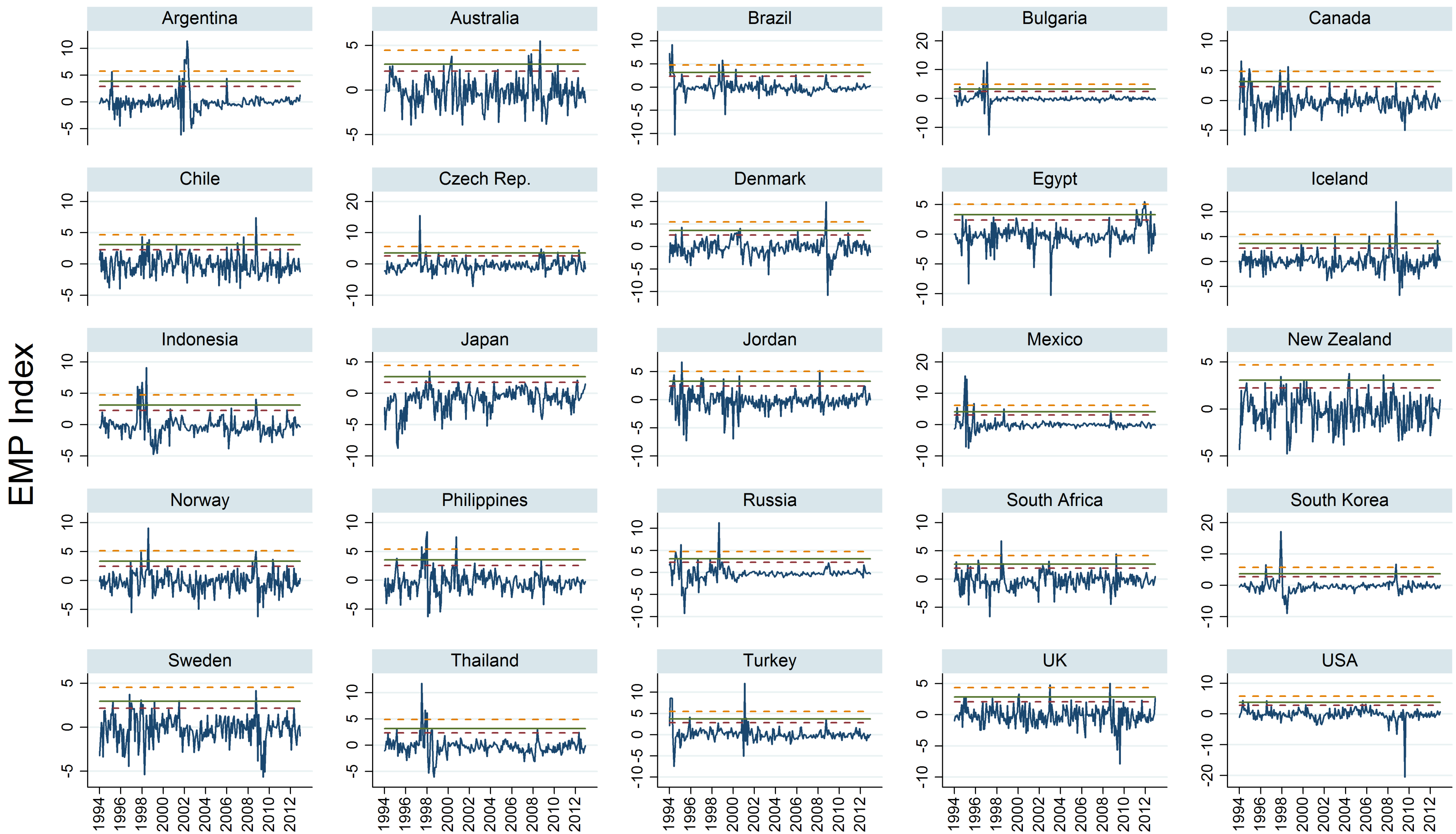

Figure 4.1: Exchange Market Pressure Index and Crisis Thresholds

Table 4.1: Currency Crises Dates by Country

Country		**Crisis Episodes**	**Months in Crisis**		
			CC1	**CC2**	**CC3**
Advanced Economy	USA	*May94-Feb95; Aug-Nov96*; Dec96-Apr97; Apr-Jul00; Dec04-Jul05; *Aug05-Mar06*; Apr-Aug06	44	22	0
	Canada	**Mar-Jun94**; *Jul-Nov94*; **Dec94-Mar95**; *Apr95*; May-Jun95; Oct97; *Nov97-Feb98*; **Aug-Nov98**; Jul-Oct02; Oct08-Jan09	33	22	12
	Japan	Dec97-Mar98; *Apr-Jul98*; May-Aug04; Mar-Jun12	16	4	0
	UK	Dec94-Jan95; *Feb-May95*; Aug-Apr98; *Jan-May00*; **Jan-Apr03**; Jan-Apr05; Jun-Sep06; **Sep-Dec08**; Jan-Apr09; Dec09-Mar10; Sep-Dec11; Dec12	49	17	8
	Iceland	Nov99-Apr00; May-Aug01; *Jan-Apr03; Apr-Jul06; Mar-Sep08*; **Oct08-Jan09**; *Feb09; Sep-Dec12*	34	24	4
	Norway	Dec96-Mar97; *Dec97-Mar98*; **Aug-Nov98**; Jun-Aug08; *Sep08-Jan09; May-Aug10*; Sep10; Sep-Dec11	29	17	4
	Sweden	Apr-Jul95; *Nov96-Feb97*; Mar-Apr97; *Dec97-Mar98*; Apr-May98; Mar-Jun99; *Jul-Oct01; Oct08-Jan09*	28	16	0
	Denmark	Aug94-Feb5; *Mar-Jun95*; Nov99-Aug00; *Sep-Dec00*; Feb-May06; **Oct08-Jan09**; Nov10-Feb11	37	12	4
	Australia	Jul94-Jan95; Aug99-Mar00; *Apr-Aug00*; Feb-May01; Sep-Dec04; *Aug07-Feb07*; Aug08; **Sep-Dec08**; May-Aug10	44	16	4
	New Zealand	Sep-Dec94; Jun-Sep96; *Dec97-Mar98*; Apr-Sep98; Oct99-Aug00; Apr04; *May-Aug04*; Mar-Jun06; *Aug-Nov07*; Jul-Oct08	46	12	0
	Total		**360**	**162**	**36**
Emerging Market	Indonesia	**Aug97-Sep98**; Jun-Sep06; *Oct08-Jan09*	22	18	14
	Philippines	Mar-Jun95; *Jul-Nov97*; **Dec97-Apr98**; May-Nov98; **Oct00-Jan01**; Jul-Oct02; Oct08-Jan09	33	14	9
	South Korea	**Jul-Oct96; Nov97-Apr98; Oct08-Jan09**	14	14	14
	Thailand	Mar-Jun95; May-Jun97; **Jul97-Apr98**; May-Oct98; Jun-Sep08	26	10	10
	Argentina	*Mar-Jun95*; *Jul-Dec01*; **Jan-Aug02**; *Sep02*; *Jan-Apr06*	23	23	8
	Brazil	**Jan-Jul94**; Aug-Sep94; Mar-Jun95; *Sep-Dec98*; **Jan-Apr99**; May99; *Apr-Jul00*	26	19	11
	Mexico	*Apr-Jul94*; **Dec94-Jun95**; Jul-Oct95; *Nov95-Feb96; Sep-Dec98*; Oct08-Jan09	27	19	7
	Chile	*Jan-Dec98*; Apr-Jul01; Jan-Apr06; *Jan-Nov07*; **Oct-Jan09**	35	27	4
	Turkey	**Feb-Jul94**; *Dec95-Mar96*; Nov00-Jan01; **Feb-May01**; Jun-Jul01 ; Oct08-Jan09	23	14	10
	Russia	Jul94; *Aug94-Jan95*; **Feb-May95**; Sep-Dec96; Nov97-Feb98; *Aug98*; **Sep-Dec98**	24	15	8
	Bulgaria	*Jul-Oct94; May-Sep96*; **Oct96-May97**	17	17	8
	Czech Rep.	**May-Aug97**; *Sep97-Mar98*; *Feb-May99*; Sep-Dec01; Aug-Sep08; *Oct08-Apr09*; *May-Aug10*; Sep-Dec11; *May-Aug12*	40	30	4
	Egypt	*Oct94-Jan95*; Feb-May95; *Sep-Dec97*; Nov99-Mar00; May-Aug01; Aug-Nov03; *Aug-Nov08*; *Mar-Nov11*; **Dec11-Apr12**; *May-Oct12*	49	32	5
	Jordan	May94; *Jun-Sep94*; Oct94-Feb95; **Mar-Jun95**; *Jan-Jun97; Feb-May99; Aug-Nov00; Mar-Jun08*	32	26	4
	South Africa	*Mar-Jun94*; Apr-Oct95; *Apr-Jul96*; Aug96; **Jun-Sep98**; Oct-Nov98; May-Nov02; *Dec02-Mar03*; **Apr-Jul09**	37	20	8
	Total		**428**	**298**	**124**

Note: Dates corresponding to $C1$ only are in plain text, while $C2$ dates are in *italics* and $C3$ dates are in **bold** format.

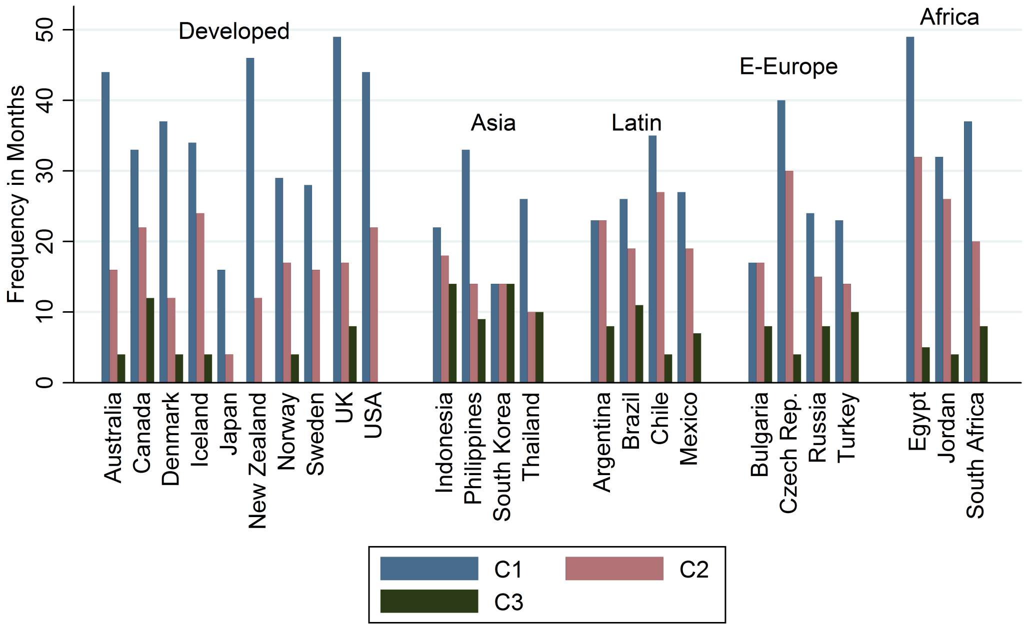

Figure 4.2: Number of Months Spent in Currency Crisis

4.3 Signalling Indicators of Currency Crises

After specifying the response variable that captures the currency crisis incidents, the following step is to identify the indicators that could be used to provide warning signals of a forthcoming crisis. These indicators can be divided into four main categories according to the symptom of economic fragility: external competitiveness, real and public sector, financial sector, and contagion. The variables included in each category, their measurement, their expected effect on the crisis dummy, along with the data sources are all summarised in Table 4.2, and are further detailed below.

4.3.1 External Competitiveness

To capture the effect of changes in the external sector and international competitiveness, four indicators are included. First, the deviation of the real effective exchange rate from its trend is used to reflect the overvaluation[1] of the domestic currency. An overvalued currency reduces competitiveness, and thus is expected to add to the vulnerability of

[1]Since the exchange rate is measured in domestic units, overvaluation is interpreted as a negative deviation from trend.

Table 4.2: Currency Crisis Signalling Indicators

Symptoms	Indicators	Measurement	Sign	Data Source
External Competi-tiveness	REEROVR	deviation of real effective exchange rate from trend[a]	-	IFS line RECE
	EXPGR	% change in exports	-	IFS line 70
	TOTGR	% change in ratio of exports to imports	- / +	imports: IFS line 71
	CURACC	current account as % of GDP	-	Oxford Economics (OE): BOP[b]
Real and Public Sector	RGDPGR	12-month % change in real GDP	-	OE: National Accounts[b]
	PUBDBT	public debt as % of GDP	+	OE: Gov. Accounts[b]
	FSCDEF	fiscal deficit as % of GDP	+	OE: Gov. Accounts[b]
	INFL	rate of change in CPI	+	IFS line 64
	FRXRES	ratio of int. reserves to GDP	-	reserves excl. gold: IFS line 1L
	POLSTB	index of political stability	-	IFO World Economic Survey[b]
Financial Sector	EQMKT	rate of change in equity market index	-	IFS line 62
	TRMSPRD	10-year bond yield less 3-month money market rate	-	bond yield: National Sources money rate: IFS line 60B
	DOMCRD	ratio of domestic credit to GDP	- / +	IFS line 32
	M2RES	% change in ratio of M2 to int. reserves	- / +	National Sources
	PRTFINV	portfolio investment as % of GDP	+	National Sources
	INTDIFF	ratio of domestic to foreign real interest rate	+	deposit rate: IFS line 60L foreign rate: weighted average[c]
	LNDEPINT	ratio of lending to deposit interest rate	- / +	lending rate: IFS line 60P
	BKLIQ	ratio of bank reserves to total assets	-	bank reserves: IFS line 20 bank assets: IFS line 21 + 22
Contagion	REGDEP	rolling correlation between domestic and regional stock index	+	regional index: S&P's index
	DEVDEP	rolling correlation between domestic & developed stock index	-	developed index: MSCI index
	CRSNGH	sum of neighbouring countries facing crises	+	neighbouring: regional & leading trade partners
	BKCRS	dummy for banking crisis	+	banking crisis episodes

Notes: (a) RER deviation: $\left(\frac{e_{it}-\mu_{e_{it-24}}}{\mu_{e_{it-24}}} \times 100\right)$, where the mean is calculated using a 2-year moving average (Bussiere and Fratzscher, 2006, p.959).
(b) Interpolated from quarterly data using Chow-Lin interpolation method. It is evidenced by Miralles *et al.* (2003) and Rashid and Jehan (2013) that this method is superior to linear, polynomial, and cubic spline interpolation methods.
(c) Ten developed countries are used to calculate the GDP weighted average: USA, UK, Germany, France, Italy, Spain, Norway, Finland, Denmark, Belgium.

the economy to speculative attacks. On the other hand, a strong external sector tends create demand for the domestic currency. Hence, an increase in the growth of exports or improvements in the current account balance in general would reduce the probability of a currency crisis. Furthermore, an increase in a country's terms of trade strengthens its balance of payments position and the external sector as a whole. On the other hand, growth in trade can also make the domestic economy more vulnerable to external shocks. Thus, its directional effect is not clear *ex-ante*.

4.3.2 Real and Public Sector

Financial crises are usually tied to a weak domestic real sector and deteriorating public accounts. Hence, periods of recessions and slowdowns in economic activities, as measured by falling real GDP growth rates, are expected to characterise the periods preceding the incidence of financial crises in general. Moreover, high rates of inflation can reflect macroeconomic mismanagement and loss in external competitiveness (Christensen and Li, 2013; Karahoca *et al.*, 2013), while the erosion of foreign exchange reserves is considered a reliable indicator that the domestic currency is facing a pressure of devaluation. In particular, it indicates that the central bank is either trying to defend a peg or is spending large amounts of reserves to avoid a devaluation.

With respect to the public sector, higher indebtedness and/or increasing deficits in the fiscal balance (relative to a country's GDP) are likely to raise the vulnerability to a reversal in capital inflows, lower investors' confidence, and reduce the government's ability to defend the domestic currency. Furthermore, periods of riots and political instability[1] do not create a suitable climate for investment. Foreign investors would rather prefer to repatriate their profits and take their business elsewhere, which adversely effects the whole economy.

[1]The "Political Stability and Absence of Violence/Terrorism" index of the World Economic Survey regularly surveys economic experts in the respective countries on their assessments of the current local political status. The scale is from 1 to 9, where 1 means 'highly unstable' with the likelihood that the government will be overthrown by unconstitutional or violent means, and 9 is 'perfectly stable'.

4.3.3 Financial Sector

The financial sector is closely related to the value of the domestic currency. Particularly, a booming stock market attracts capital inflows, and thus creates demand for the domestic currency and reduces the exchange market pressure. However, increasing portfolio inflows imply a greater share of the current account being financed by more volatile and easily reversible short-term capital. This can lead to a situation of self-fulfilling prophecies inasmuch as these inflows act as a forward-looking indicator of investors' expectations. Another variable that can provide insight to better future economic prospects is a widening yield spread[1] (Candelon *et al.*, 2012), as it reflects the expected real interest rate and the expected inflation.

Furthermore, a high domestic interest rate relative[2] to the foreign one can attract short-term capital inflows (Komulainen and Lukkarila, 2003). However, Karahoca *et al.* (2013) argued that it may also indicate underlying problems in the foreign exchange market, where the authorities have raised the domestic interest rate to fend off a speculative attack. This may result in precipitating a self-fulfilling crisis by market participants (see Ahec-Sonje, 2002; El-Shazly, 2011) as it signals devaluation expectations. On different grounds, an increase in the monetary aggregates provides liquidity to the financial sector, yet a high ratio of M2 to international reserves may indicate a loose monetary policy which leads to excess liquidity (Andreou *et al.*, 2009; Su *et al.*, 2010) and/or the vulnerability of the financial system to capital outflows (El-Shazly, 2011). These, in turn, may fuel speculative attacks on the local currency.

The health of the banking sector can also play an important role in the likelihood of a currency crisis. In principle, domestic credit expansions can either serve as a crude

[1]It is measured as the difference between long-term government bond yield and short-term money market rate.

[2]The ratio, rather than the arithmetic difference, is used to capture the possible non-linear effect of a very low foreign interest rate on capital flows. That is, the same difference between domestic and foreign rates can have a different impact on the behaviour of foreign investors depending on how low the foreign interest rate is, since a very low rate would induce more capital outflows from the foreign economy regardless the difference.

indicator of a flourishing banking sector (if the expansion is sustainable) or the fragility of banks (due to greater possibility of non-performing loans and a boom-bust cycle). Similarly, a high lending-to-deposit interest rate may, on the one hand, signify increased bank profitability and a healthy financial sector (or less intense competition among banks), or, on the other hand, declining loan quality, higher credit risk, and thus a fragile financial sector. To capture the possible adverse effect of a fragile domestic banking sector, we also consider the ratio of consolidated bank reserves to total assets, as an illiquid banking sector can augment and accelerate the likelihood of a crisis.

4.3.4 Measures of Contagion

Finally, to capture the possibility of spillover effects, four additional indicators are considered. In this respect, we include the number of neighbouring countries[1] (in the same region) and leading trade partners (regardless of region) that are facing a currency crisis. Furthermore, in the aftermath of the Asian financial crisis, studies became increasingly concerned as to whether contagion could be a financial phenomenon rather than just an economic function of trade ties and other real interdependences (Simpson, 2010). Therefore, we follow the suggestion of Fratzscher (2003) and use the monthly rolling correlation between the country's and its regional daily stock market indices as an indicator of the degree of their financial markets integration.

In addition, to the extent that the stock market of an emerging economy is more interlinked with developed financial markets rather than other regional emerging equity markets, we can expect this economy to be less affected by possible financial contagion from neighbouring and regional emerging economies. Nevertheless, its dependence on developed markets could accelerate an approaching crisis in case of difficulties, since developed countries' investors can be more sensitive and quick in pulling out their investments when they anticipate problems. Lastly, to investigate the possibility of twin crises

[1] The neighbouring economies considered for each country are detailed in Appendix A.

and whether trouble in the banking sector can add significant pressure on the domestic currency, a banking crisis dummy[1] is also examined.

After discussing the crisis definitions and outlining the signalling indicators, the next step is to apply the econometric methods explained in Chapter 3 to construct an EWS for currency crisis. Nevertheless, we first turn to a brief discussion of some descriptive statistics of the candidate indicators to assess their behaviour around crisis episodes.

4.4 Descriptive Statistics and Event Study

We begin our EWS construction process with a basic descriptive analysis of the explanatory variables that are proposed to act as currency crises indicators. For this purpose, Table 4.3 lists the candidate variables along with their means over the tranquil periods vis-a-vis their means around crisis incidents. We also conduct a simple t-test of the null hypothesis that both means are equal ($H_0 : \mu_0 - \mu_1 = 0$); that is, the behaviour of the respective variable does not change significantly around crises, and thus cannot be expected to provide good warning signals.

This primary analysis is conducted over the pool of all sampled countries, as depicted by the left panel of Table 4.3, as well as for each individual country group in the right panel, which shows the results of the t-tests at 5% level of significance. Rejecting the null hypothesis can be considered as a preliminary evidence that the corresponding variable is a potential crisis indicator, and is therefore represented by a tick symbol.

Some basic conclusions can be drawn from this quantitative analysis. First of all, there is no one variable that behaves in the same manner in all country groups. A variable that may play an important role as a crisis indicator in a certain region may be irrelevant in another. Therefore, a pooled model with both developed and developing countries can lead to very misleading conclusions, although it is frequently used in the literature (for

[1] The timing of banking crises is based on the IMF and the World Bank databases, which is described in more detail in section 5.2.

Table 4.3: Quantitative Analysis of Currency Crisis Indicators

	No Crisis	Crisis	t-stat	Developed	Asia	Latin	EE	Africa
External Competitiveness								
REEROVR	1.1	-5.7	6.1 *	✓	✓	✓	✓	×
EXPGR	1.5	-1.4	2.0 *	×	×	✓	×	×
TOTGR	0.7	3.1	-1.2	×	×	×	×	×
CURACC	-0.6	-2.4	2.5 *	×	✓	×	×	×
Real & Public Sector								
RGDPGR	2.2	0.2	2.9 *	×	✓	✓	×	×
FRXRES	154.7	106.6	4.3 *	×	✓	×	✓	✓
PUBDBT	64.2	63.3	0.1	×	×	×	×	×
FSCDEF	-1.0	-2.3	2.0 *	✓	×	×	×	×
INFL	10.1	114.3	-1.6	×	×	×	✓	×
POLSTB	5.6	4.4	4.7 *	×	×	✓	×	×
Financial Sector								
EQMKT	1.1	-3.5	1.8	✓	✓	×	✓	×
TRMSPRD	3.3	-10.7	0.2	×	×	×	×	✓
DOMCRD	10.0	10.4	-0.5	×	×	×	×	×
M2RES	0.4	6.0	-2.3 *	✓	×	×	×	×
PRTFINV	0.2	-0.3	0.5	×	×	✓	×	×
INTDIFF	-0.6	72.3	-1.4	×	×	×	×	×
LNDEPINT	2.9	2.0	5.5 *	✓	✓	×	×	✓
BKLIQ	9.1	6.9	2.7 *	×	✓	✓	✓	×
Contagion Variables								
REGDEP	0.5	0.6	-0.2	✓	×	×	×	×
DEVDEP	–	0.4	1.5	✓	×	✓	×	×
CRSNGH	0.1	0.3	-2.5 *	×	×	✓	×	×
BKCRS	0.1	0.4	-4.1 *	×	×	✓	✓	–

Notes: The t-stat is the test statistic of the mean differential t-test between the two economic states. The Welch adaptation of the t-test is used to account for the unequal variances and sample sizes of the two economic states.
Both * and ✓denote significance at the 5% level.

example in Kumar *et al.*, 2003; Su *et al.*, 2010; Frankel and Saravelos, 2012). The same is true for models that pool developing countries from different regions (see Frankel and Rose, 1996; Kamin *et al.*, 2001; Komulainen and Lukkarila, 2003; Bussiere and Fratzscher, 2006). Nevertheless, four variables seem to be highly significant in general: real exchange rate overvaluation, international reserves, stock price index, and bank liquidity.

On the other hand, there are several variables that do not appear to change much around crisis episodes in any of the country regions. These are the terms of trade, public debt, domestic credit, and interest rate differential. Accordingly, they cannot be expected to perform as crisis indicators. However, the results of the t-tests are not very accurate, because it combines pre-crisis, crisis and post-crisis observations together vis-a-vis tranquil periods. This means that the t-test does not take into consideration that a variable may change in one direction before a crisis and in another after its onset, causing its total behaviour to level out.

In order to capture this latter fact more accurately, and to get a graphical representation of the variables' behaviour, Figure 4.3 illustrates the means of each variable over the different economic phases. From the first glance of this figure, it can be noted that several variables do indeed experience a directional change before currency crisis onsets and afterwards. In fact, three of the four variables that are deemed insignificant by the t-test seem to experience a distinct directional change before crisis incidents.

In general, it is evident from Figure 4.3 that most variables considered are potentially good forewarning indicators. Some do experience a change in their behaviour before the crisis approaches and continue in the same trend after its onset: real exchange rate, real GDP growth, fiscal deficit, lending-to-deposit interest rate, political stability index, bank liquidity, and banking crisis incidents. Other variables change their behaviour twice or even three times over the course of the crisis as compared with tranquil periods. The most striking of these variables are the terms of trade, which improves before the crisis, falls at its onset, and increases again in the post-crisis periods. Likewise, export growth, current account, international reserves, public debt, stock price index, domestic credit, ratio of M2

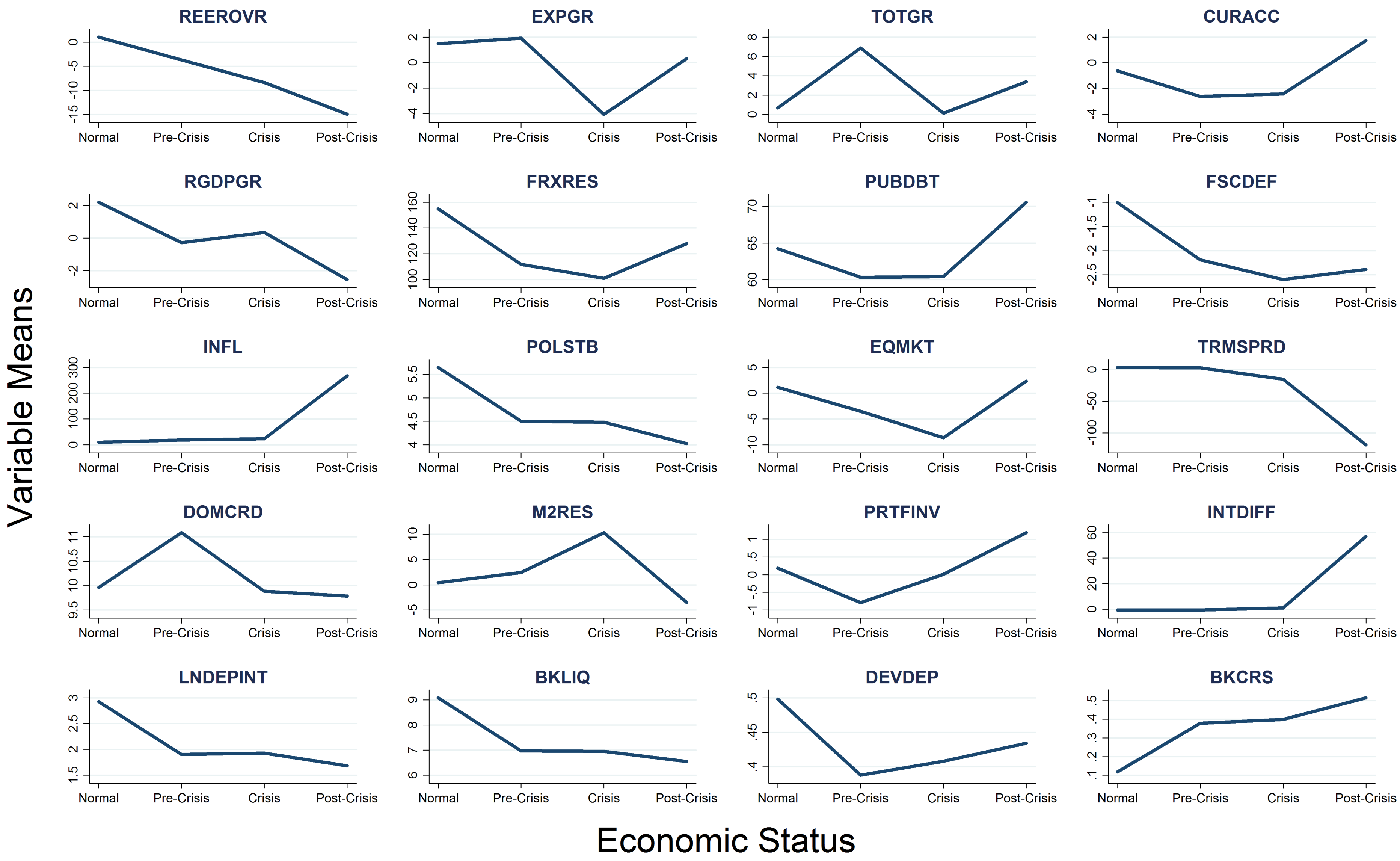

Figure 4.3: Behaviour of Candidate Variables around Currency Crisis Episodes

to reserves, portfolio investment, and equity market interdependence experience several directional changes.

Finally, there is another group of variables that are only affected after the crisis occurs, and thus, unlike the two previous groups, cannot be expected to perform well as signalling indicators. These are mainly the rate of inflation, domestic-to-foreign real interest rate, and term spread. Nevertheless, as much as this graphical event study can provide insight into the behaviour of the different candidates, a formal test is required to assess their statistical significance and their predictive power as currency crisis indicators.

Hence, in accordance with the research objectives outlined in Chapter 1, the effectiveness of these indicators in both developed and developing country regions is examined using a non-parametric dynamic signal approach, and the binary and multinomial logit regression models. The performance of these methods is then compared and contrasted using a set of evaluation criteria.

4.5 Dynamic Signal Extraction Approach

Our first formal attempt to construct an EWS for currency crises applies the recently suggested version of the signal approach, namely the *dynamic* signal extraction approach (Casu *et al.*, 2012). As detailed in section 3.1, this method starts off by constructing a forward-looking crisis response variable. This monthly time-series variable is designed so as to indicate three economic states: normal (0), pre-crisis (1), and crisis periods(2).

$$CCs_{it} = \begin{cases} 1 & if\ \exists\ k = 1, \ldots, h\ s.t.\ C_{i,t+k} = 1 \\ 2 & if\ C_{i,t} = 1 \\ 0 & otherwise \end{cases} \tag{4.3}$$

Depending on the choice of the crisis window (h), we can get different specifications of the crisis variable. It is initially set at six months ($h = 6$) in an attempt to strike a balance between giving policy makers some lead time before the onset of crises (*i.e.* specifying a wide window) and providing reliable forecasts (*i.e.* setting a narrow window). We also examine a window of three months and one year. However, the three-month window did not improve much over that of the six-month, while the twelve-month specification underperformed considerably with respect to the results of the grid search.

In addition, for each value of h there are three possible specifications of the dependent variable, namely $CC1s$, $CC2s$ and $CC3s$. These definitions correspond to the threshold levels of the EMP index (1.5, 2, and 3) above which C_{it} switches from zero to one in accordance with (4.2). Consistent with the primary intuition given by the number of crises depicted by each definition in Table 4.1 and its illustration in Figure 4.2, the grid search identified $CC3s$ as the most suitable quantification of the currency crises in all country regions.

4.5.1 Performance of Single Indicators

The next step in the dynamic signal approach is to convert the explanatory variables into 0/1 signals. This requires performing a grid search over the possible threshold levels to find the optimal threshold for each indicator that would simultaneously minimise its NTSR and maximise Youden's J-statistic in accordance with (3.3). If a variable crosses the specified threshold, a signal is generated causing the binary time series to switch from zero to one.

By comparing the signals with the forward-looking crisis variable, the performance of the respective indicator can be evaluated on different grounds. We calculate four such performance measures: optimal NTSR, percentage of crisis onsets correctly forewarned, the average lead time of the signals, and the persistence of the signals before and during crises as compared to during tranquil periods. The results of applying the grid search over the pool of countries and for each country region over the in-sample period (1994-2008) is outlined in Table 4.4.

Table 4.4: Performance of Single Indicators using Optimal Thresholds

	Global				Developed		SE-Asia		Latin America		E-Europe		Africa & ME	
	NTSR	Onsets	Lead	Persist	NTSR	Onsets	NTSR	Onsets	NTSR	Onsets	NTSR	Onsets	NTSR	Onsets
REEROVR	0.42	32.1	3.2	2.4	0.28	55.5	0.21	28.5	0.18	25.0	0.10	16.7	0.73	0.0
EXPGR	0.78	89.2	8.4	1.9	0.50	55.5	0.62	71.4	0.47	100.0	0.80	66.7	0.50	100.0
TOTGR	0.59	46.4	3.5	1.6	0.72	66.7	0.30	57.1	0.65	75.0	0.62	66.7	0.63	100.0
CURACC	0.34	64.2	7.9	2.9	0.29	66.7	0.35	85.7	0.16	75.0	0.37	50.0	0.74	0.0
RGDPGR	0.44	60.7	5.3	2.2	0.38	55.5	0.22	57.1	0.19	75.0	0.39	50.0	0.26	50.0
FRXRES	0.31	60.7	5.8	3.2	0.34	33.3	0.33	71.4	0.21	100.0	0.22	50.0	0.65	50.0
PUBDBT	0.25	32.1	2.8	3.9	0.18	33.3	0.15	28.5	0.24	50.0	0.18	33.3	0.31	100.0
FSCDEF	1.78	35.7	4.7	0.5	1.34	33.3	1.58	42.8	1.20	50.0	0.95	33.3	0.84	50.0
INFL	0.39	21.4	2.3	2.5	0.19	44.4	0.37	28.5	0.29	25.0	0.14	16.7	0.18	50.0
POLSTB	0.36	35.7	3.8	2.7	0.45	44.4	0.24	42.8	0.16	75.0	0.25	50.0	0.59	0.0
EQMKT	0.41	82.1	7.3	2.4	0.34	88.8	0.51	85.7	0.33	100.0	0.45	66.7	0.32	0.0
TRMSPRD	0.18	32.1	2.3	5.5	0.20	33.3	0.25	57.1	0.16	75.0	0.12	50.0	0.34	0.0
DOMCRD	0.30	28.5	2.5	3.3	0.15	44.4	0.22	71.4	0.21	75.0	0.22	50.0	0.36	50.0
M2RES	0.40	50.0	5.1	2.5	0.55	66.7	0.18	71.4	0.06	50.0	0.07	50.0	0.48	50.0
PRTFINV	0.52	46.4	3.9	1.9	0.36	55.5	0.23	71.4	0.38	25.0	0.64	50.0	0.29	50.0
INTDIFF	0.28	25.0	1.5	3.5	0.35	33.3	0.47	71.4	0.07	75.0	0.34	33.3	1.0	0.0
LNDEPINT	0.58	42.8	6.1	1.7	0.42	22.2	0.46	28.5	0.25	50.0	0.13	50.0	0.26	0.0
BKLIQ	0.41	32.1	3.6	2.4	0.23	33.3	0.37	57.1	0.43	50.0	0.27	66.7	0.82	50.0
REGDEP	0.73	46.3	4.3	1.3	0.76	44.4	0.53	71.4	1.11	50.0	0.49	66.7	1.01	50.0
DEVDEP	0.61	64.9	5.4	1.6	–	–	0.24	71.4	0.40	100.0	0.38	50.0	1.38	50.0
CRSNGH	0.42	39.2	2.8	2.4	1.63	22.2	0.06	42.8	1.31	25.0	0.33	50.0	0.13	100.0
BKCRS	0.11	32.4	1.7	8.7	0.09	11.1	0.02	28.5	0.14	50.0	0.04	66.7	–	–

Notes: With respect to advanced economies, the effect of the variable 'Dependence on Developed' is depicted by 'Regional Interdependence'. There were no banking crises over the sample period in the region of Africa and the Middle East.

It is readily noticeable from this table, save for Africa and the Middle East, that most candidate variables have NTSR below 0.5 in the global model as well as the individual regions. This implies that the indicators are issuing at least twice as many good signals as noise; that is, their signal persistence is above two. In some cases it is higher than five (term spread) and even eight (banking crisis dummy). Only very few variables exhibit a higher ratio of noise. The most salient of these are the fiscal deficit, which has $NTSR \geq 1$ in four out of the five regions –indicating more noise than good signals, and terms of trade. This result is consistent with the findings of the quantitative analysis, which did not find a significant change in the behaviour of these variables during crisis episodes.

Furthermore, regional interdependence of the stock market indices and crisis contagion from neighbouring countries do not seem to perform well in developed countries or Latin America, while in Africa and the Middle East almost half of the indicators exhibit a higher than 0.5 NTSR. Another striking result is the relatively low predictive power of the overvaluation of the real exchange rate variable in all developing regions. A probable explanation of this phenomenon is that these countries do not usually have a free float of their domestic currency. With either hard pegs or pegged-float regimes it is difficult to use fluctuations in the exchange rate as a leading indicator of currency crises.

Taking a closer look at each country region, we find that the volatility of the stock price index and the current account balance seem to be the most important indicators of currency crises in the advanced economies, being solely able to predict eight and six out of the nine crisis onsets, respectively. Likewise, in South-East Asia, the current account has high predictive power, followed by international reserves, domestic credit, the relative change in the money supply and portfolio investment.

In Latin America, four variables are able to perfectly predict all crisis onsets. These are export growth, reserves, the stock price index and the dependence on developed financial markets. On the other hand, the banking sector seems to be a major contributor to the probability of currency crises in Eastern and Central Europe, where bank liquidity and the banking crisis dummy are individually able to detect two thirds of the onsets there.

On different grounds, the indebtedness of the public sector and the possible contagion from neighbouring countries and close trading partners stand out as the most prominent leading indicators of currency crises in Africa and the Middle East.

In addition to the percentage of good signals, it is also important to verify how leading are the leading indicators; that is, how early these signals are issued before the crisis hits the economy. The third column (titled 'Lead') in Table 4.4 indicates that most variables issue their first signals 5-8 months before its onset. In particular, the most early signals are issued by export growth, the current account, stock price index, and lending-to-deposit interest rate. These variables have an average lead time of more than six months, which makes them quite appealing to policy makers. The other indicators start signalling an approaching crisis 2-4 months before, while interest differential and the banking crisis dummy (despite its high persistence ratio) start signalling less than two months before onsets. Accordingly, signals generated by these indicators are quite alarming, because they are less likely to be noise and can warn policy makers that immediate pre-emptive actions are extremely vital.

4.5.2 Composite Index and Crisis Probability

Analysing each variable separately provides insight into their individual usefulness as leading indicators. However, no single indicator can act as an EWS for currency crises in any region, seeing that the indicators with high signal persistence may have a short lead time and vice versa. Furthermore, having only one indicator issuing a signal (no matter how persistent) when the others are not cannot be as alarming as having five or six variables crossing their thresholds at the same time. Therefore, combining the signals generated by the individual indicators into one composite index is our next step in building the EWS.

We use the weighted average of the signals generated by the best performers (indicators with $NTSR \leq 0.5$) to construct the time series of our composite index as described in

Table 4.5: Conditional Probabilities of the Composite Index

Composite Index Values	Conditional Probabilities
0-5	2.0
5-10	3.7
10-15	8.6
15-20	21.4
20-25	36.8
25-30	37.5

(3.4). Clearly, the higher the value of the index the higher is the likelihood of a currency crash. Therefore, following (3.5) it is possible to calculate the conditional probability of a crisis based on the number of months the index takes up a value within a specific bound given an actual crisis does occur. Table 4.5 lists the different intervals for the composite index and the corresponding conditional crisis probabilities.

Overall, the calculations seem to give reasonable and coherent results, since the conditional probability of a crisis tends to increase monotonically with the value of the composite index. Constructing five such indices for the individual country regions and plotting their respective conditional probabilities in each country against its actual crisis incidents (shadowed area) gives the graphs illustrated in Figure 4.4. The horizontal line in this figure specifies the optimal cut-off probability (which maximises the J-statistic), above which the composite index as a whole is said to signal the likelihood of a currency crisis. Comparing these composite signals with the true crisis episodes can be used to assess the predictive power of the constructed EWS.

4.5.3 Predictive Power

The final step of the dynamic signal approach is to evaluate the in-sample and, more importantly, the out-of-sample forecasts of the composite indices in the global model as well as in each region separately. As illustrated in Table 4.6, we calculate three such evaluation measures. The first measure (in column 2) depicts the percentage of crisis onsets correctly predicted by the model. To get 100% in this measure, the composite

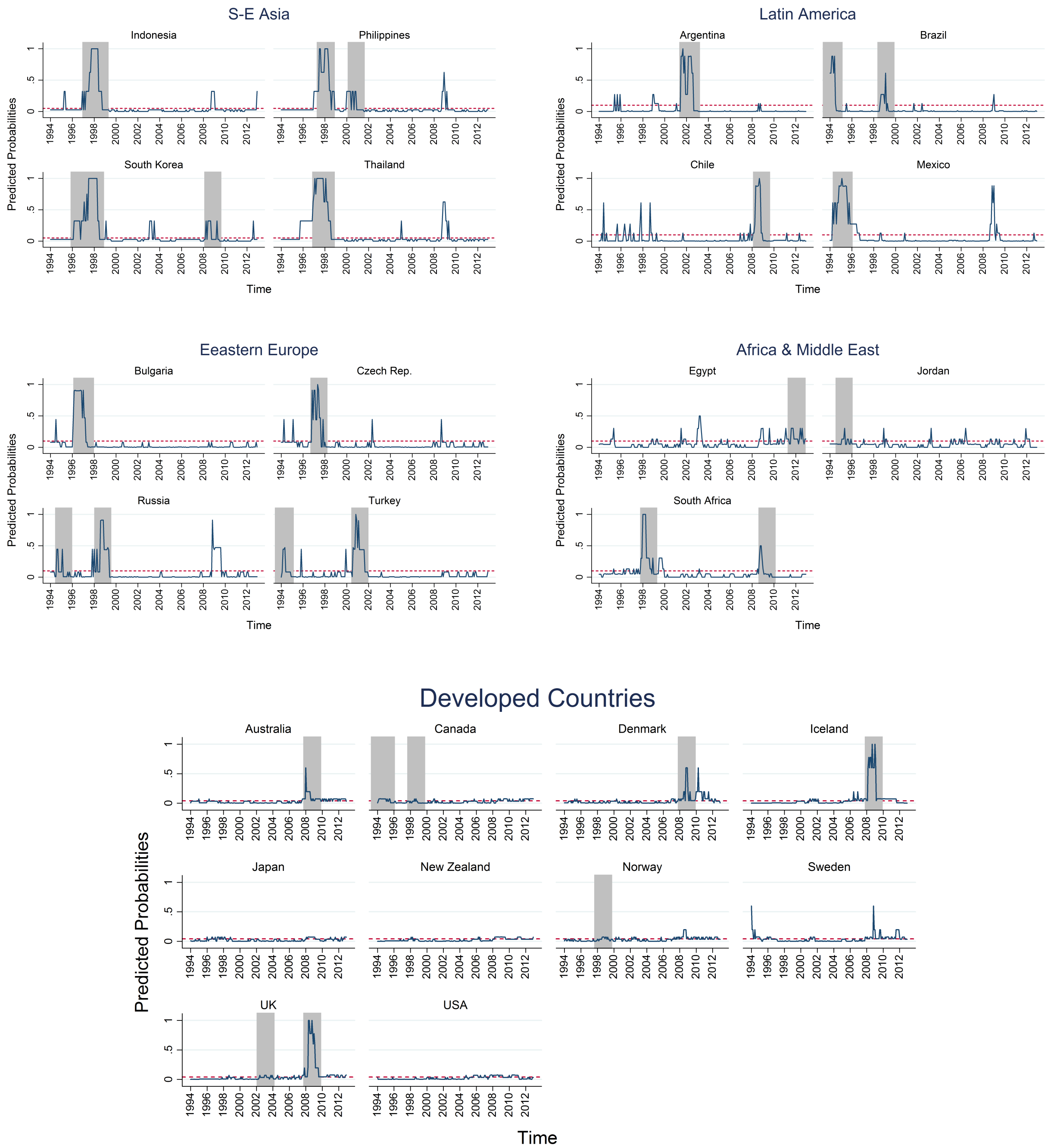

Figure 4.4: Conditional Probabilities vs. Crisis Incidents

Table 4.6: Currency Crisis Forecasts using Dynamic Signal Approach

	Optimal Cut-off	Correct Onsets	Correct Crisis	False Alarm
In-sample Forecasts (1994-2008)				
Global	5	85.7	80.3	11.5
Developed	4	87.5	83.3	13.5
S-E Asia	5	96.2	87.0	14.5
Latin America	10	100.0	95.7	12.3
E-Europe	10	100.0	76.0	6.4
Africa & ME	10	100.0	87.5	14.6
Out-of-sample Forecasts (2009-2012)				
Developed	4	–	100.0	57.5
S-E Asia	5	–	0.0	5.2
Latin America	10	–	0.0	5.2
E-Europe	10	–	–	4.2
Africa & ME	10	66.7	44.4	23.0

index must generate at least one signal within the six-month interval before every crisis onset. Furthermore, in order to analyse the effectiveness of the EWS in predicting the length of the crisis, as well as its onset, we calculate a second measure (in column 3) of crisis periods correctly called. This involves computing the percentage of correct signals generated within the six-month period before every month the country spent in crisis (*i.e.* all non-tranquil periods). The final measure (in column 4) is concerned with the percentage of false alarms signalled by the composite index; that is, how many signals were not succeeded by a crisis within the following six months.

The upper panel of Table 4.6 depicts the results of the in-sample forecasts over 1994-2008, which is the period used to calculated the EMP index, the optimal thresholds for the individual indicators, and the cut-off probability of the composite index. The same threshold levels are then used to construct the out-of-sample individual signals and the composite indices over the hold-out period 2009-2012.

It is evident from this table that the dynamic signal approach is performing remarkably well in modelling an EWS for currency crises, being able to correctly signal 90-100% of the crisis onset periods and 80-90% of the months spent in a currency crash in each region. In particular, the composite indices in Latin America, Eastern Europe, and Africa and the Middle East are able to correctly signal *all* their crisis onset periods. The indices in South-East Asia and in the advanced economies correctly predicted 25 out of the 26 and 7 out of the 8 months of crises in these regions, respectively. Interestingly, these high hit rates did not come at the expense of a high false alarm rate. In fact, all the false signals are kept within a reasonable 10-15% range in all regions.

Compared to the previous findings in the literature, the dynamic signal approach appears to outperform the static version to a great extent. With an average hit rate of 60% and a false alarm rate of around 30% in Berg *et al.* (2005) and more recently in Comelli (2013), the dynamic version using a 6-month crisis window (both articles used a 24-month window) significantly improves the predictive power of the EWS. It also improves on the single-country static models that used a 12- and a 6-month crisis window, where the hit rates were around 85% in El-Shazly (2002) and Krznar (2004).

Another important finding that can be deduced from Table 4.6 is that each of the regional models outperforms the global model with respect to the in-sample correct onsets and crisis periods. This is quite plausible given the distinct crisis symptoms and the autonomous behaviour of the indicators in each region, which is apparent in Table 4.4. We, therefore, exclude the global model from our out-of-sample analysis and conclude that the models that account for regional heterogeneity can build more effective EWSs.

With respect to the out-of-sample performance of the regional models, only the countries in Africa and the Middle East have experienced three new crises over the period 2009-2012. The composite index of this region correctly predicted two of these three incidents, but generated a relatively high number of false signals, which amounted to 23%. In the other regions, where no new crises have occurred, we consider the percentage of crisis periods correctly called by the individual composite indices. In developed countries, the last two months of crises are correctly predicted, but at the expense of a very high rate of false alarms that exceeds 50%. On the other hand, both final months of crises in Asia and Latin America were not detected by their individual composite indices.

4.6 Binary Logit Estimation

We now turn to estimate the probability of a currency crisis using a parametric model, namely the binary logit regression. This model, as opposed to the non-parametric signal approach, allows for measuring the magnitude of the effect of the individual signalling indicators on the probability of a crisis, as well as conducting statistical significance tests.

4.6.1 The Setup

Since the objective of our EWS is to predict the likelihood of an upcoming crisis, as well as its duration, we do not drop the observations after a crisis onset as is common in some studies (Candelon *et al.*, 2014; Lang, 2013) to avoid possible endogeneity (*i.e.* having the crisis itself affect the indicator variables). However, in order not to lose the post-crisis observations, and to be able to investigate ongoing currency crashes rather than just new ones, we consider two possible alternative approaches.

The first option is to treat all crisis and post-crisis months as individual crisis episodes, which is adopted in this section, and the second is to use a multinomial dependent variable that separates the post-crisis months from both tranquil and crisis periods, which is considered in section 4.7. Accordingly, the three binary dependent variables that reflect currency crisis periods ($CC1, CC2, CC3$) are designed so as to assume the value of unity when the EMP index is above the corresponding thresholds (1.5, 2, and 3) in addition to the following quarter, and are zero otherwise to reflect tranquil periods:

$$CC_{it} = \begin{cases} 1 & if\ \exists\ k = 0, \ldots, 3\ s.t.\ C_{i,t-k} = 1 \\ 0 & otherwise \end{cases} \tag{4.4}$$

The reason for adding these extra three months is to account for the post-crisis/recovery regime till the economy returns to the tranquil state[1].

Furthermore, instead of constructing a forward-looking variable with a specific crisis window, as is frequently done in the literature (refer for example to Kaminsky and Reinhart, 1999; Candelon *et al.*, 2012; Comelli, 2014), we prefer using different lags of the explanatory variables. The reason is that, on the one hand, Lin *et al.* (2008) pointed out that the choice of the window is rather arbitrary and requires some kind of trade-off. A larger window allows for less missed crises but more false alarms, and vice versa. On the other hand, using lags of the explanatory variables would still forewarn an approaching crisis while allowing for more flexibility in the signalling window, as we can use different lags for different variables.

Consequently, the logit regression is run globally on the pool of countries, and on each region separately for all three crisis definitions over the in-sample period of January 1994 to December 2008. Table 4.7 depicts the estimation results when using a 1-month lag (but a 6-month lag for domestic credit to enable time for the boom-bust cycle), while Table 4.8 presents the same with a 1-quarter lag and a semi-annual lag. These two tables apply pooled regressions assuming full homogeneity across countries and over time. Only the global model includes region dummies to capture regional heterogeneity. In addition to the pooled regressions, we also estimate panel fixed-effects models[2] that account for country-specific heterogeneity, the results of which are illustrated in Table 4.9.

Before detailing the estimation results, we first consider the performance of the different specifications of the dependent variable. We apply three criteria to choose the most appropriate crisis definition using the global sample and for each country group, namely

[1]The fluctuations of the EMP index illustrated in Figure 4.1 are used as a guide for determining the length of the post-crisis period. We also attempted using 1 month and 6 months, but the results were significantly worse in both cases

[2]Random-effects panel regressions are also considered, but the Hausmann specification test indicated that the estimator was inconsistent. Furthermore, the forecasting results of the random-effects models were very poor compared to that of the fixed-effects and the pooled regressions.

the Pseudo[1] McFadden's R^2, the log-likelihood ratio, and the Schwarz-Bayesian information criterion[2] (BIC). In addition, we check the in-sample forecasting performance of the models that use each respective crisis specification (discussed below).

Consistent with the findings of the grid search in the dynamic signal approach and the initial conjecture in section 4.2, the lower panel of Table 4.7 indicates that $CC1$ is performing very poorly relative to the other two specifications. Furthermore, the $CC3$ specification appears to outperform the other two crisis definitions in all regions. This conclusion is further confirmed by the in-sample forecasts discussed in section 4.6.3. We, therefore, continue to apply this definition in all our following analyses, dropping the other two[3].

With respect to the estimation results of the pooled logit regressions, a general overview of the $CC3$ columns in Table 4.7 suggests that there are major differences across the country groups in terms of the significant signalling indicators. This is further evidenced by the statistical significance of the regional dummies in the global model, advocating the importance of regional heterogeneity. Moreover, applying the same three criteria used to choose the appropriate crisis definition in comparing between the different models using the pooled and the fixed-effects estimations, it can readily be noticed that the regional models outperform the global in both cases. This conforms with the findings of Kamin *et al.* (2001), who considered three regional subsets: Latin America, East Asia, and other emerging economies; and Candelon *et al.* (2012) who just considered Latin America and East Asia and, yet, found evidence of significant predictor differences across these regions.

Moreover, the panel fixed-effects do not seem to be improving over the pooled models, suggesting that regional heterogeneity are more important than country-specific, which is also evidenced in the literature (Bussiere and Fratzscher, 2006; Fuertes and Kalotychou,

[1]McFadden R^2 measures the improvement of the model's log-likelihood over the basic model that includes only the constant term: Pseudo $R^2 = 1 - \frac{LL_{Model}}{LL_{Basic}}$ (Long and Freese, 2001).

[2] The reported BIC is measured as: $BIC = -2LL + ln(N)k$, where k is the number of estimated parameters and N denotes the number of observations. Since the fit is measured negatively, the larger the value, the worse the fit.

[3]We do continue to check the results of the other two specifications throughout the entire analysis, but we do not report them here as they are always inferior to the $CC3$.

2006, 2007). However, since our main purpose is to construct an EWS for crises rather than fitting a descriptive model, we advocate leaving the final decision to the forecasting performance of the models.

4.6.2 Estimation Results

Now, taking a closer look at the separate models, we can identify the different variables that act as signalling indicators in the individual regions. It is quite noticeable that the results of the variables' significance tests in each region are fairly similar to the findings of the dynamic signal approach. This confirms the notion that a specific set of leading indicators is adequate for each region.

Starting with developed countries, it can be noted that the major indicators of approaching currency crises are the overvaluation of the real exchange rate, the expansion of domestic credit, instability in the political arena, increased portfolio investments that raise the probability of reversible capital flows, and decreased financial sector profitability as measured by falling lending-to-deposit interest rates. Moreover, since tranquil periods are usually accompanied with increased public debt, as the government is induced to increase its expenditure when there is no crisis at hand, a low level of public debt may be associated with the periods before the buildup of a crisis. In addition to these variables, which play a significant role even six months before a currency crash (refer to Table 4.8), a falling stock price index can explain crashes up to one quarter *a priori*.

Turning to the emerging world, we find that the signalling indicators in the Asian country group are different from that of the developed economies. Here, current account deficit, inflation, the deterioration of the real economy as measured by retreating GDP growth rates, the erosion of foreign exchange reserves, and a narrower term spread that reflects worsening future economic prospects appear to have explanatory power up to six months before a crisis occurs. The negative coefficient of the rate of inflation implies, though, that it is associated with a growing economy (demand-pull inflation) rather than

Table 4.7: Binomial Logit Estimation of Currency Crises using 1 Lag

	Global			Developed		S-E Asia		Latin America		E-Europe		ME & Africa	
	CC1	CC2	CC3	CC2	CC3	CC2	CC3	CC2	CC3	CC2	CC3	CC2	CC3
REEROVR	-0.045**	-0.051**	-0.092**	-0.082**	-0.191**	-0.132**	-0.173**	-0.124**	-0.276**	-0.076**	-0.090**	0.094**	-0.161**
TOTGR	0.003	0.002	0.006	-0.001	-0.011	0.001	0.015	0.022*	0.061	0.023	-0.015		
CURACC	-0.035**	-0.030**	-0.045**	-0.006	0.065	-0.284**	-0.404**	0.023	-0.608**	-0.073	-0.096	-0.008	-0.114**
RGDPGR	-0.020**	-0.027**	-0.036**	-0.008	-0.027	-0.174	-0.407**	-0.064	-0.780**	-0.025	-0.075		
FRXRES	-0.004**	-0.003**	-0.005*	-0.006*	-0.011	0.005	0.013			-0.017**	-0.007	-0.000	-0.017*
PUBDBT	0.001	0.002	-0.004	-0.003	-0.049**	0.002	0.007	0.007	-0.080*	-0.055**	-0.048**	0.013**	0.061**
FSCDEF	0.014	0.029*	0.032			-0.062	-0.037			0.067	0.254**	0.017	0.032
INFL	0.002	0.007	0.017**	0.080	0.046	-0.370**	-0.412**	-0.078**	0.005	0.016*	0.027**	0.047	-0.952**
POLSTB	-0.163**	-0.196**	-0.512**	-0.197*	-1.198**	-0.174	-0.437	-0.085	-0.602**	-0.436**	-0.630*	-0.893**	-0.658
EQMKT	-0.017*	-0.023*	-0.026*	-0.037	-0.084**	0.005	0.007	-0.014	0.014	0.012	-0.010	0.000	-0.065
TRMSPRD	-0.001	-0.003	-0.005	-0.065	-0.062	-0.409**	-0.306*	-0.154**	0.054	-0.001	0.004	-0.125*	-1.513**
DOMCRD	-0.009	-0.018	0.041	0.009	0.146**	-0.014	-0.107	0.133	-0.600	0.040	-0.070		
M2RES	0.003*	0.004**	0.002	0.025*	0.005	0.011**	0.019**	0.072**	0.043	0.005	-0.015		
PRTFINV	-0.030**	-0.016	-0.008	0.002	0.026	-0.035	0.152*	-0.112**	-0.138	-0.072	-0.072	-0.078**	0.220
INTDIFF	0.002	0.025	0.061**	-0.026	0.061			0.071	0.287**	0.056	0.106**	-0.022	0.406**
LNDEPINT	-0.104	-0.357**	-0.283*	-0.319*	-1.028**	-5.000**	-9.141**	-1.134**	-0.686	1.317**	1.214*	-2.924**	-1.704
BKLIQ	0.018**	0.014	-0.011	0.011	0.041	0.492**	0.387	-0.031	0.052	-0.126*	-0.330**	-0.082**	-0.428**
REGDEP	-0.146	-0.483*	-0.512	-0.112	2.126	-0.214	-0.783	0.102	0.531			0.162	3.984*
DEVDEP	-0.097	0.016	0.179			-0.348	-0.407	-0.162	-0.402				
BKCRS	0.752**	0.988**	1.117**	0.429	-0.121	-2.439*	-2.018	2.703**	-0.178	3.838**	6.092**		
CRSNGH	0.435**	0.507**	0.866**	0.677**	0.355	1.725**	2.196**	0.055		0.015	-1.367		
Asia	-0.804**	-1.292**	-1.187*										
Latin	-0.898**	-0.553**	-2.013**										
EEurope	-0.802**	-0.717**	-1.500**										
Africa	-0.203	-0.269	-0.841										
N	4350	4350	4350	1740	1740	696	696	696	696	696	696	537	537
Pseudo R^2	0.164	0.189	0.417	0.154	0.445	0.668	0.731	0.459	0.891	0.503	0.651	0.240	0.852
Log-Likelihood	-1587.4	-1079.4	-369.3	-417.9	-84.7	-63.1	-45.4	-132.7	-19.7	-100.3	-37.5	-133.1	-12.1
BIC	3384.3	2368.2	947.5	985.1	317.3	263.683	228.4	395.6	157.3	331.6	206.7	360.6	112.2

* $p < 0.05$, ** $p < 0.01$

Table 4.8: Binomial Logit Estimation of Currency Crises using 3 & 6 Lags

	(1) Developed	(2) Asia	(3) Latin	(4) E-Europe	(5) Africa
REEROVR	-0.159**	-0.089*	-0.096	-0.069**	-0.058
TOTGR	0.007	0.015	-0.189*	0.032	
CURACC	0.010	-0.394**	-1.606**	-0.325**	-0.008
RGDPGR	-0.017	-0.287**	-2.281**	-0.000	
FRXRES	-0.006	-0.006		-0.026**	-0.013**
PUBDBT	-0.032**	0.006	-0.247**	-0.023	0.056**
FSCDEF		0.039		0.129	0.117
INFL	0.334	-0.312**	-0.547*	0.035**	-0.544
POLSTB	-0.762**	-0.757**	-3.064*	-0.748*	-1.747**
EQMKT	-0.082**	-0.015	0.036	-0.074*	-0.088
TRMSPRD	0.272	-0.212**	-0.251*	-0.010	-1.381**
DOMCRD	0.187**	-0.043	4.344**	-0.208	
M2RES	0.042*	0.007	-0.067	-0.060	
PRTFINV	-0.015	-0.001	-0.049	-0.164	0.621**
INTDIFF	-0.115		-0.082	0.153**	-0.197*
LNDEPINT	-0.981**	-2.417	-2.855*	2.912**	
BKLIQ		0.004	-1.153*	-0.164	-0.225**
REGDEP	0.940	0.682	-3.306		3.338
DEVDEP		0.109	-6.415**		
BKCRS	-0.298	-0.121	9.291*	7.327**	
CRSNGH	0.098	1.335**		2.346**	
N	1740	696	696	696	531
Pseudo R^2	0.324	0.619	0.878	0.675	0.562
Log-Likelihood	-102.5	-64.6	-12.3	-35.4	-18.2
BIC	346.8	266.7	148.9	200.9	118.5

	(1) Developed	(2) Asia	(3) Latin	(4) E-Europe	(5) Africa
REEROVR	-0.129**	0.013		-0.037*	-0.027
TOTGR	-0.000	0.024**	-0.044	0.016	
CURACC	-0.047	-0.344**	-0.199	-0.190**	
RGDPGR		-0.258**	-0.457**	0.015	
FRXRES	-0.001	-0.018**		-0.024**	-0.037*
PUBDBT	-0.022*	0.042	-0.130*	-0.014	0.033**
FSCDEF		0.020		-0.042	0.025
INFL	0.177	-0.494**	-0.178**	0.003	-0.255
POLSTB	-0.393*	-0.307	-1.281**	0.032	-0.107
EQMKT	-0.007	0.031	-0.049	0.030	-0.021
TRMSPRD	0.268*	-0.287**	0.007	0.004	-0.723**
DOMCRD	0.163**	0.235*	0.403	-0.017	
M2RES	-0.011	-0.026	0.050	0.007	
PRTFINV	0.051**	0.075	0.106	0.070	0.346*
INTDIFF			0.185	0.022	-0.960*
LNDEPINT	-0.714**	-1.872	0.105	0.918**	0.196
BKLIQ		-0.097	-0.110	-0.079	-0.072
REGDEP		0.668	0.370		-2.134
DEVDEP		0.266	-1.682*		
BKCRS	-0.184		0.952	3.000**	
CRSNGH		0.517		2.016**	
N	1740	696	696	696	522
Pseudo R^2	0.238	0.485	0.626	0.464	0.444
Log-Likelihood	-115.4	-87.2	-37.7	-57.7	-25.1
BIC	342.7	305.4	193.3	246.4	131.6

Table 4.9: Binomial Logit Estimation of Currency Crises using Panel FE

	(1) Global	(2) Developed	(3) Asia	(4) Latin	(5) E-Europe	(6) Africa
REEROVR	-0.115**	-0.153*	-0.524**	-0.220**	-0.089	-0.212
TOTGR	0.008	0.037	0.024	0.042	-0.011	
CURACC	-0.124**	-0.164	-0.816**	-0.565	-0.035	-0.142
RGDPGR	-0.048**	-0.259	-0.214	-0.158	-0.044	
FRXRES	-0.012**	0.025	-0.002		-0.018	0.004
PUBDBT	0.004	-0.063	-0.251	-0.009	-0.042*	0.093
FSCDEF	-0.005		-0.138		0.153	
INFL	0.013**	0.237	-0.256*	-0.059	0.032**	-2.260*
POLSTB	-0.457**	-0.828**	-1.693**	-0.811	-0.542	-2.832*
EQMKT	-0.025*	-0.120**	0.019		0.007	
TRMSPRD	-0.002	-0.061	-0.238*	0.019	0.003	-2.143**
DOMCRD	0.097*	0.234	2.432**	-0.278	-0.311	
M2RES	0.002	0.007	0.029**	0.016	-0.019	
PRTFINV	-0.021	-0.014	0.200		-0.096	0.001
INTDIFF	0.043**	0.321*		0.241*	0.124**	
LNDEPINT	0.354*	-4.316*	-9.586**	0.453	1.434	
BKLIQ	-0.036	-0.245		-0.284	-0.745**	-0.027
REGDEP	0.087	1.908	-1.555	1.011		2.352
DEVDEP	0.056		-0.635			
BKCRS	1.340**	0.686	-2.286	5.566*	4.558**	
CRSNGH	0.967**	1.755	2.255**			
N	3480	1044	696	696	696	358
Pseudo R^2	0.501	0.544	0.825	0.941	0.713	0.802
Log-Likelihood	-254.7	-56.2	-27.9	-5.4	-28.5	-6.9
BIC	680.8	244.4	180.2	109.1	174.8	72.7
Optimal Cut-off	0.5	0.5	0.5	0.5	0.5	0.5
% of Correct Crisis	65.9	66.7	34.8	69.6	72.0	75.0
% of False Alarm	7.0	5.2	0.9	0.0	3.7	0.0

* $p < 0.05$, ** $p < 0.01$

the loss of competitiveness. On the other hand, real exchange rate overvaluation and contagion of currency crises in neighbouring economies or trade partners are only useful three months before the crisis hits the domestic economy.

Similar to the Asian economies, the current account balance, the real GDP growth, the political situation, and the rate of inflation tend to have a relatively long-run (6 months) explanatory power with respect to the attacks on the domestic currency in Latin American countries. In addition, high public debt to GDP ratios are more commonly associated with non-crisis periods, while stronger links to more stable developed economies stock markets help to fend off regional capital flight. In the shorter run (3 months), there is strong evidence for possible spillover from the domestic banking sector, where a high ratio of credit to the private sector, low bank profitability and/or liquidity, and systematic bank distress are notably contributing to the exchange market pressure in Latin America. Furthermore, one month before a crisis, real exchange rate shoots up and a high domestic-to-foreign interest rate calls for devaluation expectations as it reflects the government's attempts to defend the domestic currency.

With respect to Eastern Europe, we find that the deviation of the exchange rate from its 2-year trend, the erosion of foreign reserves, a deteriorating current account balance, banking sector distress, the deterioration of loan quality due to increased lending-to-deposit interest rates, and contagion from neighbouring countries can signal an approaching currency crisis six months before it hits the economy. On the other hand, a falling political stability index which induces capital flight, and rising inflation and domestic interest rates which attract volatile short-term capital can explain currency crises three months in advance. Other variables, including the indebtedness and the fiscal deficit of the public sector, and diminishing bank liquidity have only 1-month explanatory power of currency crashes.

Finally, considering countries from Africa and the Middle East, variables with a 6-month explanatory power include a rising public debt, a shrinking term spread, the stock of foreign exchange reserves, and easily reversible portfolio inflows. One quarter before the crash, the political stance seems to aggravate, while bank liquidity drops. In the very short run (1 month), the current account balance seems to worsen, inflation rates fall (as in the case of Asia), rising domestic-to-foreign real interest rates attract volatile short-term capital, and the real exchange rate is overvalued.

After exploring the explanatory power of the proposed signalling indicators of currency crises in the different regions of the world, it is important to keep in mind that the actual performance of the estimated EWS can only be assessed in terms of their forecasting abilities. Therefore, we next turn to the evaluation of the simple in-sample and the more fundamental out-of-sample predictions of all the estimated models.

4.6.3 In-Sample Forecasts

With respect to the in-sample forecasts, a classification table is constructed for each case, which indicates the percentage of correctly predicted crisis and no-crisis episodes, along with their complements, namely the percentages of missed crises and false alarms. These measures are calculated with respect to the optimal cut-off point, above which the predicted probabilities calculated by the corresponding model are said to issue a signal.

Figure 4.5 provides a graphical illustration of how the optimal cut-off probability could be determined. As the cut-off level increases, the *sensitivity line* shows how the percentage of correct crisis signals diminishes and the *specificity line* shows how the percentage of correct no-crisis signals rises. Thus, the intersection between both lines gives a general hint about the optimal threshold level. However, calculating the exact point requires a grid search to identify the level that maximises Youden's J-statistic (3.2).

The optimal cut-offs for each model, along with their in-sample classification results, are presented in Table 4.10. The upper panel considers the pooled models using one lag, while the lower depicts the pooled models using three and six lags. On the other hand, the in-sample forecasts of the fixed-effects panel model are illustrated in the lower panel of Table 4.9 on page 85.

Table 4.10: In-Sample Currency Crisis Forecasts using Logit

	Optimal Cut-off	Correct Crisis	Missed Crisis	Correct NoCrisis	False Alarm
Using 1-month lag on all crisis definitions					
Global CC1	30	40.6	59.4	90.6	9.4
CC2	17	47.5	52.5	88.9	11.1
CC3	5	73.5	26.5	90.1	9.9
Developed CC2	15	42.7	57.3	90.1	9.9
CC3	2.5	**90.0**	10.0	90.3	9.7
S-E Asia CC2	7	94.4	5.6	90.3	9.7
CC3	5	**100.0**	0.0	90.5	9.5
Latin America CC2	15	84.6	15.4	89.2	10.8
CC3	5	**100.0**	0.0	96.3	3.7
E-Europe CC2	10	88.1	11.9	90.0	10.0
CC3	5	**100.0**	0.0	93.9	6.1
Africa & ME CC2	10	77.8	22.2	70.6	29.4
CC3	5	**100.0**	0.0	96.6	3.4
Using 3- and 6-month lags on the optimal ($CC3$) crisis definition					
Developed 3M	4	73.3	26.7	90.6	9.4
6M	3	70.0	30.0	87.7	12.3
S-E Asia 3M	10	87.0	13.0	92.2	7.8
6M	7	84.8	15.2	88.0	12.0
Latin America 3M	3	100.0	0.0	98.4	1.6
6M	3	100.0	0.0	92.0	8.0
E-Europe 3M	2	100.0	0.0	90.3	9.7
6M	5	84.0	16.0	89.6	10.4
Africa & ME 3M	7	87.5	12.5	96.6	3.4
6M	5	87.5	12.5	92.6	7.4

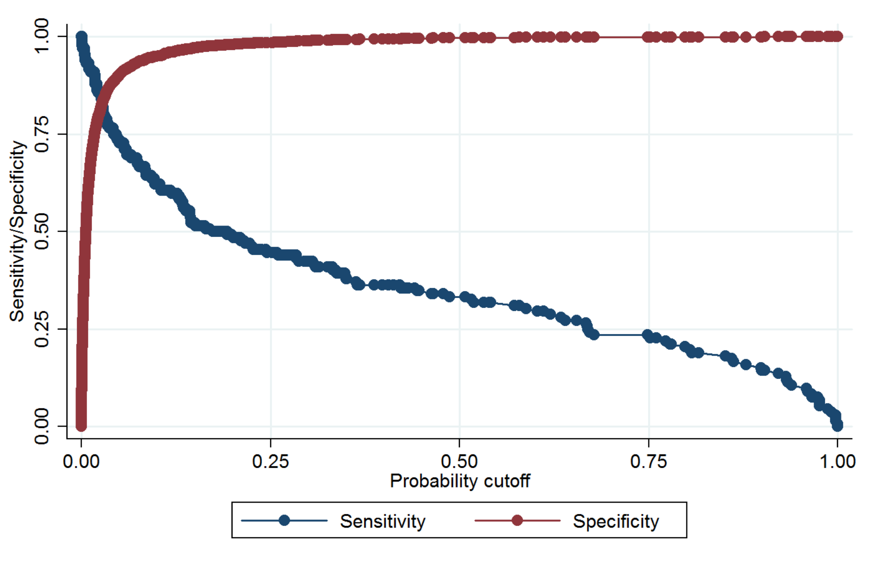

Figure 4.5: Optimal Probability Cut-off Point for Currency Crises

In conformity with the goodness-of-fit measures, the model with the $CC1$ crisis specification performs poorly relative to the other two definitions as it is quantifying too many crisis incidents. It is therefore dropped from all further analyses. Moreover, when comparing the other two crisis quantifications, the results show that $CC3$ provides the most accurate in-sample forecasts in all regions. In general, the regional pooled models using 1-month lag are able to correctly signal 90-100% of the crisis episodes without issuing more than 10% false alarms. This is considered a significant improvement over the pooled global model, which is only able to predict 70% of the total crisis incidents.

In addition, the results indicate that the pooled models tend to perform remarkably better that the rivalling panel models, where the figures stand below 80% and even below 50% in the case of Asia. This confirms our previous conclusion and that of the literature that the simple models tend to outperform the more complex ones in forecasting. It basically indicates the importance of accounting for regional rather than country-specific heterogeneity when generating forecasts[1]. Therefore, we exclude the panel fixed-effects from our further analysis, as well as the pooled global specification, and we concentrate only on the regional pooled models.

[1] We use discriminant analysis to test whether countries in the same region tend to have similar levels of financial development and close characteristics of their financial systems, and can therefore be pooled into regional models. The results of this analysis are presented in Chapter 7 in subsection 7.3.2.

Comparing our results with the literature, we find that our models outperform them to a great extent. Lestano *et al.* (2003) achieved an average hit rate of merely 30% in Asian countries, while the models of Kumar *et al.* (2003), Komulainen and Lukkarila (2003) and Bussiere and Fratzscher (2006) performed a bit better at around 50-60%. Uniformly better in-sample forecasts were provided by Lin *et al.* (2008) and El-Shazly (2011), who were able to forewarn around 85% of the sampled crisis incidents, yet they suffered a false alarm rate of around 20%. The most promising results were those of Candelon *et al.* (2014), who were able to predict 90% of the crisis episodes on average while generating 15% false signals.

It is evident, therefore, that our regional models perform better, being able to reach a hit rate of 100% in all emerging regions, and 90% in developed countries without generating as many false alarms. The predictive performance of our pooled models using the $CC3$ specification continues to surpass the previous literature even when using the 3-month and the 6-month lags. In all emerging regional models, the hit rate remains above 85% while keeping the false alarm rate within the 10% range. However, in the case of developed countries, the predictive power is lower, standing at around 70%.

Although these in-sample forecasts can provide a good insight regarding the performance of the estimated models, they do not provide much benefit in terms of policy implications. Therefore, the next section is dedicated to evaluate the out-of-sample performance of the constructed models.

4.6.4 Out-of-Sample Forecasts

In order to investigate the capability of the binary logit models to generate early warning signals of forthcoming currency crises, the estimated regressions illustrated in Tables 4.7 and 4.8 are used to provide forecasts over the out-of-sample period from January 2009 to December 2012, which accounts for nearly 50 held-out observations per country.

With respect to the regular out-of-sample forecasts, the models are estimated once over the in-sample period and the forecasts are generated for the entire holdout period. The resulting classification output is presented in the upper panel of Table 4.11. The evaluation of the $CC1$ and $CC2$ models are not reported in this table given their relatively poor performance in generating satisfactory in-sample predictions.

Given the fact that there were only very few crisis incidents during the holdout period, the reported percentages are rather extreme values. In particular, there were only two incidents in developed countries, only one of which is signalled one month in advance, while both of them are foreseen over the period of 3-6 months. The percentage of false alarms is, however, high at 20-30%.

In the Asian economies, there was only one crisis period, which is only detectable in the short run. Likewise, only one incident occurred in Latin America, but the models are able to forewarn it using any number of lags of the explanatory variables. With respect to Eastern Europe, there were no crisis incidents over the holdout period, but the percentage of correct tranquil periods signalled are around 90% for all three lagged models. Lastly, in Africa and the Middle East, nine crisis episodes have occurred, five of which are forewarned the month before, and only four 6 months in advance.

To improve on these results, we apply our dynamic-recursive forecasting technique on these models. We develop this forecasting technique, as discussed in Chapter 3, to update the EWS with the new information as it becomes available, using the last periods' indicators and predicted probabilities to provide recurring forecasts of only 1-6 (instead of 50) periods ahead into the future. The results of applying this technique are presented in the lower panel of Table 4.11. It is evident from these results, as is reasonably expected, that the forecasting performance of models is improved significantly.

Regarding the developed countries, the same number of out-of-sample crisis incidents are signalled but with much lower false alarms, which are now less than 15% (down from 31%). In South-East Asia, the models using the 3-month and the 6-month lags are now

Table 4.11: Out-of-Sample 2009-2012 Currency Crisis Forecasts using Logit

	Optimal Cut-off	Correct Crisis	Missed Crisis	Correct NoCrisis	False Alarm
Using Regular Forecasting Method					
Developed 1M	2.5	50.0	50.0	88.1	11.9
3M	4	100.0	0.0	78.9	21.1
6M	3	100.0	0.0	69.0	31.0
S-E Asia 1M	5	100.0	0.0	96.9	3.1
3M	10	0.0	100.0	99.5	0.5
6M	7	0.0	100.0	100.0	0.0
Latin America 1M	5	100.0	0.0	100.0	0.0
3M	3	100.0	0.0	97.9	2.1
6M	3	100.0	0.0	89.0	11.0
E-Europe 1M	5	–	–	94.3	5.7
3M	2	–	–	87.5	12.5
6M	5	–	–	96.4	3.6
Africa & ME 1M	5	55.6	44.4	91.1	8.9
3M	7	77.8	22.2	88.1	11.9
6M	5	44.4	55.6	88.1	11.9
Using Dynamic-Recursive Forecasting Method					
Developed 1M	50	50.0	50.0	99.4	0.6
3M	40	100.0	0.0	98.5	1.5
6M	5	100.0	0.0	85.6	14.4
S-E Asia 3M	1	100.0	0.0	94.8	5.2
6M	5	100.0	0.0	88.0	12.0
Africa & ME 1M	50	88.9	11.1	90.4	9.6
3M	40	77.8	22.2	90.4	9.6
6M	5	77.8	22.2	86.7	13.3

able to forewarn the single held-out crisis episode. Furthermore, in the African region, eight out of the nine crisis incidents are signalled using a 1-month lag, and seven using the 3-month and the 6-month lags, which is a significant improvement over the regular forecasts.

In the view of the rather satisfactory performance of the binary logit method, we next turn to the other alternative approach to deal with the possible problem of endogeneity. In particular, we estimate the logit models using a multinomial, rather than a binary, dependent variable that accounts for three economic states: tranquil, crisis and post-crisis.

4.7 Multinomial Logit Estimation

As discussed in Chapter 3, the multinomial logit regression is an extension of the binary logit that estimates the effects of the signalling indicators on the probability of a response variable with more than two regimes (here three: normal, crisis, post-crisis). The purpose of this distinction between the different states of the economy, as first pointed out by Bussiere and Fratzscher (2006), is to avoid falling into a "post-crisis bias" by combining the periods following the currency crash with those of the tranquil state. In the previous section, we addressed this bias by considering the post-crisis periods as ongoing crisis episodes, while this section treats them as a separate economic regime.

Consequently, the first step is to construct a three-state variable that assumes different values for the each of the three economic states. In this respect, the response variable (CCm_{it}) assumes the value of 1 as long as C_{it} in (4.2) is unity, which denotes that the EMP index is above its specified threshold level. For the post-crisis state, and out of concern for comparability with the logit models, CCm_{it} takes the value of 2 in the three months following the crash[1]. Otherwise, the response variable is zero to denote the tranquil periods. Hence, the multinomial dependent variable can be defined as:

[1] Refer to 4.6.1 with respect to how the length of the post-crisis period is determined

$$CCm_{it} = \begin{cases} 1 & if\ C_{it} = 1 \\ 2 & if\ \exists\ k = 1, \ldots, 3\ s.t.\ C_{i,t-k} = 1 \\ 0 & otherwise \end{cases} \tag{4.5}$$

As in the case of the logit regression, we consider three specifications of the currency crisis $CC1m$, $CC2m$ and $CC3m$, which correspond to the different threshold levels of the EMP index (1.5, 2, and 3). We also run the multinomial logit regression on the global sample of countries as well as on the individual regions using different lags of the explanatory variables.

4.7.1 Estimation Results

The results of running a multinomial logit regression using a 1-month lag of the signalling indicators (but a 6-month lag for the domestic credit as before) are illustrated in Table 4.12, while those of running the same regression but using 3- and 6-month lags are depicted in Table 4.13. The upper panel of these tables reports the marginal effects of the indicators on the probability of an approaching crisis, whereas the lower panel reports the same with respect to the post-crisis period.

Using the same criteria of the Pseudo McFadden's R^2 and the log-likelihood ratio to compare between the models that adopt the different crisis definitions, it is evident –as in the case of the logit regression that the quantification of $CC3m$ gives better fitting models than that of $CC2m$ and $CC1m$. The same conclusion can be drawn when checking the in-sample forecasting performance of the models, which is detailed later on. Moreover, these three criteria also show that each of the individual regional models provides better fits and in-sample forecasts than that of the global model which pools both developed and developing countries together.

In this respect, the results depicted in Table 4.12 and Table 4.13 are generally consistent with those of the binary logit models. In particular, it can be deduced that, in

Table 4.12: Multinomial Logit Estimation of Currency Crises using 1 Lag

		Global		Developed		S-E Asia		Latin America		E-Europe		ME & Africa	
		CCm2	CCm3	CCm2	CCm3	CCm2	CCm3	CCm2	CCm3	CCm2	CCm3	CCm2	CCm3
Crisis Period $CCm_{it} = 1$	REEROVR	-0.046**	-0.094**	-0.058**	-0.150**	-0.059	-0.144*	-0.068**	-0.189**	-0.075**	-0.083*	0.122*	-0.041
	TOTGR	0.006	0.011*	0.005		0.013	0.017	0.020	0.086**			0.004	0.075
	CURACC	-0.054**	-0.058*	-0.058	0.065	-0.344**	-0.427**	0.079	-1.340**	-0.083	-0.104	0.000	-0.113
	RGDPGR	-0.035**	-0.040	-0.014	-0.016	-0.006	-0.246	-0.306*	-0.676**	-0.026	-0.032		
	FRXRES	-0.004*	-0.007	-0.009	-0.010					-0.016*	-0.005	0.004	0.000
	PUBDBT	-0.002	-0.014	0.000	-0.030	-0.022	-0.018	-0.047**	0.054	-0.056**	-0.071**	0.013**	0.041*
	FSCDEF	0.021	-0.063			-0.081	-0.073						
	INFL	0.004	0.008	0.201	0.329	-0.350**	-0.348**	-0.044	-0.057	0.011	0.010	0.050	-0.674
	POLSTB	-0.268**	-0.656**	-0.158	-0.884*	-0.352	-0.997	-0.163	-0.635*	-0.411*	-1.023**	-0.939*	-1.759**
	EQMKT	-0.027*	-0.030	-0.023	0.016			-0.062**	-0.042	0.005		0.043	-0.159
	TRMSPRD	-0.004	-0.009	0.098	0.054	-0.457**	-0.304**			-0.000	0.007	-0.178	-1.208
	DOMCRD	-0.036	0.022	0.021	0.190*	-0.008	-0.094	0.178	-0.333	0.026	-0.005		
	M2RES	0.004**	0.004	0.026	0.017	0.005	0.014*	0.084**	0.026	0.006	0.024		
	PRTFINV	-0.038**	-0.037	-0.027	-0.004	-0.133	0.078			-0.064	-0.127	-0.031	0.405*
	INTDIFF	0.020	0.039	-0.032	0.092			0.095*	-0.192	0.038	0.017		
	LNDEPINT	-0.316**	-0.057	-0.383	-0.872*	-1.164	-4.191*	-0.657*	-0.244	1.651**	1.433*	-4.725*	-1.851*
	BKLIQ	0.020	-0.022	0.015	0.013	0.387	0.276	0.003	0.092	-0.122	-0.392**	-0.067	-0.157
	REGDEP	-0.676**	-0.475	-0.214	0.742	-0.478	-0.653					1.103	4.166*
	DEVDEP	-0.015	-0.057			-0.092	-0.230	-0.148	-0.785			-1.075	1.591
	BKCRS	1.096**	0.855*	0.271	-0.545			2.002**	3.513**	3.871**	4.744**		
	CRSNGH	0.497**	0.968**	0.558**	0.317	1.766**	1.976**			0.371	-0.561	-0.017	1.783
Post-Crisis Period $CCm_{it} = 2$	REEROVR	-0.056**	-0.095**	-0.093**	-0.141*	-0.089*	-0.058	-0.130**	-0.330**	-0.087**	-0.135**	0.084*	-0.227**
	TOTGR	-0.003	0.001	-0.005		-0.009	-0.001	0.026*	0.040			-0.017	-0.007
	CURACC	-0.003	-0.034	0.033	0.044	-0.121	-0.036	-0.122	-0.903**	0.047	-0.118	-0.008	-0.176**
	RGDPGR	-0.015	-0.036**	-0.003	-0.045	-0.150	-0.237*	-0.037	-0.362**	-0.011	-0.069*		
	FRXRES	-0.003*	-0.005	-0.005	-0.008					-0.015**	-0.003	-0.002	-0.032**
	PUBDBT	0.003*	-0.002	-0.006	-0.053**	0.006	0.064	-0.019	-0.038	-0.063**	-0.070**	0.013**	0.061**
	FSCDEF	0.033*	0.077			-0.019	0.080						
	INFL	0.008*	0.017**	-0.009	-0.329	-0.293**	-0.194**	0.035**	0.058**	0.018**	0.030*	0.071	-1.136**
	POLSTB	-0.242**	-0.500**	-0.215	-0.981**	0.252	0.518	0.122	0.590	-0.540*	-0.986**	-0.813**	-0.032
	EQMKT	-0.020	-0.023	-0.046	-0.128**			0.026	0.017	0.008		-0.028	-0.070
	TRMSPRD	-0.002	-0.002	-0.109*	-0.107	-0.287**	-0.074			-0.001	0.009	-0.098	-1.239**
	DOMCRD	-0.020	0.036	0.003	0.031	0.037	0.126	0.203	2.005**	0.078	-0.384		
	M2RES	0.004*	-0.004	0.025	-0.010	0.008**	0.008*	0.083**	0.023	-0.005	-0.021		
	PRTFINV	0.004	0.009	0.020	0.046	-0.089	0.069			-0.103	-0.014	-0.083**	-0.043
	INTDIFF	0.027	0.057**	0.017	-0.030			0.141**	0.200**	0.058*	0.093		
	LNDEPINT	-0.524**	-0.674*	-0.300	-0.823	-6.733**	-9.154**	-1.590**	-3.803**	0.514	0.529	-2.146**	-1.737
	BKLIQ	0.006	0.004	0.012	0.065	0.545**	0.171	-0.078	-0.265	-0.074	-0.199*	-0.083**	-0.481**
	REGDEP	-0.361	-0.510	-0.055	3.470	0.070	-0.343					-0.021	2.392
	DEVDEP	0.074	0.372			-0.227	-0.164	0.001	-0.231			0.045	0.099
	BKCRS	0.810**	1.257**	0.507	0.190			0.486	4.738**	3.602**	6.491**		
	CRSNGH	0.517**	0.791**	0.721**	0.240	1.113**	0.709			-0.390	-2.097	0.107	2.350**
	N	4350	4350	1740	1740	696	696	696	696	696	696	537	537
	Pseudo R^2	0.176	0.392	0.150	0.441	0.627	0.679	0.381	0.875	0.450	0.594	0.226	0.882
	Log-Likelihood	-1329.7	-441.3	-502.0	-94.5	-84.4	-64.5	-184.1	-14.6	-133.1	-53.9	-160.3	-11.0

* $p < 0.05$, ** $p < 0.01$

Table 4.13: Multinomial Logit Estimation of Currency Crises using 3 & 6 Lags

Period		Developed	Asia	Latin	E-Europe	Africa
Crisis Period $CCm_{it} = 1$	REEROVR	-0.106	-0.023	0.065	-0.006	0.073
	TOTGR	-0.021	0.030**	0.029		-0.052**
	CURACC	-0.056	-0.472**	-1.403	-0.203	0.012
	RGDPGR	-0.023	-0.311*	-1.100**	0.001	
	FRXRES	-0.001			-0.039**	-0.010*
	PUBDBT	-0.038	-0.011	-0.119	-0.023	0.016**
	FSCDEF		0.043			
	INFL	0.252	-0.425**		0.023	0.104
	POLSTB	-0.790**	-0.746*	-2.054**	-0.242	-0.087
	EQMKT	-0.081*		-0.004		-0.133
	TRMSPRD	0.423	-0.330**		-0.010	-0.081
	DOMCRD	0.169**	-0.100	0.672	-0.216	
	M2RES	0.029	-0.009	0.020	-0.019	-0.098**
	PRTFINV	0.026	-0.070			0.837*
	INTDIFF				0.106	
	LNDEPINT	-1.237*	-4.065*	0.749	1.885*	-8.966*
	BKLIQ		0.145	-0.103	0.029	0.139
	REGDEP	0.902	0.349			-1.346
	DEVDEP		0.303	-2.396**		
	BKCRS	-0.287		1.108	6.275*	
	CRSNGH		1.623**		3.326	2.158
Post-Crisis Period $CCm_{it} = 2$	REEROVR	-0.177**	-0.110**	-0.164*	-0.057*	-0.074
	TOTGR	0.018	-0.017	0.013		0.041
	CURACC	0.025	-0.348**	-2.714**	-0.189*	-0.024
	RGDPGR	-0.026	-0.281**	-0.911**	-0.002	
	FRXRES	-0.008			-0.006	-0.006
	PUBDBT	-0.032**	-0.004	0.140*	-0.023	0.076*
	FSCDEF		0.021			
	INFL	0.365	-0.227*		0.037**	-0.825*
	POLSTB	-0.765**	-0.771*	-1.112**	-0.985*	-2.195**
	EQMKT	-0.083**		-0.075		-0.129
	TRMSPRD	0.273	-0.120		-0.006	-1.888*
	DOMCRD	0.194**	-0.163	0.440	-0.226	
	M2RES	0.042	0.010*	-0.032	-0.023	0.043
	PRTFINV	-0.032*	-0.005			0.829
	INTDIFF				0.160**	
	LNDEPINT	-0.971**	-1.716	-3.027**	2.628**	-2.778
	BKLIQ		0.004	-0.020	-0.193	-0.357*
	REGDEP	0.792	1.343			7.317*
	DEVDEP		-0.173	-0.000		
	BKCRS	-0.206		4.563**	6.177**	
	CRSNGH		1.407**		1.579	0.098
	N	1740	696	696	696	531
	Pseudo R^2	0.302	0.575	0.785	0.566	0.611
	Log-Likelihood	-118.2	-85.3	-25.2	-53.9	-18.2

Period		Developed	Asia	Latin	E-Europe	Africa
Crisis Period $CCm_{it} = 1$	REEROVR	-0.141*	0.046		-0.027	
	TOTGR	0.011				
	CURACC	-0.027	-0.327**	-0.263	0.006	
	RGDPGR	-0.018	-0.151	-0.158	0.005	
	FRXRES	-0.002			-0.030**	-0.083
	PUBDBT	-0.021	-0.004	-0.239**	-0.029	0.049
	FSCDEF		0.009			
	INFL	0.168	-0.618**	-0.479**	-0.013	-0.549
	POLSTB	-0.130	-0.088	-1.144**	0.132	-0.205
	EQMKT	-0.052		-0.012		-0.600**
	TRMSPRD	0.189	-0.388**			-0.159
	DOMCRD	0.161*	0.012	-0.176	0.019	1.575
	M2RES	-0.003	0.002	0.007	0.013	-0.269*
	PRTFINV	0.046	0.110		0.177	
	INTDIFF			0.501**	-0.035	
	LNDEPINT	-0.672**	-2.738*	-0.108	0.539	3.915
	BKLIQ		0.142	-0.160	-0.092	0.122
	REGDEP	-0.482	0.100			4.158*
	DEVDEP		-0.346	-1.035*		
	BKCRS	-0.217		2.015**	3.021**	
	CRSNGH		0.407		1.780	4.532
Post-Crisis Period $CCm_{it} = 2$	REEROVR	-0.122**	-0.039		-0.020	
	TOTGR	-0.007				
	CURACC	-0.074	-0.342**	-0.350	-0.257**	
	RGDPGR	-0.031	-0.244**	-0.480*	0.003	
	FRXRES	0.001			-0.026**	-0.008
	PUBDBT	-0.024	-0.009	-0.137*	-0.003	0.019*
	FSCDEF		-0.031			
	INFL	0.205	-0.306*	-0.016	0.013	0.022
	POLSTB	-0.541**	-0.544*	-1.422*	-0.058	0.384
	EQMKT	0.010		-0.078		0.096
	TRMSPRD	0.353*	-0.147*			-0.610*
	DOMCRD	0.153**	-0.099	0.985	-0.021	-1.409
	M2RES	-0.010	-0.002	0.088*	-0.000	-0.046
	PRTFINV	0.055**	0.039		0.013	
	INTDIFF			0.029	0.054	
	LNDEPINT	-0.715**	-1.638	1.016	0.678	-1.216
	BKLIQ		0.081	-0.067	0.026	-0.108
	REGDEP	1.912*	2.070			-3.355
	DEVDEP		0.646	-1.663		
	BKCRS	-0.351		0.455	3.132**	
	CRSNGH		1.049**		1.709**	1.788*
	N	1740	696	696	696	522
	Pseudo R^2	0.239	0.452	0.624	0.428	0.440
	Log-Likelihood	-128.5	-110.2	-44.0	-70.9	-25.7

developed countries, real exchange rate overvaluation, political instability, expansion of domestic credit, and reduced lending-to-deposit interest rates increase both the probability of an approaching crisis as well as an ongoing attack even half a year in advance. Furthermore, it appears that governments are either reluctant or unable to issue public debt during times of trouble, and thus increased public debts are usually associated with tranquil periods. In the shorter run, a rising equity market index reduces the probability of an ongoing crisis.

In South-East Asia, other signalling indicators are important in explaining the likelihood of an approaching and an ongoing currency crisis. Here, real GDP growth, the balance of the current account, the rate of inflation, instability of the political arena, and the spillover of crises from regional countries play a significant role over the course of six months *a priori*. Over the same period, a diminishing term spread increases the probability of crisis onsets as it reflects worsening future economic prospects, while a low lending-to-deposit interest rate signals low profitability of the banking sector. On the other hand, one month before a speculative attack, the results detect an overvalued real exchange rate and excess liquidity in the form of rising M2 relative to the stock of foreign exchange reserves.

Turning to Latin American economies, we find that a falling growth rate of real GDP, increased tension in the political arena, and episodes of banking crises are able to signal currency crisis onsets as well as continuous attacks six months beforehand. Furthermore, increased dependence on developed world financial markets tends to reduce exchange market pressure. On the other hand, an increasing current account deficit is evidenced one quarter before and during currency crises, whereas lending-to-deposit interest rates tend to be low post speculative attacks. One month in advance, the overvaluation of the real exchange rate can explain both crisis onsets and ongoing incidents alike, while increased vulnerability to external shocks through rising terms of trade plays an important role before crashes. A growing rate of inflation and increased interest rate differential between the domestic and the foreign markets tend to prolong speculative attacks.

In case of Eastern Europe, the erosion of foreign exchange reserves and problems in the banking sector are the major signalling indicators of crisis onsets and recovery periods in the longer run, while decreased current account deficit seems to reduce the probability of ongoing crisis episodes. Over the course of three months around currency crises, real exchange rate overvaluation, a rising index of political instability, the deterioration of loan quality (as reflected by an increasing ratio of lending-to-deposit interest rate), and growing rates of inflation tend to play an important role. The other variables are only significant one month in advance. These include increased government indebtedness and the erosion of bank liquidity, which can explain both the entry and the continuation of currency crises.

Finally, looking at the region of Africa and the Middle East, we find that increased public debt, a lower money supply, stronger interdependence on regional financial markets, and reduced bank liquidity are significant indicators over the 6-month period before crisis onsets and recovery periods. Furthermore, a rising term spread and crisis incidents in neighbouring countries and major trading partners are able to explain ongoing domestic crisis episodes over the same lag length. In the shorter run, instability in the political stance and sharp reductions in foreign reserves can signal both pre- and post-crisis periods, while improving terms of trade, higher banking sector profitability (as measured by the ratio of lending-to-deposit interest rate), and lower inflows of easily reversible portfolio investments can help fend off new speculative attacks.

This concludes our discussion of the explanatory power of the multinomial logit models. Next, we turn our attention to exploring the predictive power of these models in comparison to the findings of the previous literature. As in the case of the binary logit models, the predictive performance is examined in the within-sample context as well as for the out-of-sample observations.

4.7.2 Forecasting Performance

First, we focus on the in-sample forecasts, which are illustrated in Table 4.14. The upper panel of this table depicts the predictive performance of the different models that use a 1-month lag, while the lower panel illustrates that of the models using a 3- and a 6-month lag.

The upper panel of this table emphasizes that, as mentioned before, the $CC3m$ specification of currency crises outperforms the other specifications in terms of the in-sample forecasts. In particular, the percentage of correct crisis onsets for the emerging regions lies within the range of 50-70% (except for Latin America where 90% of the crisis incidents are correctly signalled), while the percentage of correct tranquil periods is almost 100%. However, the lower panel of Table 4.14 shows that, maintaining the same accurate predictions of tranquil periods, the percentage of correct crises tends to fall significantly when using more lags of the explanatory variables.

Nevertheless, these results are in-line with those found in the previous literature, where the EWS constructed by Bussiere and Fratzscher (2006) for emerging countries was able to call correctly 65% of the crisis entry periods, but at the cost of a false alarm rate of about 20%. On the other hand, the model estimated by Racaru *et al.* (2006) has correctly forewarned 60% of the crisis incidents at a false alarm rate of 7.5%.

Considering the case of the advanced economies, which was not tackled in the previous literature using multinomial logit estimation, we find that the model performs poorly relative to a random guess (*i.e.* 50%). With only 25% of the crisis entry periods correctly called using a 1-month lag and 0-12% using a 3- or a 6-month lag, it is evidenced that the multinomial logit regression is not suitable for capturing the crisis incidents in the developed world.

A probable explanation of this phenomenon is the fact that developed countries do not require as much time and effort to recover from currency crashes as do emerging

Table 4.14: In-Sample Currency Crisis Forecasts using MLogit

	Correct Normal	Correct Crisis	Correct Post-Crisis
Using 1-month lag on all crisis definitions			
Global CCm2	99.4	9.9	5.4
CCm3	99.7	23.2	17.1
Developed CCm2	99.3	10.3	3.5
CCm3	99.9	**25.0**	18.2
S-E Asia CCm2	98.6	68.8	45.5
CCm3	98.9	**73.1**	55.0
Latin America CCm2	99.0	31.8	32.4
CCm3	99.6	**90.9**	83.3
E-Europe CCm2	98.6	26.5	24.0
CCm3	99.1	**55.6**	31.3
Africa & ME CCm2	99.2	0.0	2.6
CCm3	99.6	**50.0**	66.7
Using 3- and 6-month lags on the optimal (CC3) crisis definition			
Developed 3M	99.7	12.5	4.5
6M	100.0	0.0	0.0
S-E Asia 3M	99.2	57.7	40.0
6M	98.6	34.6	20.0
Latin America 3M	99.9	90.9	58.3
6M	99.3	45.5	41.7
E-Europe 3M	99.3	66.7	31.3
6M	99.4	44.4	18.8
Africa & ME 3M	99.2	0.0	16.7
6M	99.6	0.0	0.0

Table 4.15: Out-of-Sample Currency Crisis Forecasts using MLogit

	Correct Normal	Correct Crisis	Correct Post-Crisis
Developed 1M	98.5	–	0.0
3M	97.9	–	50.0
6M	98.7	–	50.0
S-E Asia 1M	100.0	–	0.0
3M	99.0	–	0.0
6M	99.0	–	0.0
Latin America 1M	99.5	–	0.0
3M	97.9	–	100.0
6M	94.2	–	0.0
E-Europe 1M	97.9	–	–
3M	97.9	–	–
6M	99.0	–	–
Africa & ME 1M	85.9	66.7	16.7
3M	91.9	0.0	50.0
6M	97.8	33.3	16.7

economies. This is evident from the figures presented in boldface in Table 4.1, which reflect the number and duration of currency crises in developed countries compared to that in the developing world. Therefore, the separation of crisis episodes into entry periods and post-crisis periods does not seem to fit the case of developed countries.

With respect to the out-of-sample forecasts, Table 4.15 shows that only three new crises occurred in the holdout period of 2009-2012 over the whole sample of countries, particularly in the region of Africa and the Middle East. The model estimated in this region is able to correctly call two out of those three incidents when using a 1-month lag of the signalling indicators, and only one incident using a 6-month lag. The percentage of false alarms generated by the EWS are still within the reasonable range of 10-15% as illustrated by the rate of tranquil periods correctly called.

4.8 Evaluation of EWS Methods

The criteria used to evaluate and compare the predictive performance of the constructed EWSs using the different econometric techniques are discussed in detail in section 3.4. We mainly use three evaluation criteria, namely the percentage of crisis onsets correctly predicted, the area under the ROC curve, and the QPS (or the Brier Score). The results of applying these criteria on the in-sample models that use a 1-month, a 3-month, and a 6-month lag is illustrated in Table 4.16, while the results of the dynamic signal approach are only available for the 6-month horizon. Table 4.17, on the other hand, depicts the same with respect to the out-of sample performance of the corresponding models.

It is evident from both tables that the predictive power of the EWS that uses the multinomial logit is consistently lower than that of the other two econometric techniques. With respect to the shorter-run in-sample performance, the binary logit is able to predict all the crisis entries in the emerging regions and 6 out of 8 in developed countries, whereas the multinomial logit correctly signalled only 50-70% in the emerging regions and just 2 of the 8 crisis entries in the developed region. This finding supports the notion that specifying post-crisis periods as individual crisis episodes, rather than a separate regime, can improve the effectiveness of the EWS in forewarning crisis onsets as well as duration.

Half a year before a currency crisis hits the domestic economy, the EWS based on the binary logit is able to forewarn 90-100% of these crashes in the emerging world, except in Africa and the Middle East where 1 of the 2 crises are depicted. In the advanced economies, 5 out of the 8 crises are correctly signalled. However, it is important to note that 2 of the 3 undetected episodes are the two crises that occurred in Canada, which are rather modest in severity and short in length as depicted by Figure 4.6.

The dynamic signal approach is proved to outperform the logit models in all regions, being able to provide early warning signals of almost all new crises that occurred in the in-sample period. However, this relatively high predictive power comes at the cost of a

Table 4.16: Evaluating In-Sample Performance of Currency Crises EWSs

	Developed			S-E Asia			Latin America			E-Europe			Africa & ME		
	SA	BL	ML	SA	BL	ML	SA	BL	ML	SA	BL	ML	SA	BL	ML
Models using 1-month lag															
Detected Onsets	–	6	2	–	26	19	–	11	10	–	9	5	–	2	1
Total Onsets	–	8	8	–	26	26	–	11	11	–	9	9	–	2	2
% of Correct Onsets	–	**75.0**	25.0	–	**100.0**	73.1	–	**100.0**	90.9	–	**100.0**	55.6	–	**100.0**	50.0
Area under ROC	–	0.96	0.93	–	0.99	0.98	–	1.00	1.00	–	0.99	0.97	–	0.99	0.97
QPS (Brier Score)	–	0.01	0.01	–	0.02	0.02	–	0.01	0.01	–	0.02	0.02	–	0.01	0.01
Models using 3-months lag															
Detected Onsets	–	5	1	–	22	15	–	11	10	–	9	6	–	1	0
Total Onsets	–	8	8	–	26	26	–	11	11	–	9	9	–	2	2
% of Correct Onsets	–	**62.5**	12.5	–	**84.6**	57.7	–	**100.0**	90.9	–	**100.0**	66.7	–	**50.0**	0.0
Area under ROC	–	0.92	0.90	–	0.97	0.96	–	1.00	0.96	–	0.99	0.95	–	0.97	0.94
QPS (Brier Score)	–	0.01	0.02	–	0.03	0.03	–	0.01	0.01	–	0.02	0.02	–	0.01	0.01
Models using 6-months lag															
Detected Onsets	7	5	0	25	25	9	11	11	5	9	8	4	2	1	0
Total Onsets	8	8	8	26	26	26	11	11	11	9	9	9	2	2	2
% of Correct Onsets	**87.5**	62.5	0.00	**96.2**	96.2	34.6	**100.0**	100.0	45.5	**100.0**	88.9	44.4	**100.0**	50.0	0.0
Area under ROC	0.92	0.87	0.84	0.92	0.95	0.91	0.96	0.98	0.94	0.91	0.94	0.90	0.89	0.95	0.90
QPS (Brier Score)	0.02	0.01	0.02	0.05	0.04	0.04	0.03	0.02	0.02	0.04	0.02	0.02	0.02	0.01	0.02

Note: SA denotes Signal Approach, BL Binary Logit models, and ML Multinomial Logit models

Table 4.17: Evaluating Out-Of-Sample Performance of Currency Crises EWSs

	Developed			S-E Asia			Latin America			E-Europe			Africa & ME		
	SA	BL	ML	SA	BL	ML	SA	BL	ML	SA	BL	ML	SA	BL	ML
Using 1-month lag															
Detected Onsets	–	0	0	–	0	0	–	0	0	–	0	0	–	2	2
Total Onsets	–	0	0	–	0	0	–	0	0	–	0	0	–	3	3
Percent Onsets	–	–	–	–	–	–	–	–	–	–	–	–	–	**66.7**	66.7
Using 3-months lag															
Detected Onsets	–	0	0	–	0	0	–	0	0	–	0	0	–	2	0
Total Onsets	–	0	0	–	0	0	–	0	0	–	0	0	–	3	3
Percent Onsets	–	–	–	–	–	–	–	–	–	–	–	–	–	**66.7**	0.0
Using 6-months lag															
Detected Onsets	0	0	0	0	0	0	0	0	0	0	0	0	2	2	1
Total Onsets	0	0	0	0	0	0	0	0	0	0	0	0	3	3	3
Percent Onsets	–	–	–	–	–	–	–	–	–	–	–	–	66.7	**66.7**	33.3

Note: SA denotes Signal Approach, BL Binary Logit models, and ML Multinomial Logit models

higher rate of false alarms, which can be deduced from the lower AUC statistic and the higher Brier score compared to that of the binary and the multinomial logit models.

The same results hold with respect to the holdout period, where the binary logit model (using the dynamic-recursive forecasting technique) is able to signal 2 out of the 3 crisis periods in Africa and the Middle East even six months *a priori*. The multinomial model forewarned only one period, while the dynamic signal approach has the same predictive power as the binary model but at a higher false alarm rate (refer to Table 4.6).

Thus, it may be concluded from the results of this chapter that the binary logit is the most suitable technique to construct EWSs for currency crises. However, since only few recent crises have occurred in a single region, we must be very careful when making generalized conclusions, especially that the dynamic signal approach may appear to be more adequate for policy makers who do not give much weight to the false alarm rate. Therefore, we prefer investigating the performance of these methods in the two other

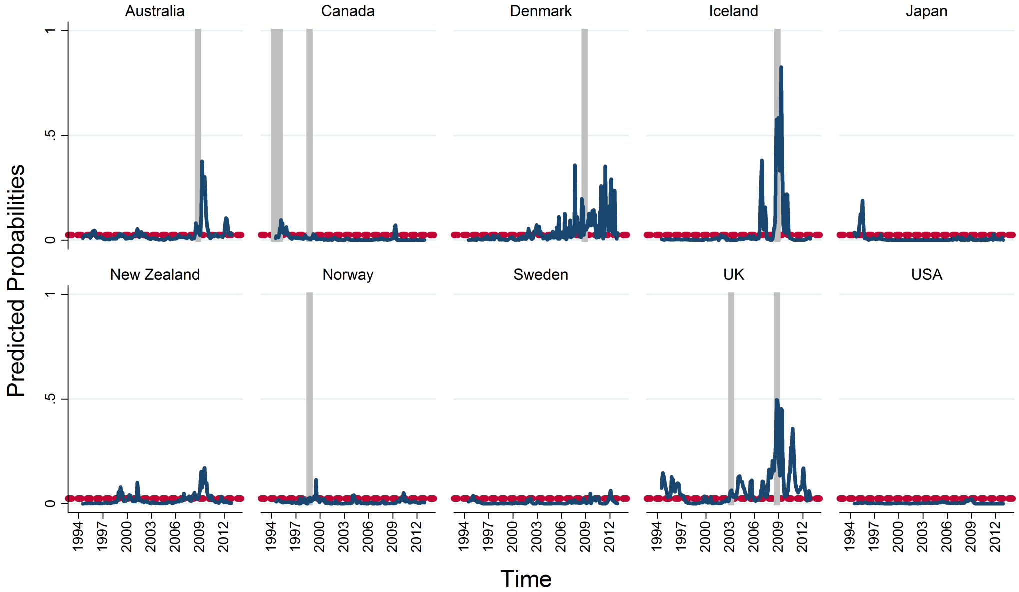

Figure 4.6: Predicted Probabilities in Developed Countries using a 6-month Lag

types of financial crises (in the next chapters) before providing a more general conclusion in Chapter 7.

Chapter 5

Modelling EWSs
The Case of Banking Crises

In the aftermath of the 2008 global financial crisis and considering the diversity of banking crisis definitions used in the literature, this chapter investigates the possibility of constructing effective EWSs to predict banking crises in both developed and developing countries. With this aim in mind, the sample data are identified in section 5.1. Then, the quantification of systemic and non-systemic banking crises is discussed in section 5.2, while section 5.3 details the proposed indicators to construct the EWSs. Brief descriptive statistics and an analytical event study are presented in section 5.4. The results of the three methods employed to build a forewarning system for banking crises are then examined in the following sections, while the last section compares the performance of the proposed methods and concludes.

5.1 Sample Data

Although most studies that investigated the construction of EWSs for banking crises tended to use low-frequency (annual) data to be able to cover a wide time span (refer for example to Bongini *et al.*, 2002; Davis and Karim, 2008a,b; Simpson, 2010; Casu *et al.*, 2012; Caggiano *et al.*, 2014), this lead to a problem of what Barrell *et al.* (2010) called "crude crises timing". Basically, a crisis that started at the very end of a year would generate the value of one for the response variable in that year and zero in the following[1], although the actual impact of the crisis occurred in that following year. Therefore, Davis and Karim (2008a) recommended the use of higher frequency data when investigating banking crises, owing to the fact that their model was unable to signal any warnings for the 2007/2008 crisis in the USA and the UK when using annual data.

Thus, to avoid this problem, a quarterly basis is chosen for the variables. This is a further contribution to the literature of EWSs for banking crises, as this frequency was not considered before, except by Wong *et al.* (2010), who investigated East Asian countries using a probit regression model, and Babecky *et al.* (2014) who considered a static signal approach. However, the use of higher frequency data is not without drawbacks. It required reducing the time period to one that spans from 1998 to 2012 due to lack of available data for some of the indicators. This period is partitioned into 1998-2007 for the in-sample estimation, while the rest of the data is left out to examine the out-of-sample predictive performance of the EWSs.

The dataset includes systemic and non-systemic crises in 30 developed and developing countries. From the advanced world, 15 economies are selected as representatives: USA, UK, Canada, Japan, Germany, France, Italy, Spain, Portugal, Greece, Finland, Belgium, Denmark, Netherlands, and Sweden. On the other hand, the developing countries chosen (mainly due to data availability) are further divided into three broad regions. From Latin America, the sample includes Argentina, Brazil, Mexico and Paraguay. The second group includes countries from South-East Asia: Indonesia, South Korea, the Philippines, and Malaysia. Finally, Turkey, Russia, Bulgaria, Latvia, Egypt, Jordan, and South Africa are selected from the region of Eastern Europe, Africa and the Middle East.

[1]So far, studies were only interested in predicting the onset of crises and the build-up of banking distress. Thus, they used to put ones for the crisis entry period(s) and either zeros for the following periods and for tranquil times, or they drop post-crisis periods altogether.

5.2 Systemic and Non-Systemic Banking Crises

As discussed in Chapter 2, there is lack of consensus in the financial economic literature regarding the most suitable way to define a banking crisis. However, following the recommendation of Barrell *et al.* (2010), we identify the timing of a systemic banking crisis using the IMF Financial Crisis Episodes database, which is reported in Laeven and Valencia (2008, 2012). The non-systemic crisis episodes are obtained from the World Bank database portrayed in Caprio and Klingebiel (2003) and its updates provided by Reinhart and Rogoff (2009, 2011). It is important to emphasise here that a systemic banking crisis is defined by the IMF as the situation in which the banking system is experiencing financial distress (expressed as significant bank runs, losses in the banking system, and/or bank liquidations) and is, therefore, receiving significant policy interventions. Particularly, a policy intervention is considered significant if at least three of the following take place[1]:

1. liquidity support (central bank claims on the financial sector) of more than 5% of deposits and foreign liabilities
2. bank restructuring costs (gross fiscal outlays directed to the restructuring of the financial sector, such as recapitalisation costs) are at least 3% of GDP
3. large-scale bank nationalisations which involve takeovers by the government of systemically important financial institutions
4. significant guarantees on bank liabilities, *i.e.* a full protection of liabilities has been issued or guarantees have been extended to non-deposit liabilities of banks
5. central bank purchases assets from financial institutions of at least 5% of GDP
6. deposit freezes or bank holidays

On the other hand, a borderline banking crisis is identified if there is evidence of significant banking problems that did not satisfy the criteria for a systemic crisis. Appendix B provides a detailed list of the crisis episodes detected in each country under investigation, as well as a description of the events causing each banking crisis.

[1] For more details refer to Laeven and Valencia (2012).

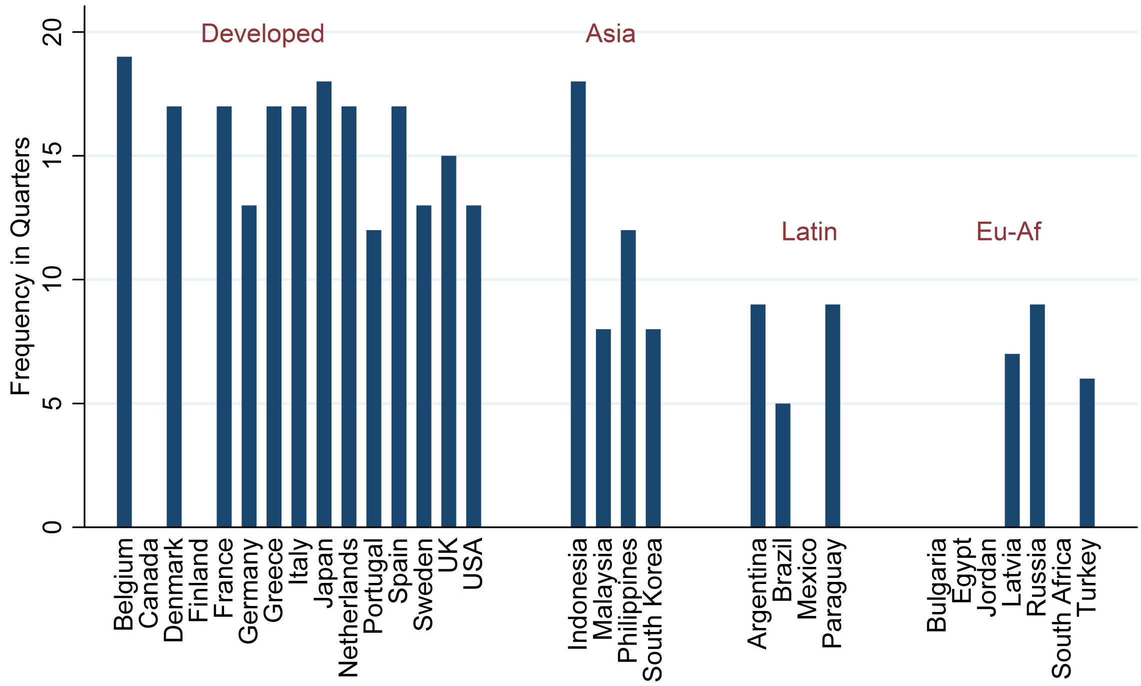

Figure 5.1: Systemic and Non-systemic Banking Crises

According to these definitions, the binary dependent variable reflecting a banking crisis in country i at time t, which is henceforth referred to as BC_{it}, assumes unity if a crisis is identified as such in these referenced databases, and is zero otherwise. Figure 5.1 summarises for each country the total number of quarters it suffered from a banking crisis over the sample period. The frequency of these crises in our sample constitutes about 17% of the total number of observations.

It is quiet remarkable from this figure that the number of quarters in which developed countries' banking sectors faced trouble are significantly greater than that in emerging economies. In fact, no banking crises were experienced in the sampled countries from Africa and the Middle East during 1998-2012. Their observations are, therefore, combined with those from Eastern European countries into a single country group[1] (refer also to Fuertes and Kalotychou, 2006).

[1] This choice of combination is based on the similarity in the descriptive statistics of most explanatory variables in both regions relative to the other groups.

5.3 Signalling Indicators of Banking Crises

The literature on EWSs discussed in Chapter 2 identified a diversity of variables that can be used for the prediction of an approaching banking crisis. These can be divided into three main categories: the first is related to the banking sector itself and the financial sector in general, the second includes real, fiscal and external factors, which can be classified under macroeconomic variables, while the third group incorporates variables that reflect possible spillover effects. Wong *et al.* (2010) showed that, although only few studies considered the contagion effect when predicting banking distress, it appears to be very useful in prediction. He argued that, just as a bank default can pose a threat to the entire banking sector within a specific country due to the banks' mutual dependence and interlinks, banking distress events in neighbouring economies may spread to the home economy.

The proposed explanatory variables to be used as signalling indicators are illustrated in Table 5.1, along with their expected directional effect on the probability of a crisis, their measurement and data sources.

5.3.1 Financial Variables

With respect to the first group of indicators, a set of consolidated bank balance-sheet variables are included as predictors. Although these variables were rarely assessed by previous studies, a recent paper by Barrell *et al.* (2010) showed their potential importance as leading indicators for banking distress in developed countries, and recommended their inclusion in the EWS. Therefore, we consider several balance-sheet items with the following justifications.

Depending on the quality, composition (loans and other earning assets) and degree of diversification of the bank assets' portfolio, the growth in banks' total assets can indicate a flourishing banking sector. However, high rates of asset growth could also result in

Table 5.1: Candidate Indicators of Banking Crisis

Symptoms	Indicators	Measurement	Exp. Sign	Data Source
Financial Sector	BKASSTGR	rate of change in total bank assets	-	IFS line 21 + 22A + 22D
	NONPERF	ratio of non-performing loans[a] to total bank liabilities	+	World Bank GFS[b]
	BKCAP	bank capital-assets ratio	- / +	bank capital: IFS line 27
	BKLIQ	bank reserves to total assets ratio	-	bank reserves: IFS line 20
	ZSCR	volatility-adjusted ROA & equity	-	World Bank GFD[b]
	CBLOAN	ratio of central bank loans to total liabilities	+	CB loans: IFS line 26G liabilities: IFS 24+25+26
	RIR	nominal deposit interest rate minus inflation rate	+	deposit rate: IFS line 60L
	IBOR	3-month interbank rate	- / +	National Sources
	LNDEPINT	ratio of lending to deposit interest rate	- / +	lending rate: IFS line 60P
	DOMCRD	ratio of domestic credit to GDP	+	IFS line 32
Macro-economic	RGDPGR	12-month % change in real GDP	-	OE: National Accounts
	INFL	rate of change in CPI	+	IFS line 64
	M2RES	% change in the ratio of M2 to foreign exchange reserves[c]	-	National Sources
	REEROVR	deviation of real effective exchange rate from 2-year rolling mean	-	IFS line RECE
	FSCDEF	budget deficit as % of GDP	- / +	OE: Gov. Accounts
	EXPGR	% change in exports	- / +	IFS line 70
	CURACC	current account balance as % of GDP	- / +	OE: Trade & Balance of Payment
	PUBDBT	gross gov. debt as % of GDP	- / +	OE: Gov. Accounts
Spill-over	EXTDBT	total external debt as % of GDP	+	OE: Trade & Balance of Payment
	HPI	% change in house price index	-	OE: Housing Market; National Sources
	BKCONT	sum of neighbouring countries facing crisis	+	neighbouring: regional & leading trading partners

Notes: (a) loans with overdue interest or principal payments for over 90 days. (b) interpolated from annual data using cubic spline. (c) With respect to Eurozone countries, M2 represents the contribution of the national component of the monetary aggregate to the Euro area, while the foreign exchange reserves are those held by the national central banks and the monetary authorities, excluding the reserves held at the European Central Bank.

greater risk-taking and deteriorating quality of lending decisions, making the financial system more vulnerable to shocks in the real sector. To reflect this latter point, we also consider the percentage of non-performing loans as an indicator of the poor health of the banking sector. On the other hand, an increase in the capital-asset ratio is expected to fend off financial distress, as the accumulation of bank capital can act as a buffer in case of trouble[1]. Nevertheless, Barrell *et al.* (2010) argued that, in the build-up of banking distress, governments try to inject massive amounts of capital in more than one large bank. Therefore, the direction of the relation is ambiguous *ex-ante*.

A more clear-cut effect is that of the share of liquid reserves in the banking sector assets, since the availability of sufficient liquidity reduces the probability of banking distress. Furthermore, to reflect the volatility-adjusted buffer (equity plus returns) of the banking system, the weighted[2] average z-score of each country's individual banks is considered.

In addition, three measures of interest rates[3] are included to assess bank profitability. Being the major cost category in the banks' financial statements, a rise in the real interest rate is considered bad news for the entire banking sector. On the other hand, a rise in the deposit rate that is associated by an offsetting rise in the lending rate may not be so alarming for banks. Therefore, the lending-to-deposit interest rate is also included in the EWS (refer to Lang, 2013). Yet, its expected effect on the probability of a crisis is not very clear, since an increasing ratio signals more bank profitability, but also higher credit costs, which may lead to a deterioration in the quality of loans, as only the highly risky investment projects can afford to pay it. The third interest rate considered is the interbank rate, where a low rate signals cheap access to funds in case of trouble, while a high rate is more profitable for the lending banks.

Another important indicator of bank distress is the share of central bank loans (being the lender-of-last-resort) in the total liabilities of the banking industry, since a significant

[1] Capital-asset ratio is used rather than the potentially more relevant risk-adjusted capital adequacy ratio due to data availability issues, especially in developing countries.

[2] The weights are based on the individual banks' total assets.

[3] Since the interest rates in the Eurozone countries are partially managed by the ECB, the coefficients of these variables should be interpreted with some caution.

increase would indicate an alarming state of illiquidity in the entire financial sector. On similar grounds, excessive expansions in domestic credit make the banking sector more vulnerable to adverse economic shocks, and thus increase the probability of systemic crises. We add the domestic credit with an extra lag relative to the other variables to capture the effect of credit boom-bust cycles (Demirguc-Kunt and Detragiache, 1998; Wong *et al.*, 2010).

5.3.2 Macroeconomic Indicators

Turning to the macroeconomic variables, a growing economy in terms of real GDP is reasonably expected to have a healthy financial sector due to improving credit quality, while crises are usually associated with periods of recession that adversely affect the ability of borrowers to pay back their loans. Likewise, high rates of inflation cause macroeconomic instability and are expected to have an adverse effect on the financial sector, as they discourage saving and reduce the value of loan repayments. On the other hand, injections of liquidity[1] in the financial sector in the form of expanding money supply can prevent individual bank problems from growing into a systemic crisis.

On fiscal grounds, a rise in the financing needs of the government (due to increased fiscal and current account deficits, a rising public debt, a slowdown in export growth, and/or increased pressure on the domestic currency[2]) can contribute to banking sector distress by hindering the government from providing it with the necessary support. However, if these financing needs are translated into granting more secure loans to a creditworthy government at the expense of risky loans to the private sector, a poor fiscal sector may indeed be beneficial to the degree of risk undertaken by the banking industry.

[1] In the Eurozone, the money supply is limited by the ECB regulations to control inflation. Therefore, one should be cautious when interpreting the coefficient of this variable.

[2] Pressure on the domestic currency is measured by a negative deviation from the 2-year rolling mean of the real effective exchange rate measured in domestic units. With respect to the Eurozone, changes in REER carry a different interpretation than the other regions due to their common nominal exchange rate. Thus, cross-section changes are either due to differences in the price deflator or the share in international trade across the zone countries.

5.3.3 Spillover Effect

Finally, banking distress may also rise due to spillovers from other domestic or foreign sectors. High on that list is the mortgage market, where growth in house prices spells good news for banks engaging in mortgage loans. However, if the price boom progresses into a bubble, its eminent burst would significantly increase the chances of borrower defaults. This could jeopardise the health condition of the entire banking system, which was the case in the 2008 global financial crisis.

Another source of possible overflow of problems is a huge bill of external debt. A heavily indebted government can put extra burdens on the banking sector to bail it out, which could eventually lead to a liquidity crisis. Furthermore, an increasing number of banking crises in the region and/or in countries with close trading and financial links could be reasonably expected to adversely affect the domestic economy to a great extent.

In order to assess the behaviour of these proposed indicator variables around crisis times, we next turn to a brief event study and analysis of their descriptive statistics over the sample period.

5.4 Descriptive Statistics and Event Study

In light of the methodology discussed in Chapter 3, a basic quantitative analysis and an illustrative event study can be quite useful in modelling a warning system. Therefore, we begin by a description of the potential crisis indicators over the different economic states as demonstrated in Table 5.2. The left panel of this table depicts the variable means over the global sample during tranquil times vs. near-crisis and crisis periods. It also reports the statistic of a two-sided mean-differential t-test along with its significance at the 5% level. The null hypothesis of the test is mean equality across both states ($H_0 : \mu_0 - \mu_1 = 0$). Similarly, the right panel of the table shows the significance of the mean-differentials in the individual country regions.

Table 5.2: Quantitative Analysis of Banking Crisis Indicators

	Global Model			Regional Models			
Indicator	No Crisis	Crisis	t-stat	Developed	Asia	Latin	EuAf
Financial Sector							
BKASSTGR	3.0	4.4	-0.9	×	×	×	×
NONPERF	5.0	8.0	-2.2*	×	✓	✓	×
BKCAP	12.1	11.9	0.2	✓	×	✓	×
BKLIQ	8.3	5.3	3.6*	✓	✓	×	✓
ZSCR	16.1	7.8	8.1*	✓	✓	✓	✓
CBLOAN	2.2	5.7	-4.2*	✓	✓	×	×
RIR	0.6	2.6	-1.8	×	×	✓	×
IBOR	6.2	13.9	-3.5*	✓	✓	✓	✓
LNDEPINT	3.1	2.1	4.0*	✓	✓	✓	×
DOMCRD	3.4	4.2	-2.1*	✓	×	×	×
Macroeconomic Variables							
RGDPGR	3.5	-1.3	7.4*	✓	✓	✓	×
INFL	4.8	8.2	-2.0*	✓	×	×	×
M2RES	2.0	-4.1	2.8*	✓	✓	×	×
REEROVR	1.3	-4.8	3.2*	×	✓	×	×
EXPGR	2.8	3.5	-0.1	✓	×	×	×
CURACC	-0.5	-0.1	-0.4	×	×	×	×
FSCDEF	-1.5	-2.8	1.8	✓	×	×	×
PUBDEBT	71.4	57.6	2.9*	×	×	×	✓
Spillover							
HPI	1.8	0.4	1.5	✓	×	✓	×
EXTDBT	2.9	4.2	-2.3*	×	✓	×	×
BKCONT	0.3	0.8	-3.3*	✓	✓	✓	✓

Notes: The t-stat is the test statistic of the mean differential t-test between the two economic states. The Welch adaptation of the t-test is used to account for the unequal variances and sample sizes of the two economic states.
Both * and ✓denote significance at the 5% level.

Without going into much detail about the probable significance of the individual indicators, as this is formally tested and discussed in the following sections, Table 5.2 illustrates that the financial sector variables tend to change substantially prior to banking crises relative to the macroeconomic indicators. Likewise, the variables that reflect the possible spillover from other sectors or countries seem to behave differently as well in the build-up of banking distress, especially the contagion variable.

The more striking finding is that the behaviour of the indicators around crisis episodes is quite different across the individual country regions. A variable that has a high potential of being an early warning indicator in one region may not be so useful in another. Nevertheless, it can be noted that the z-score, the interbank interest rate and the banking crisis contagion variable have consistently different means in tranquil times compared to crises periods in all the regions, while bank assets growth and the current account do not exert a significant shift in their behaviour.

Probably more insight can be gained from a graphical illustration of the behaviour of the individual candidate signalling indicators around crisis periods as compared to tranquil times. In this respect, Figure 5.2 shows the means of the variables during the four possible phases an economy can go through: normal times, pre-crisis period, crisis onset, and post-crisis periods. It is evident from this figure that some variables change dramatically even before the onset of the crisis: bank capital, bank liquidity, z-score, CB loans, interbank interest rate, external debt, inflation, and real GDP growth. Other variables (like real interest rate, exchange rate overvaluation, and money supply) change only at the onset of the crisis or in the post-crisis, and thus are not expected to play a significant role as warning indicators.

After discussing the quantification of systemic and non-systemic banking crises and the signalling indicators that can be used to provide early warning signals, we now proceed to the construction of EWSs for banking crises using the methods detailed in Chapter 3.

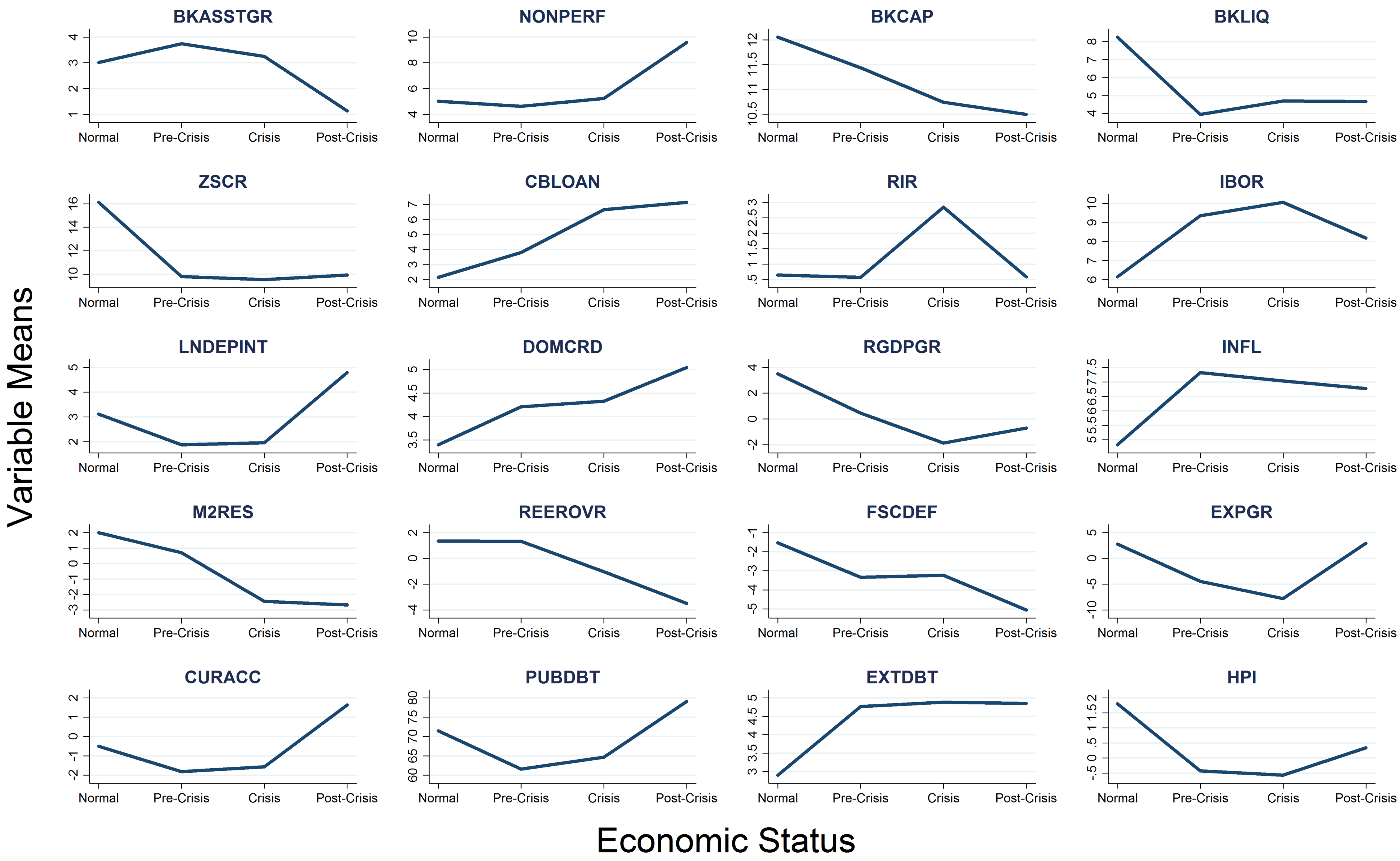

Figure 5.2: Behaviour of Candidate Variables around Banking Crisis Episodes

5.5 Dynamic Signal Extraction Approach

The econometric methods applied to build an EWS for banking crises have undergone several developments in recent years. The earliest method used was the traditional signal approach suggested by Kaminsky and Reinhart (1999). Recently, Casu *et al.* (2012) proposed a modification to this method to make it more dynamic and global. They argued that the traditional static percentile thresholds that depend on the sample-specific distribution of the variables would cause repeated application on different time periods to give different results for the same set of indicators. Experimenting with a pool of OECD countries using an annual data frequency, they found that their dynamic model performs better in both the within- and out-of-sample cases.

In this section, we extend their model application to each country region (rather than pooling them together) using quarterly (instead of annual) data, and compare the forecasting results to those found by the other papers that applied a static model. The investigation of how the predictions of the dynamic model compare to those provided by the parametric methods, namely the binary and the multinomial logit regressions, is also conducted in section 5.8.

Our analysis begins by constructing a forward-looking dependent variable of banking crises. This multinomial response variable (BCs_{it}) is set up to assume the value of one during the crisis window (h) before the onset of crises (as depicted by BC_{it}), the value of two during the crisis periods, and is zero during tranquil times. The formula used to create BCs_{it} can be outlined as follows:

$$BCs_{it} = \begin{cases} 1 & if\ \exists\ k = 1, \ldots, h\ s.t.\ BC_{i,t+k} = 1 \\ 2 & if\ BC_{i,t} = 1 \\ 0 & otherwise \end{cases} \tag{5.1}$$

We experimented with different values of h in order to identify the most appropriate crisis window that can generate accurate in-sample forecasts with sufficient lead time for policy responses. The same window will then be used to conduct out-of-sample predictions. In particular, h is first set to two quarters[1], which allows policy makers a reasonable period of six months to make pre-emptive interventions in the banking sector. Two other specifications of the crisis window are also considered, namely one quarter and one year. However, the grid search confirmed that both specifications tend to give lower $NTSR$ levels for most indicators. Hence, setting $h = 2$, we next turn to the results of the grid search to analyse the performance of the indicators that can provide early warnings for banking crises.

5.5.1 Individual Indicators and Composite Index

The purpose of the grid search, outlined in (3.3), is to find for each explanatory variable the optimal threshold level that, if crossed, the variable would issue a signal of an approaching crisis. Accordingly, the in-sample predictive performance of these signals can be evaluated on the basis of the percentage of correct crisis onsets that were forewarned six months in advance. In this respect, Table 5.3 details the results of the grid search on the individual indicators over the global pool of countries and in each country region separately.

The results in this table show that most variables considered have an optimal $NTSR < 0.5$ in all regions, which indicates that they are able to issue twice as many good signals as noise. This high signal persistence is clearly apparent from the figures depicted in column four of Table 5.3. Only in two regions of Latin America and Eastern Europe, Africa and the Middle East, there are a few indicators with relatively high $NTSR$. Another general conclusion that can be drawn from the table is that, for each region, there is a distinct set of indicators that performs significantly well in predicting the onsets of banking crises. This supports the notion from Table 5.2 that the symptoms of banking crises are different across the regions, implying regional heterogeneity of the signalling indicators.

[1]With respect to the Asian countries, where the banking crisis occurred in the beginning of 1998, only the first quarter is considered a pre-crisis period.

Table 5.3: Results of Grid Search on Individual Indicators

	Global				Developed		SE-Asia		Latin America		Eu-Af	
	NTSR	Onsets	Lead	Persist	NTSR	Onsets	NTSR	Onsets	NTSR	Onsets	NTSR	Onsets
BKASSTGR	0.37	20.0	1.1	2.7	0.43	0.0	0.07	25.0	0.20	50.0	0.20	50.0
NONPERF	0.39	60.0	1.2	2.6	0.55	50.0	0.14	75.0	0.12	50.0	0.41	50.0
BKCAP	0.29	20.0	1.9	3.5	0.25	0.0	0.28	25.0	0.45	50.0	0.08	50.0
BKLIQ	0.27	100.0	3.7	3.7	0.12	100.0	0.26	50.0	0.48	50.0	0.25	100.0
ZSCR	0.24	20.0	1.9	4.2	0.34	100.0	0.01	100.0	1.13	0.0	0.23	50.0
CBLOAN	0.32	20.0	2.5	3.1	0.74	0.0	0.04	75.0	0.36	50.0	0.33	50.0
RIR	0.33	20.0	3.9	3.0	0.24	50.0	0.02	75.0	0.33	50.0	0.37	50.0
IBOR	0.25	40.0	3.1	4.0	0.19	50.0	0.02	100.0	0.30	50.0	0.14	50.0
LNDEPINT	0.50	0.0	3.8	2.0	0.79	0.0	0.04	100.0	0.51	100.0	0.41	50.0
DOMCRD	0.15	40.0	3.1	6.7	0.11	50.0	0.09	75.0	0.33	50.0	0.34	50.0
RGDPGR	0.24	60.0	3.2	4.2	0.29	50.0	0.03	100.0	0.25	100.0	0.24	50.0
INFL	0.43	20.0	2.9	2.3	0.49	50.0	0.04	75.0	0.35	50.0	0.68	50.0
M2RES	0.24	40.0	1.5	4.2	0.24	50.0	0.04	100.0	0.36	50.0	1.11	50.0
REEROVR	0.42	20.0	0.3	2.4	0.65	50.0	0.02	100.0	0.42	50.0	1.31	0.0
FSCDEF	0.26	40.0	1.2	3.8	0.79	50.0	0.25	25.0	0.24	50.0	0.12	50.0
EXPGR	0.51	60.0	3.5	1.9	0.78	50.0	0.11	75.0	0.57	50.0	0.26	100.0
CURACC	0.34	20.0	2.8	2.9	0.81	0.0	0.35	25.0	0.38	100.0	0.29	100.0
PUBDBT	0.56	0.0	3.3	1.8	0.08	50.0	0.16	75.0	0.19	100.0	0.47	50.0
EXTDBT	0.38	20.0	3.6	2.6	0.22	100.0	0.05	100.0	0.33	50.0	1.37	0.0
HPI	0.26	60.0	3.4	3.9	0.21	50.0	0.18	50.0	0.17	100.0	1.73	0.0
BKCONT	0.18	0.0	0.5	5.4	0.05	50.0	0.06	75.0	1.33	0.0	1.32	0.0

Particularly, in developed countries, bank profitability and liquidity seem to play the major role in predicting banking distress. Furthermore, rising external indebtedness tends to precede problems in the domestic banking sector. While the macroeconomic variables do not appear to play an important role in advanced countries, they have an equally significant predictive power as the financial indicators with respect to the Asian countries. On the other hand, in Latin America, spillover from a deteriorating mortgage market, slowdown in the economic activity, and increased public debt are the main symptoms of an approaching banking crisis. In the combined region of Eastern Europe, Africa and the Middle East, bank liquidity is vital to keep the banking sector healthy, as well as a sound external sector in terms of increased export growth and an improving current account balance.

Furthermore, it is remarkable that these best performers in the different regions are able to correctly predict 100% of the crises that occurred during the in-sample period. Nevertheless, from the point of view of policy makers, it is not sufficient for a signalling indicator to provide accurate forecasts, but also to generate signals of approaching financial distress reasonably early. Therefore, it is quite satisfactory to find in the third column of Table 5.3 that more than 60% of the indicators considered can generate signals at least six months before the build up of banking distress. With respect to the financial sector variables, three indicators tend to generate their first signals almost one year in advance, namely real interest rate, lending-to-deposit rate and bank liquidity. The earliest warnings generated by the macroeconomic variables are those of export growth, public debt and real GDP growth, which are issued more than three quarters in advance. Likewise, spillover of problems from an increased sovereign debt and falling real estate prices are able to provide signals as early as three quarters before crises hit the different economies.

Inasmuch as the warning signals of the individual indicators can be alarming to policy makers, a more reliable signal would be the one issued by a composite index of underlying financial and real sector weaknesses. Basically, whereas a signal from a specific indicator, no matter how persistent, warns of a particular weakness, an alarm generated by the com-

Table 5.4: Conditional Probabilities of the Composite Index

Composite Index Values	Conditional Probabilities
0-8	0.5
9-16	0.8
17-24	2.4
25-32	13.3
33-40	22.2
41-48	66.7

posite index of different financial, macroeconomic and spillover indicators spells turmoil for the entire economy. It is, therefore, more relevant for policy makers to construct such indices for each region and evaluate their in- and out-of-sample predictive performance.

Following the formula depicted in (3.4), the composite index for each region is constructed as the NTSR-weighted average of the individual indicators that performed best in that region (*i.e.* that had $NTSR \leq 0.4$). Similarly, the global index is formed out of the best performers in the entire pool of countries. Consequently, the final step in designing an EWS using the dynamic signal approach requires converting this composite index into warning signals. This entails calculating the conditional probability of an approaching banking crisis implied by each value of the index. The calculations are performed in accordance with (3.5).

On that account, Table 5.4 depicts the different values of the global composite index and the corresponding probability of an approaching crisis conditional on that particular index level. As can be reasonably expected, the probability of an approaching crisis increases with the value of the composite index. Plotting the time-series of the conditional crisis probabilities in each country, as calculated by their respective regional composite indices, gives Figure 5.3.

The horizontal line in this figure corresponds to the optimal cut-off level, above which the composite index is said to issue a warning signal of a probable crisis. In accordance with (3.2), the optimal cut-off level is selected as the one that maximises Youden's J-

Table 5.5: Banking Crisis Forecasts using Dynamic Signal Approach

	Optimal Cut-off	Correct Onsets	Correct Crisis	False Alarm
In-sample Forecasts (1998-2007)				
Global	10	85.0	60.7	18.4
Developed	30	100.0	52.9	12.8
S-E Asia	10	100.0	63.2	6.1
Latin America	10	100.0	84.2	13.5
Eu-Af	10	71.4	70.0	2.3
Out-of-sample Forecasts (2008-2012)				
Developed	30	95.7	74.7	64.9
S-E Asia	10	–	–	12.5
Latin America	10	–	–	26.2
Eu-Af	10	100.0	66.7	11.7

statistic. Furthermore, the shaded areas denote the periods in which the economy was suffering a banking crisis. Consequently, the predictive performance of the dynamic signal approach can be assessed by comparing the quarters in which the composite index crossed the cut-off level, and hence generated a warning signal, with the actual crisis incidents over the crisis window.

5.5.2 Predictive Power

The upper panel of Table 5.5 depicts the in-sample predictive performance of the global, as well as the regional, EWSs constructed using the dynamic signal approach over the period 1998-2007. For each EWS, we calculate the percentage of crisis onset periods correctly predicted two quarters in advance, in addition to the percentage of signals that were not followed by a crisis within the crisis window (*i.e.* the false alarm rate). Furthermore, in order to assess the effectiveness of the EWSs in predicting crisis duration, as well as its onset, we also calculate the percentage of every correctly predicted crisis period.

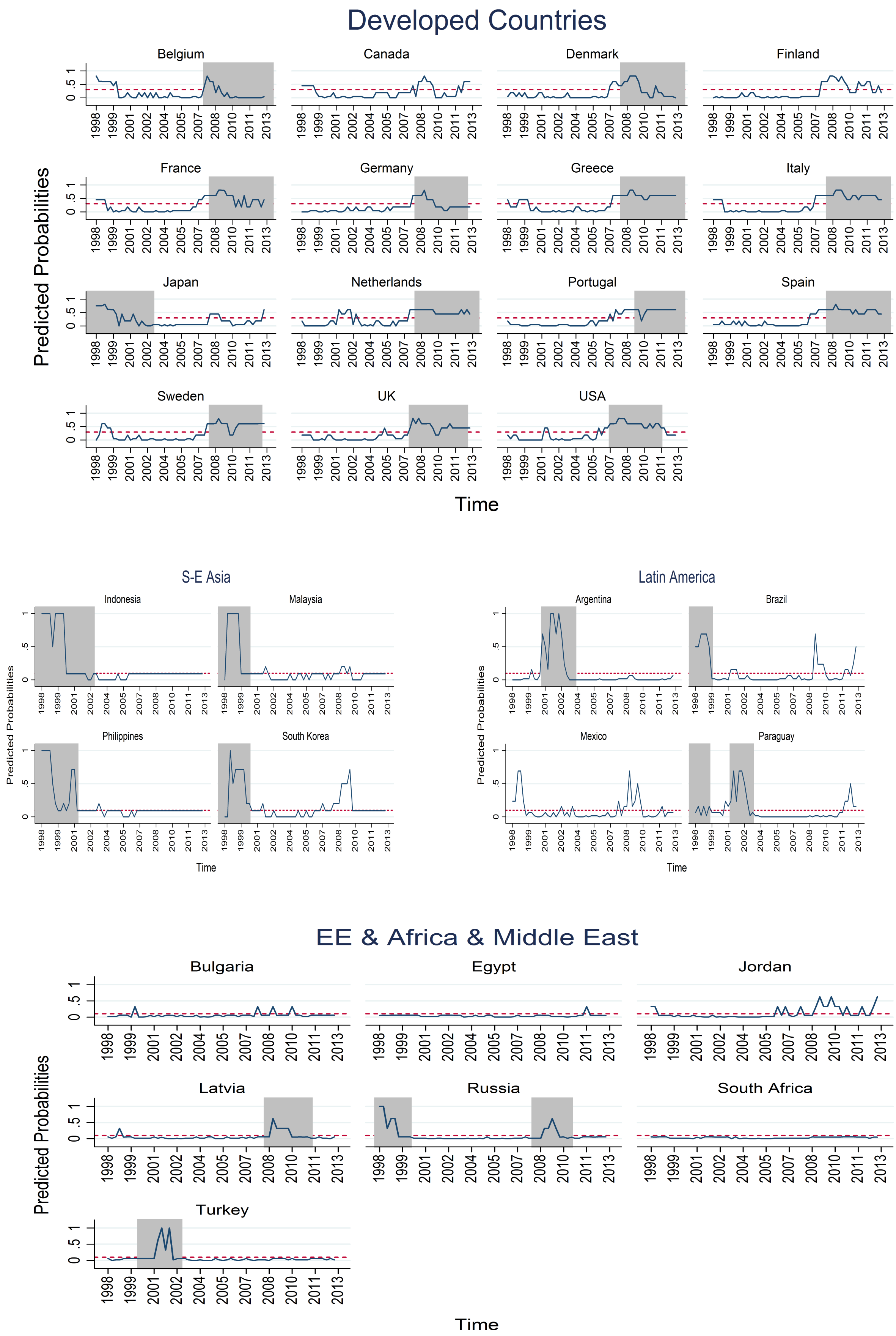

Figure 5.3: Conditional Probabilities vs. Crisis Incidents

Keeping the false alarm rate within a reasonably acceptable bound of 10-15%, the regional models in developed countries, South-East Asia, and Latin America are accurately able to predict 100% of the crises that hit over the in-sample period. In the region of Eastern Europe, Africa and the Middle East, five out of the seven crisis onsets were correctly forewarned while hardly generating any false alarms at all. On the other hand, the global model is only able to predict 85% of the crisis onsets, and it generates a higher false alarm rate. Hence, the regional models seem to outperform the global one, which confirms the necessity of accounting for regional heterogeneity when constructing EWSs for banking crises.

When considering the findings of the previous literature, it is surprising to note that the papers by Kaminsky (1999), Kaminsky and Reinhart (1999) and Goldstein *et al.* (2000), who designed the signal extraction approach, did not report the hit rates of their models. In addition, Kaminsky and Reinhart (1999) did not construct a composite index, while Kaminsky (1999) and Goldstein *et al.* (2000) only reported the QPS of their composite indices. More recently, however, studies became more interested in reporting the hit rate, as well as the false alarm rate, of their models in order to evaluate their forecasts from a policy-maker's point of view.

With respect to the static version of the signal approach, Davis and Karim (2008b) used annual data on a pool of both developed and emerging economies, and had a hit rate of a mere 15% and a false alarm rate of 12%. Significantly better results were found by Babecky *et al.* (2014) when using quarterly data, as they were able to predict correctly 70% of the crisis onset periods while issuing 35% of false signals. At a lower range of false alarms, the model constructed by Drehmann (2013) had the same hit rate of about 70%. On the other hand, using the dynamic signal approach, Casu *et al.* (2012) experienced a significantly higher false alarm rate of 70% to be able to predict correctly 100% of the crisis onset periods. Clearly, our *regional* dynamic models stand out strikingly as compared to either the static or the global dynamic versions.

The final and most important test of our EWS entails assessing the out-of-sample forecasts of the different regional models over the holdout period 2008-2012, which signifies the recent global financial crisis. Using the same cut-off probabilities, the same indicators that are found to perform best over the in-sample period, and the same thresholds and crisis window, we use the constructed composite indices to provide out-of-sample forecasts. The results of these forecasts are outlined in the lower panel of Table 5.5. It is remarkable from the results of this table that the EWS in Eastern Europe is able to forewarn correctly *all* the crisis onsets that occurred in Russia and Latvia over the holdout period, while issuing a reasonable error rate of 12%.

More interestingly, almost all banking crises which hit the developed economies in the recent years are correctly predicted by our regional model. In fact, 96% of the onsets are forewarned six months in advance, as well as 75% of every period spent in banking distress. This, however, comes at the expense of a significantly high false alarm rate that amounts to 65%. Taking a closer look at Figure 5.3, we can observe that this high rate is mainly due to the signals of banking sector problems in both Canada and Finland, which were mitigated by policy interventions[1]. Thus, in a sense, the signals in these two countries cannot be considered as real false alarms, but rather as warnings of avoided crises.

Compared to the findings of Casu *et al.* (2012), which is the only paper that reported out-of-sample forecasts, it can be noticed that our results are perfectly consistent with theirs. The dynamic model they constructed for OECD countries had a hit rate of 96% and above 60% of false alarms. The fact that our out-of-sample rates are almost identical in the case of developed countries confirms their claim that using a dynamic version of the signal approach can provide more consistent results across counties and over time. This latter finding, in addition to the better predictive performance of the dynamic models,

[1] The global financial crisis hit the Finnish economy in early 2009, but the banking sector was kept sound by holding a large buffer of capital, while suffering limited bankruptcies and non-performing loans (OECD, 2014). In Canada, the economy was adversely affected by the US crisis in the beginning of 2008, yet the banks received a huge bailout to avoid the build-up of a systemic banking crisis (MacDonald, 2012).

substantiates their superiority over the traditional static version of the signal extraction approach.

5.6 Binary Logit Model

The main advantage of running a parametric regression over a non-parametric model like the signal approach, regardless of its predictive performance, is the ability to test hypotheses about the regressors. Furthermore, it enables the estimation of each indicator's marginal effects on the probability of an approaching crisis, while accounting for the possible interactions among the various indicators, which the signal approach simply ignores. However, estimating regression models has its own limitations and difficulties that need to be carefully considered and addressed.

In this respect, and as early as Demirguc-Kunt and Detragiache (1998), there were several concerns with respect to the behaviour of some explanatory variables (e.g. domestic credit, real interest rate) after the onset of a banking crisis, which is likely to be affected by the crisis itself or the policies adopted to mitigate it. Therefore, studies have tended to drop all observations following the onset of a banking crisis to avoid such endogeneity[1] (Lestano *et al.*, 2003; Davis and Karim, 2008a; Wong *et al.*, 2010; Gourinchas and Obstfeld, 2012; Drehmann, 2013; Babecky *et al.*, 2014). However, the huge drawback of this approach is the loss of many observations, as well as the episodes of multiple crises (*i.e.* new periods of distress while the economy is still in or has just recovered from one).

Thus, as an alternative approach, we prefer to use the WB database to identify the beginning and the end of each crisis[2], and we include the crisis aftermath periods as individual crisis incidents. That is, the dependent variable takes the value of unity for the entire crises periods and is zero during tranquil times only. Another possible solu-

[1] Other studies have either used zeros for both recovery periods and tranquil times (e.g. Barrell *et al.*, 2010), assumed a common duration for all crises (Kaminsky and Reinhart, 1999), or attempted to use a continuous variable (like a fragility index (Singh, 2011), a financial stress index (Oet *et al.*, 2013), the ratio of bank liquidity to total bank assets (Christofides *et al.*, 2012), and the stock price index of the banking sector (Simpson, 2010)) instead of a binary crisis indicator.

[2] Refer to Appendix B for more details about each case study.

tion would be to define a multinomial dependent variable, as suggested by Bussiere and Fratzscher (2006), which takes different values for the various stages of the economic status. This approach is considered later in section 5.7.

With respect to applying the first approach, Table 5.6 summarises for each region the results of running a binary logit regression of the banking crises response variable (BC_{it}) on the candidate signalling indicators with a 1-quarter lag, while Table 5.7 depicts the corresponding results using two lags over the period 1998-2007. In both tables, the global model that includes all countries under consideration involves a pooled regression including only regional dummies. On the other hand, Table 5.8 displays the results of applying fixed- and random-effects models.

5.6.1 Regional Heterogeneity

Before going into detail regarding the explanatory power of the individual indicators, we first compare the three reported goodness-of-fit measures (McFadden's Pseudo R^2, log-likelihood ratio, BIC) across the different models. It is quite striking that the composite models in Table 5.6 and 5.7 (*i.e.* the global model (1) and that of the consolidated emerging markets (3)) have relatively poor fits compared to the models of the individual regions. This result is formally confirmed by the in-sample predictive performance, which is discussed in detail further below. This finding is also reported in the literature as cited in Caggiano *et al.* (2014).

Taking a closer look at the coefficients and their significance in the various regions provides a reasonable explanation for this phenomenon. Foremost, the regional dummies in Table 5.6 and 5.7 are all statistically significant. Furthermore, it seems that there is great discrepancy in the magnitude and the importance of the marginal effects of the individual indicators across the country groups. That is, there is no general agreement as to the leading indicators of banking crises.

Table 5.6: Binary Logit Regression of Banking Crises using 1 Lag

	(1) Global	(2) Developed	(3) Emerging	(4) S-E Asia	(5) Latin Am.	(6) Eu-Af
BKASSTGR	0.013	0.093**	0.000	-0.097		0.173**
NONPERF	0.280**	0.127	0.208**	-0.129	2.037**	-0.128
BKCAP	0.061*	0.215	0.066*	0.074*	1.736**	0.946**
BKLIQ	-0.079**	-8.411**	-0.053*	-0.707**	-0.561**	-1.353**
ZSCR	-0.117**	-0.029	-0.104**	-0.216**	-0.703**	0.002
CBLOAN	0.181**	1.069**	0.082	0.004	0.081	1.017**
IBOR	0.022	-0.022	0.023	-0.380*		
LNDEPINT	0.087**	0.386**	-0.519	-2.255		
DOMCRD	0.021					
RGDPGR	-0.281**	-1.141**	-0.177**		-0.656**	-0.427
INFL	-0.030		-0.045*		-0.035	-0.058
M2RES	-0.003	-0.177**	0.006		0.013	
REEROVR	-0.067**	-0.448**	-0.059**	-0.081*	0.128	
FSCDEF	-0.059	-1.093**				
CURACC	0.046	-0.779**				
PUBDBT	-0.045**	-0.103**				
HPI	-0.040	-1.048*	-0.032			-0.074**
EXTDBT	-0.397**		-0.215	7.366**	-2.781	0.648
BKCONT	0.480**	7.093**	0.355	0.745		
Asia	-1.377*					
Latin	-1.969**					
EuAf	-2.578**					
N	1140	585	585	156	156	273
Pseudo R^2	0.609	0.876	0.565	0.718	0.790	0.811
Log-Likelihood	-125.5	-7.9	-95.8	-25.6	-12.9	-8.1
BIC	405.8	117.9	293.6	111.8	81.4	77.9
Optimal Cut-off	10	15	20	20	15	20
% of Correct Crisis	89.3	100.0	80.8	92.9	100.0	90.0
% of False Alarm	8.3	0.7	7.6	9.6	6.7	1.5

* $p < 0.05$, ** $p < 0.01$

Table 5.7: Binary Logit Regression of Banking Crises using 2 Lags

	(1) Global	(2) Developed	(3) Emerging	(4) S-E Asia	(5) Latin Am.	(6) Eu-Af
BKASSTGR	0.006	-0.392	0.008	-0.135		0.217**
NONPERF	0.231**	0.119	0.171**	-0.280*	1.153**	-0.224
BKCAP	0.044	0.790**	0.047	0.048	0.813	0.912**
BKLIQ	-0.057*	-32.554**	-0.037	-0.667	-0.260**	-0.759**
ZSCR	-0.113**	0.004	-0.097**	-0.231*	-0.323*	-0.141
CBLOAN	0.137**	2.672**	0.050	-0.110	0.188	0.709**
IBOR	0.034	-0.031	0.037	-0.403*		
LNDEPINT	0.052	1.180**	-0.377	-3.245		
DOMCRD	0.075					
RGDPGR	-0.284**	-2.234*	-0.187**		-0.595**	-0.209
INFL	-0.049		-0.063*		-0.108	-0.063*
M2RES	-0.022	-0.281	-0.012		-0.037	
REEROVR	-0.039*	-0.178	-0.033	-0.095	0.137	
FSCDEF	-0.056	-3.143**				
CURACC	-0.003	-2.090**				
PUBDBT	-0.037**	-0.142*				
HPI	-0.058	-2.456**	-0.032			-0.079*
EXTDBT	-0.412**		-0.131	9.120**	-1.386	0.039
BKCONT	0.359*	16.585**	0.271	1.159*		
Asia	-0.940					
Latin	-1.708**					
EuAf	-1.825**					
N	1140	570	570	152	152	266
Pseudo R^2	0.586	0.788	0.528	0.747	0.686	0.687
Log-Likelihood	-135.8	-2.0	-97.4	-21.6	-17.9	-13.3
BIC	426.5	105.5	296.3	103.6	91.2	88.1
Optimal Cut-off	20	25	15	30	20	5
% of Correct Crisis	84.5	100.0	83.6	92.1	100.0	90.0
% of False Alarm	4.8	0.2	9.5	7.9	6.8	3.9

* $p < 0.05$, ** $p < 0.01$

Table 5.8: Binary Logit Regression of Banking Crises using Fixed / Random Effects

	Global		Developed		Emerging	
	FE	RE	FE	RE	FE	RE
BKASSTGR	0.041	0.032			0.042	0.039
NONPERF	0.202**	0.295**	1.481	-0.183	0.224**	0.220**
BKCAP	0.055	0.056			0.043	0.064
BKLIQ	-0.235	-0.088	-4.578*	-4.515*	-0.107	-0.035
ZSCR	-0.250**	-0.172**	0.765	0.226	-0.313**	-0.160*
CBLOAN	0.090	0.217**		0.560	0.057	0.091
IBOR	0.044	0.043			0.032	0.040
LNDEPINT	-0.015	-0.002		0.252	-0.742	-0.546
DOMCRD	0.975	0.596*		0.207	-0.595	0.296
RGDPGR	-0.188*	-0.214**	-2.005	-0.339	-0.167*	-0.205**
INFL	-0.094**	-0.050*			-0.096**	-0.065*
M2RES	0.018	0.007	-0.136	-0.163	0.019	0.022
REEROVR	0.004	-0.034			-0.009	-0.042
FSCDEF	-0.032	-0.032		-0.806	-0.023	-0.006
CURACC	0.034	0.030		-0.275	0.035	0.071
PUBDBT	-0.074**	-0.045**			-0.046*	-0.032
HPI	-0.028	-0.030	-0.707	-0.555	-0.024	-0.025
EXTDBT	2.757*	-0.219			2.094	0.657
BKCONT	-0.113	0.167		2.995	-0.328	-0.093
N	418	1140	78	570	342	570
Pseudo R^2	0.623	0.502	0.862	0.895	0.628	0.539
Log-Likelihood	-64.5	-112.9	-3.9	-8.5	-53.5	-84.3
BIC	249.7	380.7	33.9	105.9	217.8	302.1
Optimal Cut-off	1	1	1	1	1	1
% of Correct Crisis	38.1	48.8	55.6	88.2	44.8	62.7
% of False Alarm	12.9	0.6	6.7	0.2	5.1	1.2

* $p < 0.05$, ** $p < 0.01$
Note: Fixed effects model excludes all countries that did not experience a banking crisis during the in-sample period. Therefore, it is run on a smaller number of observations.

In particular, the macroeconomic variables seem to play an equally important role as those of the financial sector in explaining the occurrence of banking distress in developed countries. However, there is no evidence of the real sector's significance with respect to any of the individual emerging markets, save for the growth of real GDP, which reduces the probability of macroeconomic shocks in Latin America, and the overvaluation of the real exchange rate, which adversely affects banks with debts denominated in foreign currencies in South-East Asia. An overvalued currency can also drain the foreign reserves of the central bank, as it attempts to defend the domestic currency from devaluation, which in turn reduces its ability to bail out banks in trouble (especially those with high foreign liabilities). This situation may, therefore, lead to a twin currency-banking crisis.

In the advanced economies, four additional macro variables appear significant even half a year before the crisis hits the economy. First, directing credit to a financially distressed government to cover its budget deficit and/or pay back public debt seems to be enforcing some degree of discipline on the credit-granting choices of banks, as it leaves them with a lower amount of funds to grant to private borrowers with lower creditworthiness. Furthermore, the injection of liquidity in the economy, as measured by an increasing ratio of M2 to international reserves, has a significant positive effect on developed-country banks as it helps prevent distress from turning into systemic crises. Finally, a growing and unsustainable current account deficit seems to be adversely affecting the financial sector in general.

Likewise, the significance of the variables reflecting the possibility of spillover either from the real estate sector, as measured by the house price index, or from the banking sector in neighbouring economies is again only evident in developed countries. However, the real estate sector appears to be influential as well in Eastern Europe, Africa and the Middle East, while banking crisis contagion is only marginally significant in Asia. A growing stock of external debt, on the other hand, puts extra burden on banks to bail out the government, and thus increases the probability of banking sector problems mainly in South-East Asia.

With respect to the emerging markets in general, the financial sector and the consolidated bank balance-sheet variables appear to be playing the major role in explaining an approaching banking crisis. Consistent among all developing countries is the significance of an increase in the capital-assets ratio (which appears to accumulate at the expense of liquidity), the erosion of bank liquidity, and the fall of the consolidated z-score. On the other hand, the ratio of non-performing loans is a significant indicator in Latin America, while increased acquisition of credit from the central bank and growing bank assets are pertinent mainly in Eastern European countries, Africa and the Middle East.

Putting together the results from Table 5.6 and 5.7, it is evident that the effects of almost all these leading indicators across the regions are significant up to two quarters before crises. Thus, the estimated models can give policy makers a period of up to six months in advance to take necessary actions in case of financial turmoil.

5.6.2 Simplicity vs. Complexity

Another important finding can be drawn by comparing the results of the pooled logit with regional dummies to those of a fixed- and random-effects models. Consistent with the literature[1], as described in detail in Chapter 2, the fixed-effects model which accounts for country-specific heterogeneity fits the data considerably better than the pooled logit and the random-effects model in terms of the Pseudo R^2, the log-likelihood ratio and the BIC criteria. Despite that fact, however, the last panel of Table 5.6 and 5.8 shows that the pooled models profoundly outperform those of the random- and the fixed-effects in terms of the in-sample predictions. This is what Fuertes and Kalotychou (2006) and Savona and Vezzoli (2015) quoted as "simplicity beats complexity in forecasting"[2].

In fact, the pooled models that use the 1- or even the 2-quarter lag are able to forewarn 100% of the crisis episodes that occurred in developed countries and in Latin America. Furthermore, over 90% of the crises that took place in South-East Asia and in Eastern

[1]For more details refer to Fuertes and Kalotychou (2006, 2007).
[2]A more detailed discussion of this finding is provided in subsection 7.3.2.

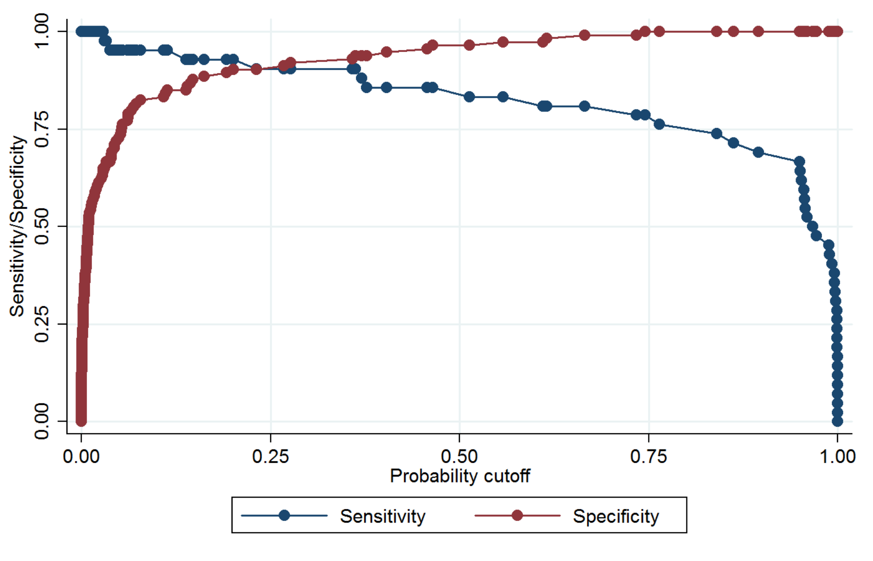

Figure 5.4: Optimal Probability Cut-off Point for Banking Crises

Europe, Africa and the Middle East are predicted without issuing higher than 10% of false signals. On the other hand, the fixed-effects models are not able to improve over a random guess, as they only predict 50% of the crisis incidents; while the random-effects models are able to signal 60% of crises in emerging markets and 88% of the crises in developed economies.

It is important to note here that the optimal cut-off probability reported in these tables refers to the threshold above which the corresponding model is said to issue a signal of an approaching crisis. This threshold is calculated so as to maximise Youden's J-statistic (3.2). A graphical presentation of how this threshold is chosen is provided in Figure 5.4, where the downward-sloping line shows the sensitivity of the correct crisis signals, while the upward-sloping line shows the specificity of the correct tranquil periods predicted at every possible cut-off level. The level that maximises the J-statistic tends to be around the intersection of both lines.

Comparing the estimated models' in-sample forecasts with those found in the literature of constructing EWSs for banking crises using a binary logit model, it is evident that the results of our regional models that account for the entire crisis periods stand out fairly well. Starting with hit rates as low as 30-40% in Lestano *et al.* (2003) and Ari and

Dagtekin (2007) to a rate of 60-70% in Demirguc-Kunt and Detragiache (1998), Barrell *et al.* (2010) and Caggiano *et al.* (2014), it was deduced that such EWSs are not very useful in predicting banking crises. Even in Bongini *et al.* (2002), where the authors were able to significantly improve the predictive power of their model to around 90%, and in Wong *et al.* (2010), where the hit rate reached 100%, they had to endure a false alarm rate of 25-30%, which is quite high even for conservative policy makers.

Notwithstanding the very satisfactory results of our in-sample forecasts compared to those found in the literature, the true predictive power of an EWS can only be effectively tested using out-of-sample forecasts, which we turn to next.

5.6.3 Predictive Performance

In order to test formally the out-of-sample predictive power of the proposed models, the regressions, which are estimated over the period 1998-2007, are used to provide predictions over the 2008-2012 holdout period of observations. Using the same optimal cut-off points calculated over the in-sample, a classification table is constructed with the percentages of correct crises and tranquil periods forewarned by the EWSs, as well as the missed crisis episodes and the false alarm signals, which are all detailed in Table 5.9.

The upper panel of the table shows the results of a regular forecast, where the regression is estimated once over the sub-sample and the predicted probabilities are calculated for the entire holdout period using these same estimates. With an average of 50-70% chance of correctly signalling an approaching crisis, it can be concluded that the models are far less useful in practice than within-sample. This fact is already established by the previous literature, and it was mainly attributed to the changing, and even unique, nature of banking crises which results from the continuously evolving financial systems, instruments and integrations that bring about new risks and threats through new channels.

However, the picture changes completely in the lower panel of the table, which depicts the results of applying our novel dynamic-recursive forecasting technique. By continu-

Table 5.9: Out-of-sample 2008-2012 Banking Crisis Forecasts

	Developed		S-E Asia		Latin America		Eu-Af	
	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags
Regular Forecast								
% of Correct Crisis	54.3	48.4	–	–	–	–	75.0	50.0
% of Missed Crisis	45.7	51.6	–	–	–	–	25.0	50.0
% of Correct Tranquil	92.1	95.6	75.0	80.0	100.0	100	95.3	84.4
% of False Alarm	7.9	4.4	25.0	20.0	0.0	0.0	4.7	15.6
Dynamic-Recursive Forecast								
% of Correct Crisis	82.3	83.9	–	–	–	–	91.7	83.3
% of Missed Crisis	17.7	16.1	–	–	–	–	8.3	16.7
% of Correct Tranquil	88.6	87.7	93.7	100.0	100.0	100.0	90.6	90.6
% of False Alarm	11.4	12.3	6.3	0.0	0.0	0.0	9.4	9.4

ously updating the model every period with the new information (*i.e.* observations) as it becomes available, and by feeding the model with the lag of the previously predicted probabilities, the out-of-sample forecasts are immensely improved.

In fact, the model is able to predict about 85% of the current global financial crisis incidents that occurred in developed countries even two quarters in advance, and 85-90% of the crises that occurred during the past five years in Eastern Europe. In South-East Asia and Latin America, where no banking crisis occurred during the holdout period, the model is still capable of correctly signalling 95-100% of the tranquil periods.

Very few papers in the literature have attempted calculating the out-of-sample forecasts of their models, save for Wong *et al.* (2010) that had an average hit rate of 85% with around 30% of false alarms, and Barrell *et al.* (2010) who provided predictions of a two-year holdout period and was only able to predict 60% of the crisis episodes at a false alarm rate of 20%. Thus, once more, our EWS and forecasting technique seem to improve remarkably on the findings of the previous literature.

5.7 Multinomial Logit Model

An alternative approach to construct an EWS for banking crises, while neither losing the post-crisis observations nor falling into an endogeneity problem, is to adopt a multinomial logit method. This econometric technique entails defining a three-state (rather than a binary) dependent variable to capture the different states of the economy: normal, crisis, and post-crisis/recovery periods.

Accordingly, as discussed in section 3.3, the first step to apply this method is to transform the binary BC_{it} into a multinomial variable. In order to make our results comparable to those of the previous literature[1], we set the crisis entry periods to the first four quarters (*i.e.* first year) of the crises depicted by BC_{it}. The following periods till the economy returns to the normal state, as indicated by the WB database detailed in Appendix B, are classified as post-crisis episodes. Hence, the multinomial response variable BCm_{it} can be defined as:

$$BCm_{it} = \begin{cases} 0 & if\ BC_{it} = 0 \\ 1 & if\ \exists\ k = 0, \ldots, 3\ s.t.\ BC_{it-k} = 1 \\ 2 & otherwise \end{cases} \tag{5.2}$$

where BC_{it} denotes the binary dependent variable used in the binomial logit regression, while the value of zero reflects the tranquil periods, the value of unity the crisis entry quarters, and the value of two the post-crisis episodes.

5.7.1 Estimation Results

Accordingly, Table 5.10 summarises the results of regressing the constructed multinomial dependent variable on the first lag of the explanatory variables using the cumulative logistic distribution, while Table 5.11 reports the same when using the second lag of the indicators. The upper panel of these tables illustrates the marginal effects on the proba-

[1]See, for example, Davis and Karim (2008a); Wong *et al.* (2010); Caggiano *et al.* (2014)

bility of entering into a new crisis due to a small change in the corresponding indicators, while the second panel depicts the marginal effects on the probability of being in the post-crisis or recovery period.

The lower panel of both tables summarises the results of the goodness-of-fit criteria for each model. It is evident from these figures, as is the case with the binary logit regressions, that the separate regional models provide better fits than the consolidated models with both developed and developing countries or with all developing countries pooled together. We, therefore, drop these consolidated models in columns (1) and (3) from our further analyses and focus only on the regional models.

With respect to the financial sector in advanced economies, a rising ratio of non-performing loans, the erosion of bank liquidity, and the rapid growth of bank assets at the expense of liquidity are among the major signalling indicators of approaching, as well as ongoing, banking crises even six months in advance. Furthermore, increasing bank capital seems to signal government injections to bail out banks, and thus increases the probability of an approaching crisis. The interbank interest rate appears to play a significant role in explaining both economic stances as well. In this respect, a high rate implies expensive interbank loans and, thus, increases the probability of going into crisis; while the post-crisis period is more associated with a low rate, as the central bank intervenes to lower this rate and facilitate access to funds in times of trouble.

Turning to the macroeconomic variables, the results show that the injection of liquidity into the financial system (reflected by the growth of M2) can help in preventing banking sector problems from growing into a systemic crisis, as well as recovering from one. On the other hand, increased exchange market pressures caused by an overvalued domestic currency tends to contribute to banking sector distress. Likewise, a slowdown in the growth of real GDP and a growing current account deficit raise the probability of a crisis onset. Other variables that play an important role over the long term (6 months) with respect to avoiding the onset of a banking crisis include an increasing government budget deficit and/or a rising public debt, which tend to reduce the riskiness of the total

Table 5.10: Multinomial Logit Regression of Banking Crises using 1 Lag

		(1) Global	(2) Developed	(3) Emerging	(4) S-E Asia	(5) Latin Am.	(6) Eu-Af
Crisis Period $BCm_{it} = 1$	BKASSTGR	0.021	0.039	0.047	0.102		0.343**
	NONPERF	0.281**	0.698**	0.244**		1.644**	-0.269*
	BKCAP	0.107	0.319*	0.157*	0.385**	0.642**	1.029**
	BKLIQ	-0.068*	-2.317**	0.014	0.021	-0.408**	-0.638*
	ZSCR	-0.159**		-0.161**	-0.349**	-0.115	-0.099*
	CBLOAN	0.137		0.092			0.800**
	IBOR	0.013	1.048**	0.036	-0.437	0.183	-0.073*
	LNDEPINT	0.017		-1.389*	0.754	-3.243*	-0.050
	DOMCRD	-0.261					
	RGDPGR	-0.295**	-1.203**	-0.219**		-0.525**	-0.106
	INFL	-0.045		-0.049			-0.027
	M2RES	0.003	-0.072*	0.004	-0.192*	0.012	
	REEROVR	-0.091**	-0.495**	-0.087**	-0.089		
	FSCDEF	-0.005	-0.530**	0.157			
	CURACC	0.024	-0.317*	-0.112			-0.187**
	PUBDBT	-0.042*	-0.047*	-0.006		-0.237	
	HPI	-0.026	-0.626*	-0.029			-0.116**
	EXTDBT	-0.657*		-0.388	8.825**	1.849	
	BKCONT	0.299	4.189**	0.368	2.977**		
Post-Crisis Period $BCm_{it} = 2$	BKASSTGR	-0.001	-0.083	-0.007	-0.091		0.113
	NONPERF	0.293**	0.608**	0.230**		1.246**	0.238*
	BKCAP	0.061*	0.112	0.078*	-0.064	0.916**	0.232
	BKLIQ	-0.098**	-1.772**	-0.069*	-0.767**	-0.269	-0.261*
	ZSCR	-0.111**		-0.079**	-0.106	-0.437*	0.026
	CBLOAN	0.200**		0.109			0.408**
	IBOR	0.027	-2.949**	0.040	-0.257	0.174	-0.024
	LNDEPINT	0.093*		-0.273	-2.603*	0.552**	-1.194
	DOMCRD	0.030					
	RGDPGR	-0.252**	0.160	-0.176**		-0.392	-0.227*
	INFL	-0.006		-0.046			0.015
	M2RES	-0.007	-0.290**	0.009	0.022	0.007	
	REEROVR	-0.067**	-0.194*	-0.056**	-0.084*		
	FSCDEF	-0.082	-0.638	0.022			
	CURACC	0.051	0.198	0.092*			-0.045
	PUBDBT	-0.052**	-0.061*	-0.044**		-0.106	
	HPI	-0.086	-0.237	-0.033			-0.018
	EXTDBT	-0.386**		0.609	3.443	0.837	
	BKCONT	0.488*	2.994**	0.121	-0.599		
	N	1140	585	585	156	156	273
	Pseudo R^2	0.595	0.906	0.544	0.723	0.793	0.814
	Log-Likelihood	-154.4	-8.3	-120.2	-30.0	-15.7	-9.1

* $p < 0.05$, ** $p < 0.01$

Table 5.11: Multinomial Logit Regression of Banking Crises using 2 Lags

		(1) Global	(2) Developed	(3) Emerging	(4) S-E Asia	(5) Latin Am.	(6) Eu-Af
Crisis Period $BCm_{it} = 1$	BKASSTGR	0.034	-2.335**	0.067	-0.040		0.111
	NONPERF	0.164**	3.034**	0.188**		2.062*	-0.213
	BKCAP	0.107*	3.166**	0.154*	0.337**	0.660	0.788**
	BKLIQ	-0.014	-8.263**	0.034	0.179	-0.521	-0.415**
	ZSCR	-0.135*		-0.163**	-0.254**	0.279	-0.595**
	CBLOAN	0.079		0.087			0.750**
	IBOR	0.047	9.223**	0.050	-0.024	0.157	-0.085**
	LNDEPINT	-0.032		-0.947*	2.446	-1.498	-2.016**
	DOMCRD	0.080					
	RGDPGR	-0.175*		-0.124		-0.289	-0.284**
	INFL	-0.058		-0.071			-0.086*
	M2RES	-0.022	0.120	-0.021	-0.151**	-0.057	
	REEROVR	-0.025	0.211	-0.032	0.039		
	FSCDEF	0.031	-1.708**	0.087			
	CURACC	-0.098	-0.847*	-0.192**			
	PUBDBT	-0.013	-0.542**	-0.006		-0.733*	
	HPI	-0.022	-2.162*	-0.024		-0.609	-0.035
	EXTDBT	-0.342		-0.361	4.368**	11.362*	
	BKCONT	0.315	18.736**	0.083	2.574**		
Post-Crisis Period $BCm_{it} = 2$	BKASSTGR	0.001	-0.150**	-0.006	-0.064		0.354*
	NONPERF	0.188**	0.260	0.204**		7.097**	-0.049
	BKCAP	0.060	0.097	0.052	0.048	4.602**	1.068**
	BKLIQ	0.005	-4.454**	-0.055	-0.408*	-1.933**	-0.380*
	ZSCR	-0.092**		-0.075*	-0.166**	-2.577**	-0.148
	CBLOAN	0.159**		0.065			0.917**
	IBOR	0.053	-4.815**	0.044	-0.282*	-0.147	-0.167**
	LNDEPINT	0.024		-0.188	-1.646	3.481**	-8.881**
	DOMCRD	0.722**					
	RGDPGR	-0.277**		-0.221**		-1.298**	-0.769**
	INFL	-0.036		-0.068*			-0.131**
	M2RES	-0.023	-0.278**	-0.013	-0.053	-0.180**	
	REEROVR	-0.003	0.020	-0.037	-0.092**		
	FSCDEF	-0.009	-0.680	0.012			
	CURACC	-0.059	0.143	0.084*			
	PUBDBT	-0.009	0.009	-0.032**		-0.437*	
	HPI	-0.106	-0.346*	-0.075		3.802*	-0.173*
	EXTDBT	-0.131		0.497	4.585**	-3.281	
	BKCONT	0.623**	3.018**	0.182	0.606*		
	N	1140	570	570	152	152	266
	Pseudo R^2	0.573	0.971	0.530	0.708	0.785	0.637
	Log-Likelihood	-147.7	-2.4	-115.4	-28.0	-15.1	-16.9

* $p < 0.05$, ** $p < 0.01$

amount of credit granted by banks. Regarding the possibility of contagion, the results indicate that spillovers from the real estate sector, as well as banking crises in financially interlinked countries, seem to have a crucial effect on the probability of suffering a crisis in the domestic banking sector.

We next turn to the region of South-East Asia, where a diminishing z-score indicates the fragility of the domestic banking sector. Furthermore, an increasing capital-asset ratio reflects government interventions during crisis entry periods, while lower levels of liquidity tend to prolong the recovery period. In addition to the financial sector, there are two macroeconomic variables that appear significant in the Asian economies: real exchange rate overvaluation, which increases the probability of a twin crisis, and the growth of the money supply, which reflects injections of liquidity into the financial system. On the other hand, a growing stock of external debt burdens the banking sector (specifically the central bank) to bail out the government, and contagion from bank distress in countries with close financial links increases the probability of entering into and remaining in a banking crisis.

With respect to Latin America, non-performing loans, bank capital and liquidity are all major signalling indicators of pre- and post-crisis periods. In addition, the z-score and the lending-to-deposit interest rate are important in explaining ongoing banking crises. With respect to the real sector, a growing real GDP reduces the probability of a crisis onset, while an increasing public debt helps discipline bank credit-granting schemes by requiring banks to lend to a more creditworthy government rather than to the private sector. On the other hand, the spillover variables do not seem to play a significant role in the Latin American economies.

Finally, we consider the countries in the combined region of Eastern Europe, Africa and the Middle East, where the results indicate the importance of the bank balance-sheet variables over the other types of indicators. Even two quarters in advance, the bank capital-to-asset ratio, liquidity and z-score, the percentage of credit acquired from the central bank, and the interbank interest rate appear to have a significant effect on the probability of banking crises. With respect to the macroeconomic variables, both the real GDP growth and the rate of inflation exhibit explanatory power of approaching banking crises, as well as ongoing ones. Moreover, rapidly decreasing asset prices appear to be contributing to banking sector distress in these countries.

Following this detailed discussion of the statistical significance of the candidate signalling indicators of banking crises and their ability to explain the occurrence of new, as well as ongoing, periods of distress, we next turn to investigate the predictive ability of the estimated models and to evaluate their performance as EWSs for banking crises.

5.7.2 Predictive Performance

We investigate the predictive performance of the estimated models in the within- and out-of-sample cases using a 1- and a 2-quarter lag of the explanatory variables. The results are detailed in Table 5.12, where the upper panel depicts the in-sample percentages of correct tranquil, crisis entry, and post-crisis periods forewarned by the different regional models. The second and the lower panels outline the same with respect to the out-of-sample performance of the models using the regular and our novel dynamic-recursive forecasting techniques, respectively.

With regards to the in-sample forecasts, the model estimated in the developed region is able to predict all the crisis onsets and 85-100% of the ongoing crisis episodes without issuing almost any false alarms. Compared to the predictive performance of the EWS constructed by Barrell *et al.* (2010), which focused on developed economies, where they were able to predict correctly 66% of the crisis entry periods while generating a false alarm rate of 29%, it is obvious that our model outperforms significantly.

In the emerging regions, 85-100% of the crisis entry periods are correctly predicted three months in advance at a false alarm rate that does not exceed 3%. When predicting the crisis entries 6-months in advance, the accuracy of the models falls to around 70-75% in Latin America and Eastern Europe, Africa and the Middle East, but remains at 100%

Table 5.12: Forecasting Performance of Multinomial Logit EWSs for Banking Crises

	Developed		S-E Asia		Latin America		Eu-Af	
	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags
In-Sample Forecasts								
% of Correct Tranquil	99.8	100.0	97.4	97.4	99.3	97.7	99.6	99.6
% of Correct Crisis Entry	100.0	100.0	100.0	100.0	87.5	75.0	85.7	71.4
% of Correct Post-Crisis	86.7	100.0	75.0	80.0	84.6	90.9	100.0	100.0
Regular Out-of-Sample Forecasts								
% of Correct Tranquil	90.4	97.4	90.0	93.8	98.8	98.8	95.3	79.7
% of Correct Crisis Entry	55.3	27.7	–	–	–	–	50.0	37.5
% of Correct Post-Crisis	20.1	27.3	–	–	–	–	0.0	50.0
Dynamic-Recursive Out-of-Sample Forecasts								
% of Correct Tranquil	83.3	87.7	100.0	100.0	98.8	98.8	95.3	95.3
% of Correct Crisis Entry	55.3	31.9	–	–	–	–	62.5	37.5
% of Correct Post-Crisis	59.7	64.0	–	–	–	–	25.0	25.0

in South-East Asia. These results are considered a substantial improvement over those found in the literature, where Caggiano *et al.* (2014) reached a sensitivity rate of 65% at a false alarm rate of 27% in African countries.

With respect to the more policy-relevant out-of-sample forecasts, the models that are estimated over the period 1998-2007 are then used to generate predictions of the holdout quarters from the beginning of 2008 till the end of 2012. Using the regular h-period ahead forecasting technique, the second panel of Table 5.12 shows that the estimated models are only able to predict 30-50% of the new crises that occurred during the holdout period. The percentage of false alarms is also relatively high ranging from 10-20%.

However, these results improve to some extent when using the dynamic-recursive forecasting technique, which is depicted in the lower panel of Table 5.12. In advanced economies, the hit rate of crisis entries improves marginally, while the percentage of correct post-crisis periods forecasts has almost tripled (from 20-25% to 60-65%) but at the expense of higher false alarms. In Eastern Europe, Africa and the Middle East, the hit rate increased to 60% for the model that uses the 1-quarter lag, while the false alarm rate of the model using the 2-quarter lag has diminished significantly to 5% (down from 20%). Although the previous literature has not yet attempted to investigate the out-of-sample performance of the multinomial logit models in forecasting banking crises, it is evident that these results do not improve much, if at all, over a random guess.

5.8 EWS Evaluation and Conclusion

Following our discussion of the different econometric techniques that can be used to construct EWSs for banking crisis, it is rather important to compare their predictive performance in order to identify the most accurate method. In this respect, Table 5.13 evaluates both the in- and the (dynamic-recursive) out-of-sample forecasts of all the estimated models in this chapter according to the three evaluation criteria detailed in section 3.4.

It is clearly noticeable from the boldfaced figures in the upper (in-sample) panel of this table that the *binary logit* model outperforms the other two techniques with respect to the percentage of correctly forewarned crisis onsets, the area under the ROC curve and the Brier score. This result is valid when using either the 1- or the 2-quarter lagged models. Note that the forecasts of the dynamic signal approach are only comparable with the 2-quarter lagged models as it uses a fixed crisis window of two quarters.

Particularly, the binary logit method is able to call correctly 100% of the in-sample new crisis episodes that occurred in three of the four country regions six months in advance. The multinomial logit model could not reach this level of accuracy in Latin America, while the dynamic signal approach, though it correctly predicted all the onsets in these regions, has a relatively lower ROC statistic and a higher QPS, indicating a higher false alarm rate. Furthermore, in Eastern Europe, Africa and the Middle East, the binary

Table 5.13: Evaluating the Performance of Banking Crises EWSs

		Developed			S-E Asia			Latin America			Eu-Af		
		SA	BL	ML	SA	BL	ML	SA	BL	ML	SA	BL	ML
In-Sample Performance	*Models using 1-quarter lag*												
	Detected Onsets	–	3	3	–	6	6	–	8	7	–	6	6
	Total Onsets	–	3	3	–	6	6	–	8	8	–	7	7
	% of Correct Onsets	–	**100.0**	100.0	–	**100.0**	100.0	–	**100.0**	87.5	–	**85.7**	85.7
	Area under ROC	–	1.00	0.99	–	0.97	0.96	–	0.99	0.99	–	0.99	1.00
	QPS (Brier Score)	–	0.00	0.00	–	0.05	0.07	–	0.03	0.02	–	0.01	0.01
	Models using 2-quarters lag												
	Detected Onsets	2	2	2	3	3	3	8	8	6	5	6	5
	Total Onsets	2	2	2	3	3	3	8	8	8	7	7	7
	% of Correct Onsets	100.0	**100.0**	100.0	100.0	**100.0**	100.0	100.0	**100.0**	75.0	71.4	**85.7**	71.4
	Area under ROC	0.81	1.00	1.00	0.83	0.98	0.95	0.90	0.98	0.98	0.94	0.99	0.97
	QPS (Brier Score)	0.06	0.00	0.00	0.12	0.04	0.06	0.08	0.04	0.03	0.03	0.01	0.01
Out-of-Sample Performance	*Models using 1-quarter lag*												
	Detected Onsets	–	36	26	–	0	0	–	0	0	–	7	5
	Total Onsets	–	47	47	–	0	0	–	0	0	–	8	8
	Percent Onsets	–	**76.6**	55.3	–	–	–	–	–	–	–	**87.5**	62.5
	Models using 2-quarters lag												
	Detected Onsets	45	31	15	0	0	0	0	0	0	8	6	3
	Total Onsets	47	47	47	0	0	0	0	0	0	8	8	8
	Percent Onsets	**95.7**	66.0	31.9	–	–	–	–	–	–	**100.0**	75.0	37.5

Note: SA denotes Signal Extraction Approach, BL Binary Logit models, ML Multinomial Logit models model correctly specified six, compared to only five using the other two methods, out of the seven crisis onset periods.

As mentioned before, these results are very satisfactory compared to the ones found in earlier literature. This could be partially attributed to the higher frequency of the data and the variation of the indicators used: consolidated balance sheet, real and financial sector, and spillover variables, as well as indicators that reflect the build-up of trouble in the domestic currency or the sovereign debt. More importantly, our EWS accounts for regional heterogeneity, which is attested to be even more important than country-specific factors for the accuracy of forecasting. Furthermore, our specification of the binary dependent variable seems to enable the EWS to capture the onset of banking crises more effectively compared to the multinomial specification and the more commonly used technique of dropping post-onset periods. Another critical factor that significantly enhances the predictive power of our EWS is using the dynamic-recursive forecasting technique, which enables the system to learn from the new information as it becomes available and to account for its previous predictions.

Nevertheless, although the in-sample performance of the binary logit is very satisfactory in the within-sample case, it is clear that it improves only modestly over the other two methods. However, much more discrepancy in the performance of the different models can be found with respect to their out-of-sample forecasts. In fact, the predictive performance of the *dynamic signal approach* stands out strikingly above that of the other two techniques in the holdout period. Specifically, six months in advance, this approach is able to correctly forecast almost all the onset periods that occurred in developed countries and in Eastern Europe, Africa and the Middle East. However, one should bear in mind that this comes at the expense of a much higher false alarm rate as discussed in section 5.5.

Another important finding that is worth noting in this respect is that, in the case of developed countries, only 31 onsets are correctly called using the binary logit and 15 using the multinomial models. However, if we consider the onsets that are identified in

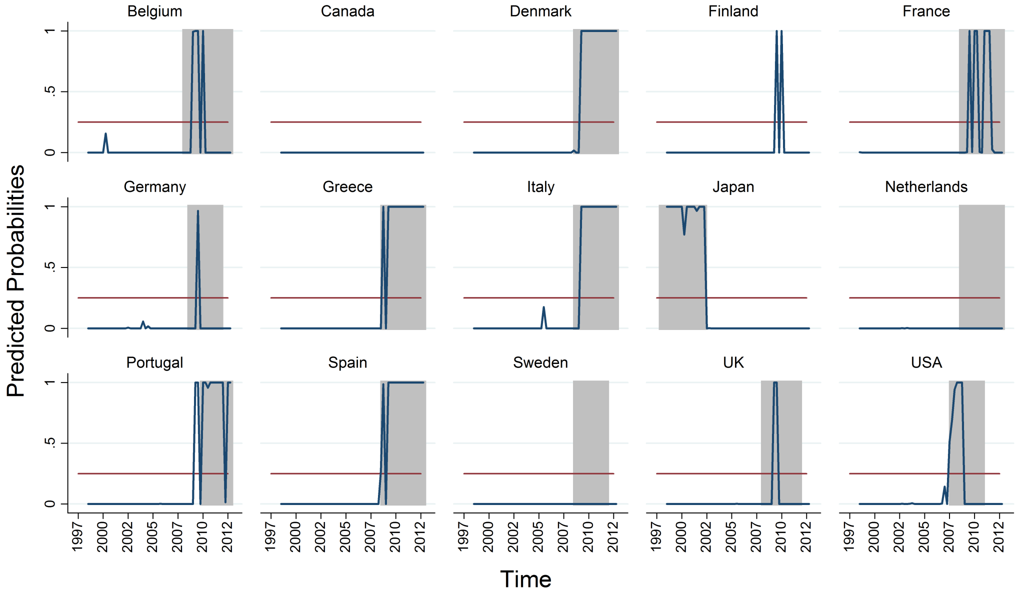

Figure 5.5: Predicted Probabilities of BC in Developed Countries

the following quarter to that specified by the WB (refer to Figure 5.5 for the predicted probabilities calculated by the binary model in developed countries), the hit rate of the binary logit model jumps to 90% (42 periods). Furthermore, with respect to Eastern Europe, Africa and the Middle East, where the binary model is only able to forecast six entry periods, the hit rate again jumps to 100% when considering the episodes called in the following quarter. Regarding the multinomial models, the figures only rise to 24 episodes in developed countries, and five episodes in Eastern Europe, Africa and the Middle East.

In conclusion, therefore, the results signify that the performance of the multinomial logit models is consistently lower than that of the binary models and the dynamic signal approach. However the choice between the binary logit and the non-parametric methods is not as straight forward. While a conservative policy maker, who does not wish to incur large expenses to bail out a banking sector that is not actually facing serious problems, would prefer the EWS based on the binary logit model, another decision maker may prefer the dynamic signal approach if his/her purpose is to avoid a systemic banking crisis at all costs and keep the banking sector sound and healthy at all times. We will discuss the policy implications of our results in more detail in Chapter 7.

Chapter 6

Modelling EWSs
The Case of Sovereign Debt Crises

In the light of the literature review discussed in Chapter 2, very few studies have attempted to construct EWSs for sovereign debt crises. This could mainly be due to the fact that, compared to currency and banking crises and until very recently, there were no major concerns about governments in developed countries not being able to meet their external or domestic obligations to an extent that would progress into a serious debt crisis. Therefore, the few papers that studied the possibility of forecasting sovereign debt crises have mainly focused on developing economies.

Apart from the two very recent articles by Jedidi (2013) and Savona and Vezzoli (2015), which pooled some developed countries in their main sample of emerging economies, no other study has investigated the possibility of constructing a forewarning system for sovereign debt crises in the advanced world. Such an EWS is becoming increasingly important, though, especially after the calamitous situations in several European countries (mainly in Greece, Ireland, and Portugal) that were triggered by the current global financial crisis.

Accordingly, this study contributes to the literature by investigating the possible forewarning indicators of government debt crises in both developed and developing countries. In particular, we consider fitting separate models for each country region, and compare their in-sample and out-of-sample predictive performance to a model that includes both. This is repeated for all our proposed methodologies used to construct an EWS, as discussed in Chapter 3, to identify the appropriate model that produces the most accurate forecasts.

Therefore, this Chapter is further divided into several sections, where section 6.1 presents the sample data and the different sources used to collect it. The specific definition of a sovereign debt crisis and the proposed indicators used as warning signals are outlined in section 6.2 and section 6.3, respectively. This is followed by a brief discussion of the descriptive statistics and an event study analysis in section 6.4. The following sections are then dedicated to modelling EWSs for debt crises using each of our three proposed methodologies, and investigating how their predictive power compares to the previous findings in the literature. The final section cross-evaluates the performance of the three methods and concludes.

6.1 Sample Data

The panel data considered in the sample consists of 38 advanced and emerging economies during the period 1980-2012. We rely on an annual frequency of the data, as sovereign debt crises tend to last for prolonged periods and show persistence (Manasse *et al.*, 2003). The 38 countries chosen cover four main regions: Africa and the Middle East, South and East Asia, Latin America, and Western Europe.

It is important to note that the selection of the sampled countries is guided mainly by the availability of the data. Furthermore, we do not include countries from Eastern and Central Europe, because their data are only available from 1995 onwards, which would have reduced the sample size considerably. In addition, given the fact that these countries have experienced a very limited number of sovereign debt crises (refer to Table 1 in Manasse and Roubini, 2009), excluding them from the dataset seems appropriate. An alphabetical list of the countries considered is illustrated in Table 6.1, along with the frequency of their entry into sovereign defaults over the entire sample period (column 1), the average (column 2) and the total number of years they spent in default (column 3).

The data on the indicator variables are collected from four main databases: the IMF International Financial Statistics, the World Bank Development Indicators, the World Economic Outlook, and the World Bank Global Financial Database. Details on the specification of the response variable, the signalling indicators, and how they are measured are pointed out in the following sections.

6.2 Defining Sovereign Defaults

Out of concern for the comparability of our results with the previous studies, we prefer to employ the same definition of a sovereign debt crisis as specified by the few papers that addressed this issue in the literature. Hence, an aggregated crisis index (DC_{it}) is constructed to capture the timings of sovereign defaults and rescheduling or restructuring episodes. In the case of emerging markets, this index assumes unity if any of the four following events occurs, and is zero otherwise:

1. Failure to meet external obligations: accumulated interest and/or principal arrears exceed 5% of the total amount of the outstanding debt.

2. Receiving a loan from the IMF in excess of 100% of the country quota.

3. The cumulative credit obtained from the IMF increases above 200% of the quota.

4. Engaging in a debt restructuring (buybacks or reductions) or rescheduling scheme that involves more than 20% of the outstanding debt.

With respect to developed countries, we use a slightly different rule due to the lack of reported details on the arrears and the amounts involved in restructuring and rescheduling programmes. Therefore, in addition to the two events involving loans from the IMF, the crisis index is also set to one if the outstanding government debt exceeds 150% of the nominal value of the GDP. This particular ratio is chosen following the estimates of the IMF[1] that the cross-country median of government debt ranges between 50-75% of GDP for the advanced economies, while the median maximum sustainable debt level (*i.e.* the level beyond which a debt distress event is inevitable) ranges between 100-190% of GDP. Furthermore, Reinhart *et al.* (2003) argued that ratios of external debt to GNP above 150% are unsustainable and run a significant risk of default.

Given these definitions, a total of 288 sovereign debt crisis periods is identified in both developed and emerging economies, which accounts for 23% of the total number of observations, while 3% of the data are crisis entry periods (refer to Table 6.1). Furthermore, the number of years every country spent in debt crisis is illustrated by region in Figure 6.1. It is obvious from this figure, that Latin American economies were the most frequently hit by sovereign debt crises, followed by several African countries; while Asia and Western Europe suffered a limited number of crisis episodes. Further details on each crisis incident and the exact causes of sovereign defaults in every country over the sample period are outlined in Appendix C.

6.3 Signalling Indicators

After specifying the response variable that captures the crisis incidents, the following step is to identify the indicator variables that can be used to provide warning signals of a forthcoming crisis. These variables, as illustrated in Table 6.2, can be grouped into four main categories.

The first group is meant to reflect the exposure of a country to sovereign debt problems. Therefore, we include the total stock of external debt (as percentage of GDP) and the amount of credit the country acquired from the IMF. Naturally, an increasing stock of debt and/or IMF credit compared to the country's resource base increases the chances that the debt would become unsustainable, which in turn increases the probability of

[1]For further details, refer to "Modernising the Framework for Fiscal Policy and Public Debt Sustainability Analysis" available at: http://www.imf.org/external/np/pp/eng/2011/080511.pdf

Table 6.1: Sovereign Defaults 1980-2012

Country	**Entry to Default** ($\Delta DC_{it} = 1$)	**Average Length**	**Years in Default** ($DC_{it} = 1$)
Algeria	1	7.0	7
Argentina	2	8.0	16
Belgium	1	3.0	3
Bolivia	2	9.0	18
Brazil	3	4.7	14
Central Africa	1	26.0	26
Chile	1	8.0	8
China	0	0.0	0
Costa Rica	1	11.0	11
Dominican Republic	3	8.0	24
Ecuador	2	8.0	16
Egypt	1	12.0	12
Germany	0	0.0	0
Greece	1	3.0	3
India	0	0.0	0
Indonesia	1	6.0	6
Ireland	1	2.0	2
Italy	0	0.0	0
Jordan	1	6.0	6
Lebanon	1	7.0	7
Malaysia	0	0.0	0
Mexico	2	6.0	12
Morocco	1	9.0	9
Nigeria	1	12.0	12
Panama	1	13.0	13
Paraguay	1	5.0	5
Peru	1	16.0	16
Philippines	1	10.0	10
Portugal	2	1.5	3
Singapore	0	0.0	0
South Africa	1	5.0	5
South Korea	2	2.5	5
Spain	0	0.0	0
Sweden	0	0.0	0
Thailand	2	2.5	5
Tunisia	1	6.0	6
UK	0	0.0	0
Venezuela	1	8.0	8
Total	40		288
Rate	3.03%		22.97%

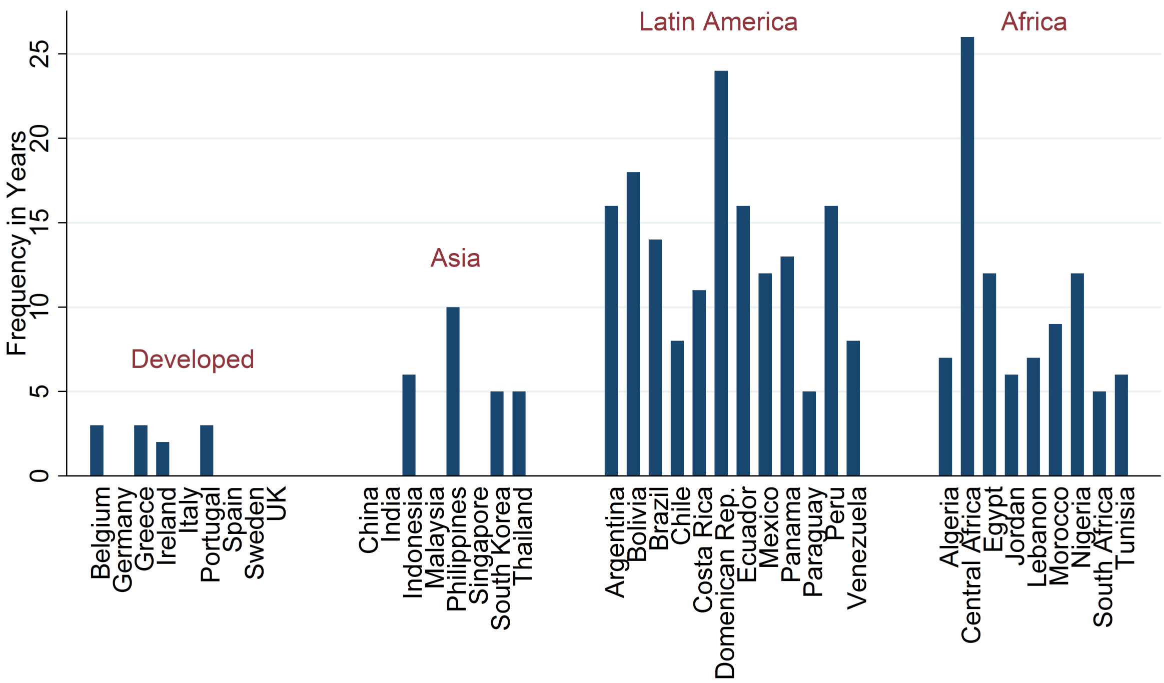

Figure 6.1: Years in Sovereign Debt Crisis

default. Moreover, to measure the burden of servicing the external debt, the GDP-weighted average of the bank lending interest rates in seven major developed countries is also considered in the model, not as a country-specific variable but as an international factor that affects all (developing) countries alike.

Next, we consider the health and the stability condition of the country's external sector. Thus, the effect of an erosion of foreign exchange reserves on the likelihood of sovereign defaults is considered as a potential indicator, since a growing external debt (denominated in foreign currency) usually drains the economy's stock of foreign reserves. On the other hand, an improving current account balance, growth of export revenues, and net inflows of FDI reduce the country's financial need for acquiring credit and, hence, its dependence on foreign debt. In contrast, a larger current account deficit or FDI outflows (relative to GDP) would compound the problem of servicing maturing debt, making it difficult for the country to meet its obligations. A less clear impact on the probability of default is that of the change in trade openness, for a low degree of openness can have an

Table 6.2: Signalling Indicators of Sovereign Debt Crises

Symptoms	Indicators	Measurement	Exp.Sign
Debt Exposure	TODBT	gross external debt as % of GDP	+
	IMFCRD	loans from IMF as % of GDP	+
	GLBINT	GDP-weighted global lending interest rate[1]	+
External Sector	FRXRES	foreign exchange reserves as % of GDP	-
	TRDOPEN	ratio of exports plus imports to GDP	+ / -
	EXPGR	annual exports growth rate	-
	CURACC	current account balance as % of GDP	-
	FDI	net inflows as % of GDP	-
Domestic Macro Conditions	RGDPGR	annual growth of real GDP	-
	REEROVER	deviation of real effective exchange rate from 5-year rolling mean	-
	INFL	rate of change in CPI	+
	M2RES	ratio of M2 to foreign exchange reserves[2]	+
	NATSAV	ratio of national savings to GDP	-
	GOVEXP	gov. expenditures as % of GDP	+ / -
Banking Sector	DOMCRD	ratio of domestic credit to private sector to GDP	+ / -
	BKASST	ratio of consolidated bank assets to GDP	-
	GOVBKCLM	net bank claims on central gov.	+

Notes: (1) It is composed of the GDP-weighted bank lending interest rates in seven developed countries: USA, Canada, UK, Germany, France, Italy, and Sweden. (2) With respect to Eurozone countries, M2 represents the contribution of the national component of the monetary aggregate to the Euro area, while the foreign exchange reserves are those held by the national central banks and the monetary authorities, excluding the reserves held at the European Central Bank.

adverse effect on trade surplus and make the country more willing to repudiate its debt, whereas freer trade can make the economy more vulnerable to external shocks.

With respect to the third group, namely the domestic macroeconomic variables, it is reasonably expected that these indicators would show some deterioration prior to a debt crisis. Therefore, a lower growth of real GDP and plummeting national savings are associated with a higher probability of distress as they reduce the country's ability to pay. Furthermore, a rise in the rate of inflation is associated with increased nominal interest rates and reduced external competitiveness, making it more difficult for the government to meet its external obligations (Manasse *et al.*, 2003; Manasse and Roubini, 2009). In addition, it may lead to a confidence crisis, as lenders suspect that the government is attempting to inflate away the value of its external debt. On different grounds, while larger government expenditures can expedite the pressure of an increasing debt and multiply the likelihood of a crisis, governments usually undergo some austerity measures during times of trouble (Cole and Kehoe, 2000; Ari and Dagtekin, 2007; Balteanu and Erce, 2014). Thus, higher public spending can also be associated with tranquil periods, where the likelihood of a debt crisis is minimal.

On the other hand, the ratio of M2 to the stock of international reserves[1] can measure the capacity of the government (or the central bank) to defend the domestic currency, since a high ratio reflects the extent of unbacked implicit government liabilities. This may cause a sudden loss in confidence in the domestic currency to ripple into a currency crisis, which in turn may progress into an external default situation[2] due to the debt unsustainability (Peter, 2002; Savona and Vezzoli, 2015). Furthermore, to capture the effect of an approaching currency crisis on the ability of the government to meet its external obligations, we also include the overvaluation of the real exchange rate[3] as a possible indicator. This variable is measured as the negative deviation of REER (measured in domestic currency) from its long-run trend.

Finally, we include three variables to investigate the possibility of spillover from the banking sector. A growing banking industry, measured by an increase in the ratio of consolidated bank assets to GDP, can reflect the health of the financial sector and the economy in general. Furthermore, a higher ratio of domestic credit granted to the private sector (if sustainable) may reflect the development of the banking industry and the potential of a growing economy (Fuertes and Kalotychou, 2006; Lausev *et al.*, 2011). However,

[1] In the Eurozone countries, the money supply is limited by the ECB to control inflation. Therefore, one should be cautious when interpreting the coefficient of this variable.

[2] It is reported in Manasse *et al.* (2003) that more than 80% of debt crises are usually preceded by a currency crisis.

[3] With respect to the Eurozone, changes in REER carry a different interpretation than the other regions due to their common nominal exchange rate. Thus, cross-section changes are either due to differences in the price deflator or the share in international trade across the zone countries.

higher private sector indebtedness can also increase the vulnerability of the banking sector to macroeconomic shocks. In addition, to signal the amount of credit obtained by the public sector from the banks, we also consider the net bank claims (loans minus deposits) on the central government.

Subsequently, our analysis starts off by conducting an event study to investigate how these candidate indicator variables tend to behave around default episodes given our sample dataset. Hence, the following section provides and discusses the results of a primary descriptive analysis and a brief event study of the proposed signalling indicators.

6.4 Descriptive Statistics and Event Study

Before we formally investigate the effectiveness of the proposed variables in generating forewarning signals of sovereign debt crises, we first examine whether the behaviour of these variables tends to change significantly prior and during crisis episodes as compared to tranquil periods. For this purpose, Table 6.3 depicts the respective mean of each variable in the global sample during non-crisis vs. pre- and crisis years, along with the results of the mean-differential t-tests over the global sample and in each country group separately at 5% level of significance.

It is evident from this table that there is a tangible difference across the country regions with respect to the candidate EWS indicators. Specifically, while the variables of the external sector seem to behave significantly different around crises in Asia and Latin America, only the ratio of foreign reserves is relevant in developed countries and in Africa. In fact, the external sector appears to be the main potential indicator of sovereign defaults in South and East Asia.

Likewise, the domestic macroeconomic conditions seem to play the major role as debt crisis indicators in Africa, but they do not exhibit much change in behaviour in Asia or the advanced world. Furthermore, only in the case of Latin America is there evidence of

Table 6.3: Quantitative Analysis of Debt Crisis Indicators

	Full Model			Regional Models			
Indicator	No Crisis	Crisis	t-stat	Dev.	Asia	Latin	Africa
Debt Exposure							
Total External Debt	69.1	96.7	-1.3	×	×	✓	×
IMF Credit	0.3	1.7	-6.1*	✓	×	✓	×
Global Interest Rate	8.4	11.0	-5.1*	✓	✓	✓	✓
External Sector							
International Reserves	16.4	6.2	9.3*	✓	✓	✓	✓
Reserves Growth	11.6	7.0	0.5	×	✓	×	×
Export Growth	5.9	3.0	1.8	×	×	×	×
Current Account	-0.7	-4.1	4.9*	×	✓	✓	×
Trade Openness	81.8	63.5	3.7*	×	✓	✓	×
FDI	3.3	1.6	5.9*	×	✓	✓	✓
Macroeconomic Condition							
Real GDP Growth	4.1	2.0	2.4*	✓	×	✓	×
GDP per Capita	10.9	6.0	4.9*	×	×	✓	×
Inflation	6.8	28.9	-3.9*	×	×	✓	✓
M2/Reserves	10.0	15.0	-1.2	×	×	✓	✓
REER Overvaluation	2.2	-10.5	5.4*	×	×	✓	✓
Gov Expenditures	15.7	15.0	0.7	×	×	×	×
National Savings	23.7	17.2	6.1*	×	✓	✓	✓
Banking Sector							
Domestic Credit	69.6	60.3	1.2	×	×	✓	×
Bank Assets	71.0	56.0	2.5*	✓	×	✓	×
Gov Bank Credit	12.7	16.6	-1.4	×	×	✓	×

Notes: The t-stat is the test statistic of the mean differential t-test between the two economic states. The Welch adaptation of the t-test is used to account for the unequal variances and sample sizes of the two economic states.
Both * and ✓denote significance at the 5% level.

possible spillover effects from the banking sector on the probability of debt crises, while in developed countries only the bank assets seem to grow slower when the government is facing debt problems. Effectively, only a few variables appear to behave differently around crisis episodes in the case of developed countries, namely the debt exposure variables.

Despite this apparent distinction of the probable indicators of debt crises in the different regions, a small set of variables appear as good crisis indicators in most regions. Primarily, a rise in the average lending rate in developed countries significantly increases the cost of servicing external debt and magnifies the likelihood of sovereign defaults in general. Likewise, the erosion of foreign exchange reserves can act as a potentially good indicator of debt problems. In the case of emerging economies, two additional variables seem to play an important role in the possibility of crises, namely FDI flows and national savings.

Nonetheless, to act as an effective forewarning indicator of sovereign debt crises, it is not sufficient for a variable to act differently during times of distress, but rather before trouble starts building up. Therefore, in order to highlight the candidate indicators that can signal an approaching crisis, Figure 6.2 depicts how each variable changes on average from normal periods to pre-crisis years, during crisis episodes, and after the crisis hits the economy.

According to this event-study graph, factors like foreign exchange reserves, M2, export growth, current account balance, trade openness, and national savings have a distinct behaviour during pre-crisis periods compared to after the crisis hits the economy. They fall (rise) sharply before the crisis occurs, and then gradually rise (fall) back again after the crisis hits the economy. Thus, the results of the t-test, which combines both pre- and crisis periods, may be misleading to some extent with respect to these variables. Other factors, like total external debt, global interest rate, FDI, real exchange rate, and bank claims show a sharp change of behaviour before the crisis hits the economy and only change slightly afterwards, but in the same direction.

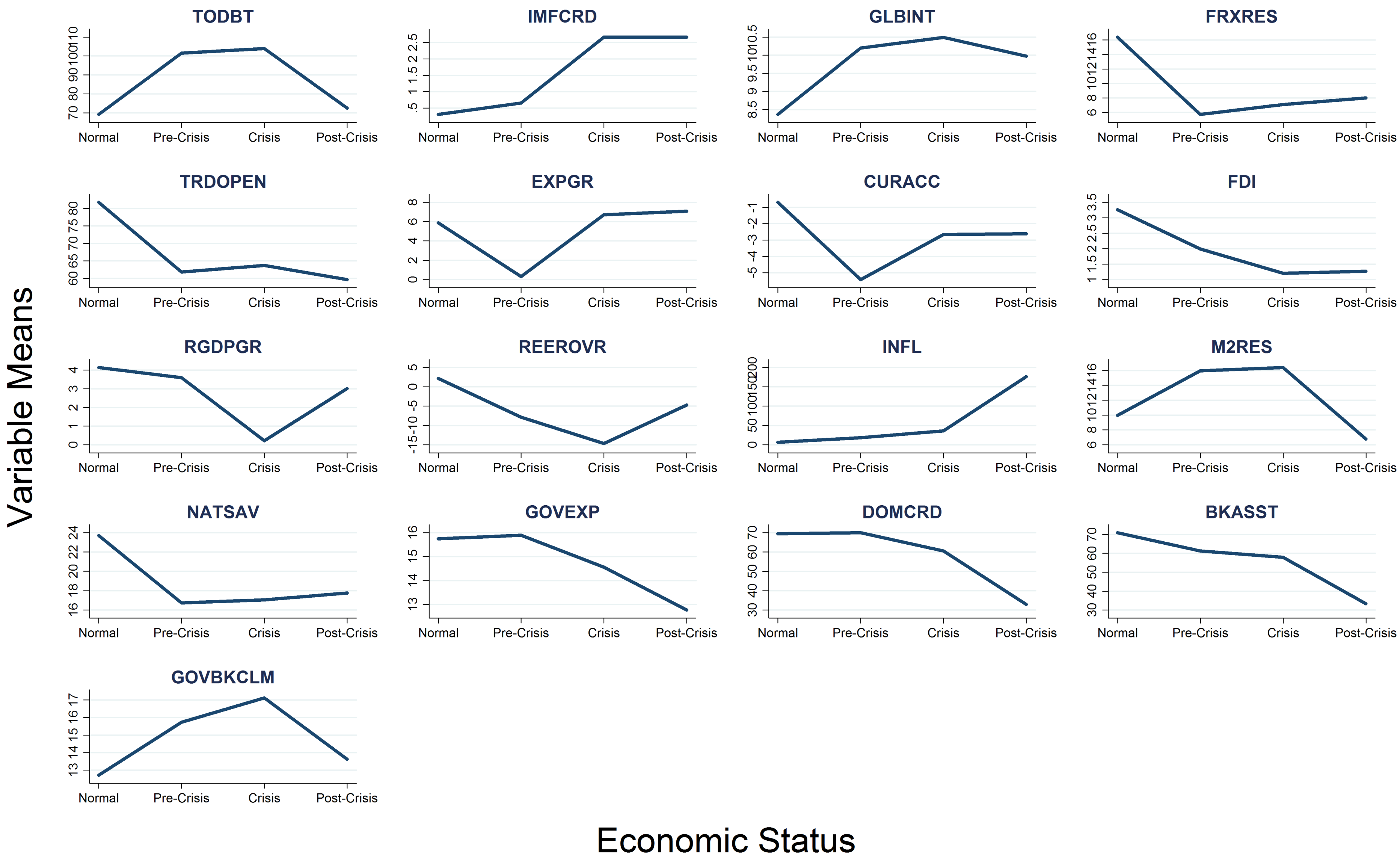

Figure 6.2: Behaviour of Candidate Variables around Debt Crisis Episodes

Unlike the two previous types of factors, which are expected to prove significant in predicting debt crises, there is another group of factors that only changes behaviour markedly after the onset of the crisis. These are mainly: inflation, IMF credit, government expenditures, domestic credit, and bank assets. This group of variables is not expected to perform well as EWS signalling indicators; although IMF credit does increase well before crisis onsets, but only slightly compared to afterwards.

Consequently, in order to examine formally the effectiveness of these candidate indicators in forewarning sovereign debt crises, we employ the dynamic signal approach and the binary and multinomial logit regression models to construct EWSs. The performance and results of these EWSs is illustrated and compared in the following sections.

6.5 Dynamic Signal Extraction Approach

Remarkably, the signal approach is very uncommon in the literature of modelling EWSs for sovereign debt crises. In fact, to the best of our knowledge, only one very recent study by Savona and Vezzoli (2015) considered the static version of the signal approach and tested its performance against that of a binary logit and a regression tree model. Their results showed that the static version performed relatively poorly with respect to both the in- and the out-of-sample forecasts compared to the other two competing methods. Thus, its use was not recommended for further research. However, in this section, we investigate the effectiveness of the dynamic version of the signal extraction approach in both developed and developing countries, and proceed to compare its predictive performance to the static version. We also analyse its forecasting ability relative to the binary and the multinomial logit models in section 6.8.

We apply the dynamic signal approach in accordance with the suggestions of Casu *et al.* (2012) and as explained in detail in section 3.1. Following this methodology, a forward-looking response variable (DCs_{it}) is constructed to capture the incidents of approaching debt crises in the sampled countries (i) over the time period (t) 1980-2012 within a specific crisis window (h). Hence, this multinomial variable is defined as follows:

$$DCs_{it} = \begin{cases} 1 & if\ \exists\ k = 1, \ldots, h\ s.t.\ DC_{i,t+k} = 1 \\ 2 & if\ DC_{i,t} = 1 \\ 0 & otherwise \end{cases} \tag{6.1}$$

where DC_{it} denotes the binary crisis index defined in section 6.2 and detailed in Appendix C. According to this definition, DCs_{it} takes the value of one during the crisis window prior to the onset of debt crises, the value of two over the course of the crisis itself, and is zero during tranquil periods.

We attempt two different specifications of the crisis window (h), namely one year and two years. The results of the grid search indicate that the latter specification is preferable, as it enables the EWS to provide warning signals up to two years before the onset of crises without causing significant losses in the $NTSR$ of the majority of indicators compared to the one-year window. Therefore, we set $h = 2$ and proceed to test formally the predictive performance of the individual indicators.

6.5.1 Performance of the Signalling Indicators

The next step in designing the EWS is to transform the indicator variables into binary signals. This requires identifying optimal threshold levels for these variables, so that a signal is said to be issued when a variable crosses its respective threshold at any time period. We perform a grid search in accordance with (3.3) to identify such optimal thresholds for each individual indicator that would simultaneously minimise its $NTSR$ and maximise Youden's J-statistic. The results of the grid search, in terms of the optimal $NTSR$ and the percentage of correct crisis onsets forewarned by each indicator, are reported in Table 6.4 with respect to the global sample and in each country region.

It can generally be noticed from this table that the majority (about 75%) of the variables have $NTSR \leq 0.5$ in Latin America and in Africa and the Middle East, while in

Table 6.4: Results of Grid Search on Individual Indicators

	Global				Developed		SE-Asia		Latin America		Africa	
	NTSR	Onsets	Lead	Persist	NTSR	Onsets	NTSR	Onsets	NTSR	Onsets	NTSR	Onsets
TODBT	1.20	28.6	1.1	0.8	0.18	100.0	0.38	50.0	0.64	22.2	0.38	33.3
IMFCRD	0.21	54.3	1.8	4.9	0.05	50.0	0.26	50.0	0.24	72.2	0.32	22.2
GLBINT	0.33	48.6	1.8	3.1	0.62	50.0	0.18	66.7	0.19	50.0	0.36	66.7
FRXRES	0.36	54.3	1.7	2.8	0.94	50.0	0.78	16.7	0.25	55.6	0.10	77.8
TRDOPEN	0.41	31.4	1.3	2.5	0.64	50.0	0.53	66.7	0.33	33.3	0.17	55.6
EXPGR	0.67	34.3	1.4	1.5	1.22	50.0	0.54	50.0	0.64	38.9	0.34	55.6
CURACC	0.33	48.6	2.0	3.0	0.71	50.0	0.22	83.3	0.20	55.6	0.30	77.8
FDI	0.48	31.4	1.5	2.1	0.63	100.0	0.67	50.0	0.31	38.9	0.59	22.2
RGDPGR	0.75	28.6	1.3	1.3	0.58	50.0	0.48	33.3	0.54	27.8	0.37	33.3
INFL	0.68	25.7	1.1	1.5	0.35	50.0	0.30	50.0	0.50	22.2	0.46	33.3
M2RES	0.42	42.9	1.6	2.4	0.50	50.0	0.64	16.7	0.38	50.0	0.20	55.6
REEROVR	0.89	22.9	0.6	1.1	1.08	50.0	0.74	16.7	0.50	27.8	0.16	44.4
GOVEXP	0.61	28.6	1.3	1.6	0.15	100.0	0.60	50.0	0.32	44.4	0.57	22.2
NATSAV	0.42	34.3	1.4	2.4	0.23	100.0	0.57	33.3	0.38	44.4	0.25	66.7
DOMCRD	0.33	25.7	0.8	3.0	0.51	50.0	0.38	33.3	0.77	38.9	0.58	55.6
BKASST	1.29	17.1	0.9	0.8	0.77	50.0	0.74	33.3	0.59	27.8	0.71	22.2
GOVBKCLM	0.55	25.7	0.9	1.8	0.31	50.0	2.25	16.7	0.32	33.3	0.14	66.7

the advanced world and in South and East Asia only few indicators can provide reliable signals of approaching debt crises. Nonetheless, the average persistence of the signals (column 4) is rather high for most variables. In fact, the percentage of credit acquired from the IMF can generally provide five times as many good signals as noise. This is followed by the global interest rate, foreign exchange reserves, current account balance, and domestic credit, which show signal persistence of three times or more.

The overall lead time of the signals (column 3) is not too long, though. Only four variables tend to issue their first signals two years in advance, namely IMF credit, global interest rate, the current account, and foreign exchange reserves. The signals of four other variables have a lead time of more than 18 months; these are export growth, FDI, ratio of M2 to reserves, and national savings. The rest of the indicators considered start signalling an approaching debt crises only one year in advance. The shortest average lead time is that of the warnings issued by the overvaluation of the domestic currency. This could be reasonably expected given that the fluctuations of the exchange rate tend to be rather short termed, which can be readily observed from Figure 4.1 on page 59.

Taking a closer look at the separate regions, and consistent with the primary t-tests conducted in the previous section, the debt exposure variables are the major signalling indicators in developed countries, having the lowest $NTSR$ ratios. In addition, government expenditures and national savings are able to predict accurately all the crises that occurred over the in-sample period in this region. The debt exposure variables are also important forewarning indicators in the case of South-East Asia, particularly the global interest rate, which is already suggested by Table 6.3. Furthermore, the balance of the current account can forewarn 83% of the Asian sovereign defaults, while neither the domestic macroeconomic variables nor the banking sector seem to act as significant indicators.

On the other hand, the external sector appears to provide more accurate warning signals of debt crises in Latin America and Africa. Particularly, two variables stand out fairly well with low $NTSR$ ratios and relatively high percentages of correctly predicted crisis incidents. These indicators are foreign exchange reserves and the current account balance (which is shown to be quite significant in all emerging economies). In addition, the debt exposure variables act as good indicators in Latin America. On the other hand, national savings and bank claims on the central government are able to predict two thirds of the crisis onsets that occurred in Africa.

As can be noted from the results of the grid search in Table 6.4, and save for the debt exposure variables that appear to issue significant and reliable warning signals in all regions, there is a distinct set of indicators that performs best in each region, which supports our notion of regional heterogeneity of the signalling variables. Hence, the next step in constructing our EWS using the dynamic signal approach is to aggregate the signals provided by these best performers in each country group into a single composite index for that corresponding region, and then testing the predictive performance of these indices.

6.5.2 Performance of the Composite Index

In this respect, the formula illustrated in (3.4) is used to construct a composite index of the warning signals issued by all indicators with $NTSR \leq 0.5$, *i.e.* that are able to issue at least twice as many good signals as false alarms. According to this formula, the composite index is designed so as to aggregate the NTSR-weighted signals of the individual best performers, giving more weight to the more reliable indicators' signals.

It could reasonably be expected that the higher the value of the composite index, the higher is the likelihood of an upcoming crisis over the specified window. Thus, we next apply (3.5) to transform these aggregated weighted signals into conditional probabilities of approaching debt crises. Accordingly, Table 6.5 illustrates the composite signal values and their corresponding crisis probabilities. The results are consistent with our previous expectation as the probabilities are monotonically increasing with the values of the composite index.

Table 6.5: Conditional Probabilities of the Composite Index

Composite Index Values	Conditional Probabilities
0-4	2.0
5-8	4.5
9-12	11.7
13-16	23.5
17-20	27.3
21-24	75.0

Testing the predictive power of the global, as well as each of the regional, composite indices requires identifying cut-off probabilities above which the respective index is said to issue an alarm of an approaching sovereign debt crisis. Then, by comparing these warning signals with the actual crises incidents in our sample, we are able to calculate the percentage of correct onsets, false alarms and whole crisis periods that are forewarned by each composite index. These are depicted in Table 6.6, while Figure 6.3 illustrates the time series of the conditional probabilities of sovereign defaults in the sampled countries, the chosen cut-off levels (horizontal line) and the actual crisis episodes (shaded area). It is important to emphasise that the choice of the cut-off probabilities is made on the basis of the one that maximises Youden's J-statistic.

Whereas the upper panel of Table 6.6 reports the in-sample predictions over the period 1980-2005, the lower panel focuses on the forecasts provided by the composite indices over the seven-year holdout period[1] 2006-2012. The latter years are considered out-of-sample, since the signals provided by the composite indices over this period are calculated using the same indicators that are found to perform best during the in-sample period, the same dynamic thresholds of the in-sample grid search, and the same cut-off probabilities that are found to be optimal.

Focusing first on the in-sample forecasts, we find that the regional composite indices significantly outperform the global one with respect to both the percentage of crisis periods and onsets correctly forewarned. More specifically, the global index is only able to

[1]This period is chosen to allow for some out-of-sample crisis incidents.

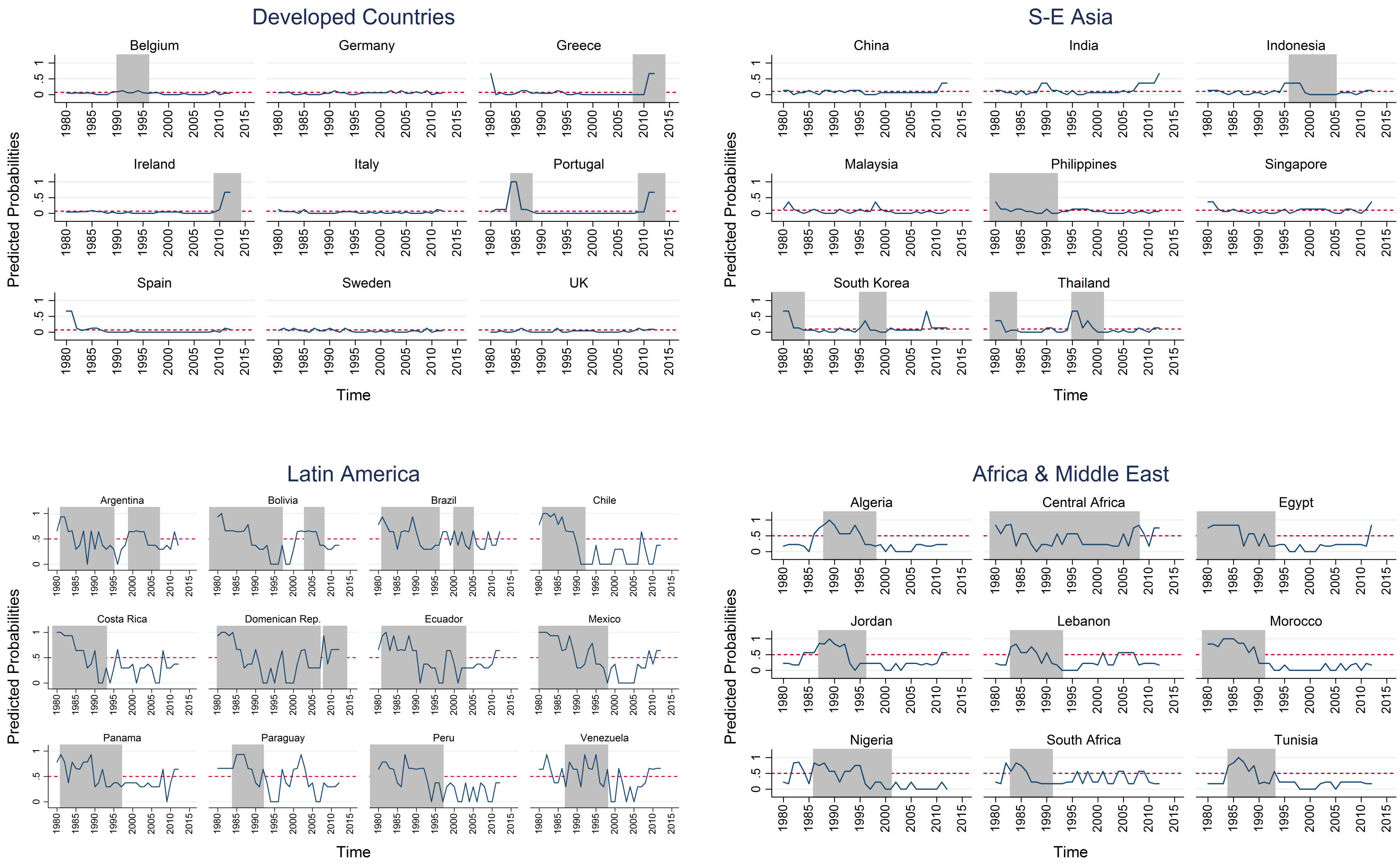

Figure 6.3: Conditional Probabilities vs. Crisis Incidents

Table 6.6: Sovereign Debt Crisis Forecasts using DSA

	Optimal Cut-off	Correct Onsets	Correct Crisis	False Alarm
In-sample Forecasts (1980-2005)				
Global	35	23.1	20.2	10.8
Developed	5	100.0	100.0	25.9
S-E Asia	10	66.7	40.9	28.2
Latin America	50	86.7	58.6	26.5
Africa	50	100.0	62.4	22.9
Out-of-sample Forecasts (2006-2012)				
Developed	5	66.7	85.7	23.2
S-E Asia	10	–	–	39.3
Latin America	50	100.0	100.0	22.5
Africa	50	–	0.0	19.4

correctly signal 23% of the crises that hit all the countries over the period 1980-2005. On the other hand, the regional indices accurately predicted 100% of the onsets that occurred in advanced Europe and in Africa and the Middle East, 87% in Latin America, and two of the three crisis entry periods in South-East Asia. The false alarm rate in these regions amounts to about 20-30%, which is substantially higher than our targeted 10-15%.

Compared to Savona and Vezzoli (2015), which is the only paper that investigated the construction of an EWS for sovereign debt crises using the signal extraction approach, we find that the dynamic version that takes the regional heterogeneity of the indicators into consideration significantly outperforms the static version where the developed and emerging economies are pooled together. More specifically, their model was able to predict correctly about 80% of the crises that occurred over the in-sample, while generating a false alarm rate of 45%. Our models, on the other hand, have a collective hit rate of about 90% (being able to correctly predict 23 out of the 26 crises that occurred over the sample period) and generate almost half as many false alarms (25% on average) as the static version.

Finally, we investigate the more policy-relevant out-of-sample forecasts, which are depicted in the lower panel of Table 6.6. It can generally be noted that the rather satisfactory performance of the regional composite indices still holds in the holdout period. In fact, at a lower level of false alarms of around 20-25%, the models are able to predict two of the three crisis entry periods in developed countries and 86% (six of the seven) of their entire crisis years. Furthermore, in Latin America *all* crisis onsets and default periods are correctly forewarned two years in advance. In Africa and the Middle East, where no new crises occurred during 2006-2012, the false alarm rate remains around the in-sample range of 20%. However, in South-East Asia, it doubled to almost 40%. Taking a closer look at Figure 6.3, it is obvious that the warning signals in India, South Korea and China are the main drivers of the high false alarm rate in South-East Asia.

In fact, a study conducted by Jiang and Xu (2014), which analysed the effects of the western sovereign debt crisis on China's economy, has reported the alarming rapid growth of government debt and argued that the outbreak of a debt crisis is very likely in China. Moreover, a recent report by Moody's (2014) highlighted the fact that India has high fiscal deficit and a large government debt burden. They warned that "if current lower growth and high inflation persist over the medium term, the domestic financial system's capacity to absorb government debt could fall quite considerably. This could change the structure of government debt, raise debt financing costs and weaken government debt ratios". With respect to South Korea, it can be noted from Figure 6.4 that the gross government debt to GDP ratio has grown significantly over the holdout period. This lead the representative of the ruling party in South Korea to declare[1]: "The sum of the sovereign, public, and pension debts reached 1.641 trillion Won . . . I am dubious about whether the government can endure the current fiscal deficit and debt surge".

Thus, although no actual debt crises occurred in these countries over the out-of-sample period, it is evident that their sovereign debt condition was rather worrisome. Conse-

[1] Business Korea (2014, October 17), Korean Government Debt Exceeds 115 percent of National GDP. Retrieved from http://www.businesskorea.co.kr/article/6853/government-debt-korean-govt-debt-exceeds-115-percent-national-gdp

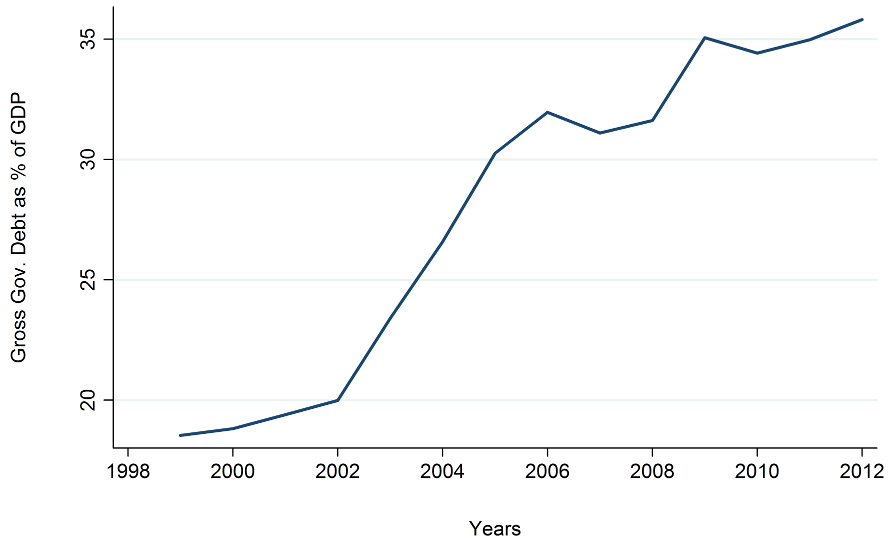

Figure 6.4: Conditional Probabilities vs. Crisis Incidents

quently, the warning signals generated by the South-East Asian composite index with respect to these countries cannot be considered as real false alarms, but as indicators of an alarming debt situation that did not progress into a full-fledged crisis. Hence, we can conclude that the regional EWSs constructed using the dynamic signal approach are able to issue highly accurate in- and out-of-sample forecasts of approaching debt crises in both developed and developing countries. We, therefore, proceed to test the effectiveness of the parametric methods in designing comparable EWSs of sovereign defaults.

6.6 Binary Logit Model

Before turning to the more complex multinomial logit regression model to assess the significance of the proposed signalling indicators in predicting the economic states of the sampled countries with respect to their sovereign debt, this section is dedicated to investigating the predictive power of the basic binary model. For this purpose, we include the years from the start of the crisis to its resolution as individual crisis periods. That is, the dependent variable is set to one for the entire period of sovereign distress[1] and is zero during tranquil times. This enables us to retain the observations following a debt crisis, instead of having to drop them to avoid endogeneity (as commonly done in Fuertes and

[1]For further details about the beginning and the end of each crisis episode, as well as the event that caused the crisis, refer to Appendix C.

Kalotychou, 2006, 2007; Savona and Vezzoli, 2015), and thus attempt to predict new as well as ongoing defaults.

6.6.1 Fitting Estimation Models

We examine the fit of five models: the global model that incorporates all countries together –developed and emerging, and four separate regional models. All models are estimated over the period 1980-2005, leaving out the observations of the most recent seven years from 2006 till 2012 to investigate the models' out-of-sample performance. The marginal effect of each indicator on the probability of a debt crisis and its corresponding statistical significance according to the likelihood ratio test are depicted in the upper panel of Table 6.7 using a 1-year lag and in Table 6.8 using a 2-year lag. In addition to using a pooled regression in the previous two tables, Table 6.9 estimates the five models using fixed-effects and random-effects panel regressions to account for possible country-specific heterogeneity.

The middle panel of the three tables reports the corresponding McFadden's Pseudo R^2, along with the log-likelihood and the BIC criteria of each model. The lower panels, on the other hand, show the in-sample optimal cut-off probability above which the model is said to signal a crisis, as well as the percentages of correct crisis signals and false alarms that are generated by the estimated models. The optimal cut-off probability is calculated so as to maximise Youden's J-statistic as described in (3.2), and is illustrated graphically in Figure 6.5. According to this figure and because the sensitivity of the correct crisis episodes signalled by a model decreases as the probability cut-off rises, while the specificity of the correct tranquil periods increases, the intersection of both lines can act as a fair guide of the optimal cut-off ratio.

The first glance at the estimation results evidences the consistent statistical significance of the debt exposure variables in all regions. Particularly, the ratio of external debt to GDP is a powerful indicator of approaching sovereign debt crises even when using a

Table 6.7: Binary Logit Regression of Sovereign Defaults using 1 Year Lag

	(1) Global	(2) Asia	(3) Latin	(4) Africa	(5) Developed
TODBT	0.019**	0.112*	0.026**	0.014	1.284**
IMFCRD	0.638**	2.727*	0.138**	0.558*	23.587**
GLBINT	0.121*	-0.060	0.025	-0.093	
FRXRES	-0.157**	-0.178	-0.017	-0.158**	0.045
TRDOPEN	0.021**	-0.031		0.052**	0.292**
CURACC	-0.027	-0.406*	-0.015		-2.049**
FDI	-0.372**		-0.276**	-0.378	-1.120*
RGDPGR	-0.059	0.143	-0.017	-0.011	-4.577**
INFL	0.002	0.149		0.071*	
M2RES	-0.045		0.142**	0.095	
REEROVR	-0.025**	-0.007	-0.010*	-0.036**	-0.773*
GOVEXP	-0.151**		-0.097**	-0.053	-5.018**
NATSAV	-0.062*		-0.019	-0.109*	
DOMCRD	0.013**	0.218**	-0.011**	-0.010	
BKASST	-0.027*	-0.159*		-0.051*	
GOVBKCLM	0.052**		0.021*	0.040*	
Asia	2.539*				
Latin	4.494**				
Africa	4.267**				
N	912	192	288	216	225
Pseudo R^2	0.610	0.705	0.729	0.658	0.940
Log-Likelihood	-213.6	-20.1	-54.1	-49.4	-1.207
BIC	563.6	103.4	181.8	184.9	56.5
Optimal Cut-off	35	10	40	30	10
% of Correct Crisis	89.0	95.5	96.1	96.5	100.0
% of False Alarm	7.4	8.2	11.0	11.5	0.9

* $p < 0.05$, ** $p < 0.01$

Note: For developed countries, total external debt is proxied by gross government debt.

Table 6.8: Binary Logit Regression of Sovereign Defaults using 2 Years Lag

	(1) Global	(2) Asia	(3) Latin	(4) Africa	(5) Developed
TODBT	0.028**	-0.006	0.024**	0.016	1.001**
IMFCRD	0.300**	1.064**	0.088	0.164	22.638**
GLBINT	0.154**	0.076	0.083**	0.000	
FRXRES	-0.119**	-0.346**	0.005	-0.136**	-1.974**
TRDOPEN	0.010*	0.004	-0.004	0.017	0.735*
CURACC	-0.060**		-0.038*		-6.186**
FDI	-0.472**		-0.230**	-0.088	-7.418
RGDPGR	-0.078**	0.055	-0.038*	-0.037	-4.439
INFL	0.001	0.182		0.046*	
M2RES	0.005		0.164**	0.037	
REEROVR	-0.025**	0.004	-0.008*	-0.039**	
GOVEXP	-0.121**	-1.217**	-0.069**	0.065	-6.157
NATSAV	-0.099**	-0.059	-0.032*	-0.136**	0.378
DOMCRD	0.010*	0.086**	-0.010**	-0.008	
BKASST	-0.016			-0.040*	
GOVBKCLM	0.038**		0.011	0.031	
Asia	3.450**				
Latin	5.225**				
Africa	4.610**				
N	912	192	288	216	216
Pseudo R^2	0.584	0.595	0.665	0.622	0.947
Log-Likelihood	-227.9	-27.6	-66.7	-54.7	-1.1
BIC	592.1	118.4	218.5	195.4	55.8
Optimal Cut-off	35	15	45	30	30
% of Correct Crisis	87.1	90.9	93.4	94.1	100.0
% of False Alarm	8.6	8.8	12.5	12.2	0.0

* $p < 0.05$, ** $p < 0.01$

Note: For developed countries, total external debt is proxied by gross government debt.

Table 6.9: Binary Panel Logit Regression of Sovereign Defaults using FE and RE

	Global		Asia		Latin		Africa		Developed	
	FE	RE	FE	RE	FE	RE	FE	RE	FE	RE
TODBT	0.077**	0.020**	-0.018	0.159*	0.219**	0.143**	0.088**	0.076**	0.851	0.683
IMFCRD	0.807**	0.910**	5.326*	3.984**	0.958**	0.965**	0.371	0.293	12.775	15.564
GLBINT	0.183**	0.120*	-0.602	-0.408	0.004	0.036	0.043	-0.011		
FRXRES	-0.212**	-0.184**	-2.434*	-1.167*	-0.341*	-0.183	-0.326**	-0.230*	1.509	-0.406
TRDOPEN	0.021	0.017*	-0.063						-1.337	
CURACC	0.018	-0.033		-0.646*	0.037	-0.007	0.101	0.153*		-0.988
FDI	-0.603**	-0.327**	-2.008*	-0.135	-0.948**	-0.965**	-0.748	-0.515	3.900	0.692
RGDPGR	-0.052	-0.073**	0.700*	0.181	0.010	-0.055	0.083	0.081	-2.941	-2.868
INFL	0.001	0.002*	0.843*	0.237*			0.143	0.161**		-0.434
M2RES	0.106*	-0.044	-2.029	-1.019	0.543*	0.643**	0.111	0.105		
REEROVR	-0.017*	-0.029**	0.017	0.052	-0.034	-0.039	-0.025	-0.028	-0.794	0.070
GOVEXP	-0.058	-0.111**			-0.197	-0.238*	0.337*	0.221		-1.370
NATSAV	0.006	-0.029	-0.420	0.385	-0.199*	-0.135	0.125	-0.074	-1.651	0.248
DOMCRD	0.014	0.020*	0.646*	0.161*	-0.021	-0.029	0.013	-0.009		
BKASST	-0.008	-0.049**			-0.109	-0.085	-0.058	-0.067		
GOVBKCLM	0.021	0.041**	0.167	-0.079						
N	624	912	96	192	288	288	192	216	50	225
Pseudo R^2	0.618	0.460	0.796	0.733	0.824	0.719	0.752	0.625	0.858	0.814
Log-Likelihood	-120.4	-230.6	-8.7	-16.4	-28.1	-54.4	-25.4	-49.2	-1.5	-3.4
BIC	343.8	583.9	76.7	110.9	129.8	193.7	124.4	184.4	34.4	71.9
Optimal Cut-off	1	1	0.1	1	1	0.1	1	0.1	1	0.1
% of Correct Crisis	43.9	70.0	18.2	77.3	77.3	28.3	90.8	73.8	80.0	75.0
% of False Alarm	8.8	5.1	0.0	0.9	1.2	2.2	10.3	18.3	7.6	0.0

* $p < 0.05$, ** $p < 0.01$
Note: For developed countries, total external debt is proxied by gross government debt.

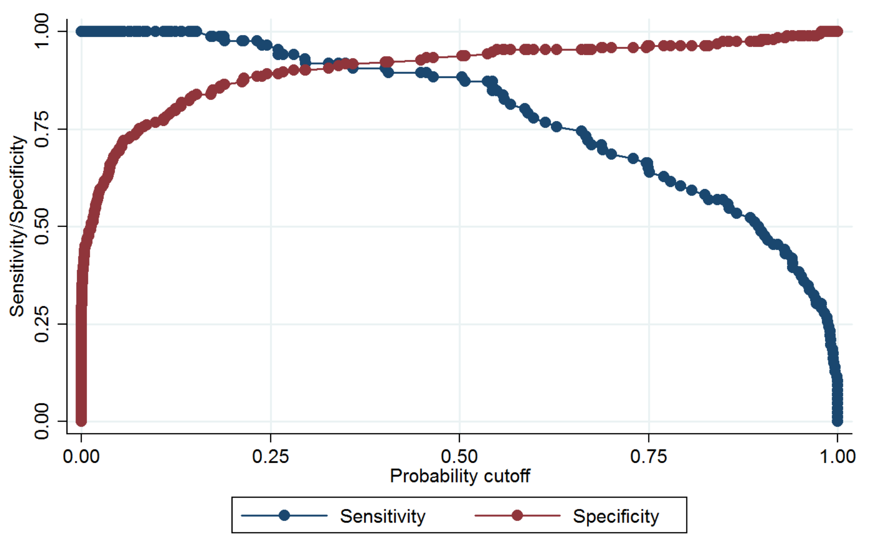

Figure 6.5: Optimal Probability Cut-off Point for Sovereign Defaults

2-year lag (except for the African countries). On the other hand, credit acquired from the IMF, though important in all regions one year in advance, is significant using a 2-year lag in Asia and advanced Europe only. In contrast, the global lending rate has explanatory power over the long run (2 years) in Latin America alone.

With respect to the external sector, and contrary to the findings of the *t*-tests in Table 6.3, these variables do not seem to play an important role in predicting debt crises, especially in emerging economies, once the debt exposure factors are taken into account. Nevertheless, in Latin America, net FDI inflows and current account improvements tend to signal a decreased need for external credit, and thus have a negative impact on the probability of debt crises. In Asian and African countries, the accumulation of foreign reserves increases the ability of the government to service its external obligations in the long run, while trade openness seems to be doing more harm than good by making the African economies more vulnerable to foreign shocks. When examining the developed world, however, all the external sector variables appear as significant signalling indicators of sovereign defaults even two years in advance.

Turning to the macroeconomic variables, and consistent with the quantitative analysis, they appear to have a major impact on the probability of a debt crisis, especially in

Latin America and Africa, even when using a lag of two years. In particular, speculative attacks on the domestic currency tend to drain the required foreign reserves to service maturing sovereign debts, while the growth of national savings accumulates reserves of funds and thus reduces the likelihood of defaults. Inflation is also important in the case of Africa, as it causes loss of external competitiveness and thus reduces the government's ability to meet its external obligations. The ratio of government expenditures to GDP is another important factor in Latin America, as well as in Asia. The negative effect of this variable indicates that governments tend to increase their spending only during tranquil times when the finances are available and there is no serious threat of compounding unsustainable debt. Furthermore, the growth of real GDP reflects a progressing economy with a lower probability of default both in Latin America and advanced Europe. In addition, an increase in unbacked government liabilities, as measured by the ratio of M2 to international reserves, makes debt crises more likely to occur in Latin America.

Finally, considering the banking sector variables, domestic credit seems to be the most effective indicator in Asia and Latin America. Yet, the results show that a growing amount of credit granted to the private sector reflects a vulnerable banking sector and loose credit regulations that adversely affect the health of the Asian financial system, while, in Latin America, it reflects a growing banking sector and a progressing economy. The growth of bank assets, on the other hand, reports a healthy banking sector that can support the government in case of trouble in Asia and Africa. Furthermore, the bank net claims on the government appears to be a significant indicator in Latin America and Africa only one year before the crisis, as it signals an indebted public sector with a reduced ability to service external debts.

With respect to the regional heterogeneity, it is evident from the highly significant coefficients of the regional dummies included in the global model, and from the basic goodness-of-fit measures depicted in the middle panels, that the debt crises in each country group tend to have distinct features that are better captured using a separate regional model. Furthermore, when comparing the Pseudo R^2, the log-likelihood ratio, and the information criterion between the pooled models and the fixed-effects panel models, it can be noticed that there is some country-specific heterogeneity as well. Generally, the models with the fixed-effects tend to provide a better fit of the data than the random-effects and the pooled models.

However, this result changes completely when considering the in-sample forecasts as depicted in the lower panel of each of the three tables. Therefore, next we turn to evaluating the fit of the estimated models and their ability to provide accurate forecasts of sovereign defaults in both developed and developing countries.

6.6.2 Assessing Predictive Power

The regional heterogeneity prescribed by the crude goodness-of-fit measures is further confirmed by the results of the in-sample forecasts, where the hit rates are well above 90% and the false alarms are around 10% for all pooled regional models even when using a 2-year lag. In fact, the model estimated for developed countries is able to predict correctly all the crisis incidents that occurred over the period of 1980-2005. The predictive power of the global model, on the other hand, is below 90% in both cases (using a 1- or a 2-year lag).

With respect to our fixed-effects panel regressions, which seem superior when fitting the models, the hit rates achieved using a 1-year lag range between 70-90% in most regions, and a mere 20% in Asia[1]. This result is in-line with the literature that applied a fixed-effects model whether on a specific country group (Lestano *et al.*, 2003) or on both developed and developing countries (Jedidi, 2013). Moreover, the performance of the random-effects panel models is even worse than that of the fixed-effects (except in the case of Asia), with a range of 30-75% of correct crisis predictions. Again, these findings are consistent with the previous studies that applied random-effects models (Fioramanti, 2008;

[1]Note also that the number of observations have diminished radically, because the fixed-effects model excludes all countries that did not experience a debt crisis over the in-sample period.

Lausev *et al.*, 2011), indicating that the assumption of independence of the unobserved heterogeneity from the covariates seems to be very strong.

Thus, once again the empirical evidence proves that simple models outperform the more complex ones in terms of the forecasting accuracy (Fuertes and Kalotychou, 2006; Fioramanti, 2008; Savona and Vezzoli, 2015). This finding is further tested and discussed in more detail in subsection 7.3.2. Consequently, due to their unsatisfactory in-sample performance, we exclude the panel models, as well as the pooled global model, from our further analyses.

When comparing the forecasting ability of our pooled regional models with that of the EWSs constructed in the literature, the results show that our models improve on the previous findings. In particular, Ciarlone and Trebeschi (2005) generated 36% false signals while only correctly predicting 72% of the in-sample crisis episodes, whereas the model estimated by Pescatori and Sy (2007) had a sensitivity of 86% and a false alarm rate of 14%. Even Manasse *et al.* (2003), who were able to issue about 5% false signals, could barely foresee 75% of the crisis episodes. Furthermore, the only study that included developed countries, yet pooled them with emerging markets, had an in-sample hit rate of 77% with a false alarm rate of 16% (Savona and Vezzoli, 2015).

Although our pooled in-sample forecasts look very promising, the true predictive power of the models should be assessed by their forecasts over the period that they do not include any information about in terms of the indicators or the true crisis incidents. Therefore, Table 6.10 examines the predictive performance of the estimated models over the period 1980-2005 in the out-of-sample periods, which extend from 2006 to 2012. The upper panel of the table investigates the regular forecasts over the entire holdout period using the estimated regressions from 1980-2005, while the lower panel improves on the forecasting results by applying our novel dynamic-recursive forecasting technique developed in Chapter 3, which updates the models with the new observations as they become available.

Table 6.10: Out-of-sample 2006-2012 Debt Crisis Forecasts

	Asia		Latin		Africa		Developed	
	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags
Regular Forecast								
% of Correct Crisis	–	–	50.0	0.0	100.0	100.0	71.4	71.4
% of Missed Crisis	–	–	50.0	100.0	0.0	0.0	28.6	28.6
% of Correct Tranquil	94.6	98.2	98.8	95.0	90.3	90.3	94.6	87.5
% of False Alarm	5.4	1.8	1.2	5.0	9.7	9.7	5.4	12.5
Recursive-Dynamic Forecast								
% of Correct Crisis	–	–	100.0	100.0	100.0	100.0	71.4	71.4
% of Missed Crisis	–	–	0.0	0.0	0.0	0.0	28.6	28.6
% of Correct Tranquil	94.6	100.0	93.8	87.5	95.2	93.5	96.4	89.3
% of False Alarm	5.4	0.0	6.2	12.5	4.8	6.5	3.6	10.7

In this respect, the upper panel may reveal the inadequacy of the estimated models in providing appropriate out-of-sample forecasts, especially in Latin America. None of the four crisis incidents is depicted using the model with the 2-year lag and only two using the 1-year lagged model. In developed countries, however, five out of the seven episodes (70%) are correctly forewarned. These results are in-line with the few papers that reported out-of-sample forecasts, where Ciarlone and Trebeschi (2005) was able to predict two out of five (40%) crisis episodes in emerging economies with a false alarm rate of 18%, and Manasse *et al.* (2003) correctly signalled 45% of sovereign defaults in the holdout period while generating 6% false signals.

Nevertheless, our findings improve substantially when applying the dynamic-recursive forecasting technique, proving the superiority of this method over the regular forecasts. Particularly, in Asia, where no crises occurred during the holdout period, all tranquil periods are captured without issuing any false alarm at all. In Latin America and Africa, *all* crisis incidents are correctly signalled even two years *ex-ante*, while generating false signals around 10%. Moreover, the estimated model in developed countries is able to foresee the debt crises that occurred in several European countries as a result of the 2008 global financial crisis, having correctly predicted the periods of distress in Greece, Portugal and Ireland at a lower false alarm rate than that generated by the regular forecasting technique.

These ratios outperform to a great extent the most accurate EWSs constructed so far. Between Fuertes and Kalotychou (2006) and Savona and Vezzoli (2015), a maximum of 75% of the out-of-sample crisis episodes was forewarned with a false alarm rate of 15-30%. Fuertes and Kalotychou (2007) were able to make improvements, having a sensitivity ratio of 82%, but again a relatively high false alarm ratio of 23%.

So far, our results correspond to the models that use a binary dependent variable. Next, we attempt to construct an EWS for sovereign debt crises using a multinomial crisis definition that treats the post-crisis years as a separate economic state from the onset of a crisis and the tranquil periods.

6.7 Multinomial Logit Model

In order to avoid the problem of endogeneity in the estimated models, where the crisis itself affects the economic indicator variables, several studies preferred dropping all post-crisis observations after the first year of the crisis onset (refer for example to Fuertes and Kalotychou, 2007; Savona and Vezzoli, 2015), while Ciarlone and Trebeschi (2005) suggested the use of a multinomial logit model instead, which considers the years after a crisis onset as a distinct economic state.

In the previous section, we considered a third alternative, that is, to treat all post-crisis periods as separate crisis episodes. Yet, to make a fair comparison with the findings in the literature, and to test the superiority of our models, we also consider constructing an EWS using a multinomial dependent variable. In this respect, we follow the suggestion of the literature with respect to the timing of a sovereign debt crisis, and consider the periods after the first year of crisis entry as a post-crisis episode. Accordingly, the multinomial dependent variable can be defined as:

$$DCm_{it} = \begin{cases} 0 & if\ DC_{it} = 0 \\ 1 & if\ DC_{it-1} = 0\ and\ DC_{it} = 1 \\ 2 & otherwise \end{cases} \tag{6.2}$$

The maximum likelihood approach is, then, utilised to regress this multinomial dependent variable on the lags of the proposed economic indicators using the cumulative logistic distribution. Accordingly, the results of the regional regressions using the first lag are illustrated in Table 6.11, while Table 6.12 summarises the results of using the second lag of the explanatory variables. The upper panel of these tables depicts the marginal effects of the variables on the probability of entering into a new sovereign debt crisis, whereas the lower panel focuses on the probability of being in a post-crisis/recovery period.

6.7.1 Estimation Results

According to these tables, and with respect to the Asian countries, the ratios of total external debt and IMF credit to GDP have a significant effect on the probability of going into crisis, as well as on being in one. It is remarkable, however, to find that IMF credit is low before crisis onsets and high afterwards. A probable explanation of this phenomenon is the slow procedure of the IMF credit granting scheme, especially for developing countries. Governments may apply for a loan before the onset of a crisis, but actually get the funds after the crisis has hit the economy. Apparently, when using the binary logit estimation, the positive effect is dominant (refer to Table 6.7 and 6.8).

Furthermore, the external sector variables, which were not significant in explaining debt crises in Asian economies using a binary logit regression, appear to be significant for the onset of a crisis, but not for the recovery period, and only one year in advance. In this respect, the improvement of the current account balance seems to help fend off external debt problems, while trade openness makes the economy more vulnerable to external shocks.

Table 6.11: Multinomial Logit Regression of Sovereign Defaults using 1-Year Lag

		(1) Global	(2) Asia	(3) Latin	(4) Africa	(5) Developed
Crisis Period $DCm_{it} = 1$	TODBT	0.016*	0.402**	0.048*	0.167**	0.122**
	IMFCRD	-0.196	-7.260**	-0.763	-2.469**	4.279**
	GLBINT	0.162*			1.347**	
	FRXRES	-0.223*	-0.036	-0.051	-1.399**	-0.314
	TRDOPEN	-0.000	0.062**	-0.035*		0.105*
	CURACC	-0.145**	-0.500**	-0.191*	-0.093	-0.462**
	FDI	-0.199		0.353	0.527	
	RGDPGR	-0.036	-0.844**			-0.704
	INFL	-0.007	-0.497*		-0.276	
	M2RES	-0.043	0.306**	0.122*		-2.346*
	REEROVR	-0.046**	-0.341**	-0.027	-0.140**	-0.166
	GOVEXP	-0.035		0.165	0.469	-0.538
	NATSAV	0.019			0.284	0.051
	DOMCRD	0.019*	0.296**		0.174**	
	BKASST	0.011	-0.477**		-0.146*	
	GOVBKCLM	0.036**	0.464**	-0.008	-0.181	
Post-Crisis Period $DCm_{it} = 2$	TODBT	0.018**	0.422**	0.029*	0.073**	0.242**
	IMFCRD	0.854**	5.385**	0.381**	0.267	4.664*
	GLBINT	0.122*			-0.051	
	FRXRES	-0.166**	-0.148	-0.077	-0.123**	-2.286*
	TRDOPEN	0.030**	0.048*	0.002		0.010
	CURACC	-0.001	-0.649**	-0.004	0.178**	1.890**
	FDI	-0.470**		-0.481*	-0.258	
	RGDPGR	-0.076	0.775**			-0.496
	INFL	0.003	0.718**		0.182**	
	M2RES	-0.047	-0.010	0.122**		-1.981*
	REEROVR	-0.021*	-0.166**	-0.008	-0.026	-0.261
	GOVEXP	-0.195**		-0.195**	0.047	-1.650
	NATSAV	-0.072*			-0.202**	-1.447*
	DOMCRD	0.015**	0.054		-0.010	
	BKASST	-0.044*	-0.098		-0.025	
	GOVBKCLM	0.063**	0.185*	0.026	0.005	
	N	912	192	300	216	225
	Pseudo R^2	0.595	0.911	0.664	0.709	0.806
	Log-Likelihood	-256.3	-6.9	-87.2	-48.4	-5.3

* $p < 0.05$, ** $p < 0.01$

Table 6.12: Multinomial Logit Regression of Sovereign Defaults using 2-Years Lag

		(1) Global	(2) Asia	(3) Latin	(4) Africa	(5) Developed
Crisis Period $DCm_{it} = 1$	TODBT	0.020*	0.742**	-0.001	0.012	0.176*
	IMFCRD	-0.357	-7.290**	-0.888	-1.825*	2.262**
	GLBINT	0.212**		0.154	0.465*	
	FRXRES	-0.114	-0.056	-0.027	-0.079	-1.989*
	TRDOPEN	-0.009	0.110	-0.024		0.120*
	CURACC	-0.149**		-0.080		
	FDI	-0.184		0.778*	-1.147*	
	RGDPGR	-0.067*				-0.102
	INFL	-0.012	-0.409		-0.247	
	M2RES	-0.049		0.002		-1.018*
	REEROVR	-0.026*	0.110	-0.001	-0.088**	
	GOVEXP	-0.027		0.058	0.094	-2.343*
	NATSAV	-0.026			-0.134*	-0.738**
	DOMCRD	0.010	0.464*	-0.004	-0.003	
	BKASST	0.019	-0.778**		0.009	
	GOVBKCLM	0.021	1.017*	0.003	0.009	
Post-Crisis Period $DCm_{it} = 2$	TODBT	0.032**	0.335**	0.047**	0.025*	0.197**
	IMFCRD	0.421**	-0.050	0.226*	0.181	4.133**
	GLBINT	0.148**		0.083*	-0.019	
	FRXRES	-0.139**	0.184	-0.018	-0.178**	-1.092**
	TRDOPEN	0.016**	-0.057*	-0.007		0.100**
	CURACC	-0.031		-0.065*		
	FDI	-0.579**		-0.555**	0.061	
	RGDPGR	-0.091**				-0.470*
	INFL	0.001	0.132		0.072**	
	M2RES	0.019		0.263**		-1.600*
	REEROVR	-0.026**	-0.083*	-0.009	-0.040**	
	GOVEXP	-0.150**		-0.096*	0.100	-1.502**
	NATSAV	-0.116**			-0.148**	-0.809**
	DOMCRD	0.012*	0.223**	-0.017**	-0.010	
	BKASST	-0.032*	-0.349**		-0.036	
	GOVBKCLM	0.047**	0.382*	0.017	0.021	
	N	912	192	288	216	216
	Pseudo R^2	0.566	0.725	0.638	0.612	0.786
	Log-Likelihood	-275.2	-21.2	-89.9	-64.6	-5.8

* $p < 0.05$, ** $p < 0.01$

With respect to the macroeconomic variables, increased pressure on the real exchange rate seems to be increasing the likelihood of a debt crisis. On the other hand, periods of economic progress, as reflected by inflation and real GDP growth, are more associated with post-crisis years, where the economy is recovering from a previous crisis. Therefore, the slowdown in either rate can signal off an approaching crisis. This change in the directional effect of GDP growth and inflation before and after a crisis was also evidenced in Bussiere and Fratzscher (2006).

As for the possible spillover effect from the banking sector, and using a lag of two years, it is evident that an increase in bank claims, shrinking bank assets, and expanding domestic credit are all able to explain the increase in the probability of an approaching debt crisis, as well as an ongoing one, in the Asian economies.

Turning to the next country group, the results show that, especially when using a 2-year lag, the indicators are only able to explain the post-crisis periods rather than crisis onsets in Latin America. This finding implies that the debt situation in these countries tends to worsen after the entry year. This conclusion is further supported by the fact that all the indicators retain their signs in the post-crisis period and even increase in magnitude compared to the crisis onset periods. Moreover, as discussed below when evaluating the forecasting performance of the model in this particular region, it is evident that the multinomial approach is unable to detect the crisis onsets, because it is not the peak of distress in the Latin American economies.

Focusing on the model using a 1-year lag, it is evident that the ratio of total debt to GDP and the growth in money supply are significant indicators of sovereign debt crises in Latin America. Credit from the IMF shows similar behaviour to that in Asia. Inflows of FDI and an improving current account seem to help the economy recover from debt crises, while the government tends to keep its expenditures low during post-crisis periods to focus on servicing and paying off its outstanding debts. Finally, the banking sector does not appear to be contributing much to the probability of sovereign defaults in Latin America once the macroeconomic variables are accounted for.

Regarding the countries in Africa and the Middle East, it is evident that the debt exposure variables exhibit a similar effect on the probability of debt crises as in the case of Asia. That is, total debt makes a crisis more likely to occur and to continue, while credit from the IMF is lower before the onset and higher afterwards. Furthermore, the GDP-weighted average lending rate increases the burden of servicing external debts, and thus makes sovereign defaults more likely in this region. Several indicators from the external and the macroeconomic sectors appear significant as well: the erosion of foreign exchange reserves, rising rates of inflation, devaluation pressure on the domestic currency, and diminishing national savings are all associated with times of sovereign debt defaults. As in the case of GDP growth in Asia, and as evidenced by Bussiere and Fratzscher (2006), the current account is likely to deteriorate before a debt crisis onset, but it tends to improve afterwards during periods of recovery.

Finally, the estimated model for the developed country group shows the statistical significance of the ratio of debt to GDP both before crisis onsets and during post-crisis periods. In contrast to the developing countries, credit from the IMF has a positive sign before and after the entry year, which indicates that developed countries have easier and quicker access to funds from the IMF than do emerging economies. Furthermore, foreign exchange reserves and the growth of national savings play an important role in the likelihood of debt crises.

Consistent with the emerging markets, trade openness increases the probability of debt crises in the developed economies as well, while the current account balance tends to improve after the onset of a crisis. In addition, government expenditures and money supply are also kept low before and after crisis periods, which could partially explain the improvement in the current account. On the other hand, expansion of domestic credit to the private sector tends to contribute to debt problems, whereas a healthy and growing banking sector, as measured by the growth of bank assets, reduces the probability of debt crises.

Table 6.13: Forecasting Performance of Multinomial Logit EWSs for Debt Crises

	S-E Asia		Latin America		Africa		Developed	
	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags	1 Lag	2 Lags
In-Sample Forecasts								
% of Correct Tranquil	99.4	98.8	92.4	91.9	93.1	90.8	100.0	100.0
% of Correct Crisis Entry	100.0	66.7	50.0	20.0	83.3	50.0	50.0	50.0
% of Correct Post-Crisis	100.0	78.9	92.1	93.4	89.9	87.3	100.0	100.0
Regular Out-of-Sample Forecasts								
% of Correct Tranquil	91.1	83.9	98.8	96.3	95.2	90.3	98.2	100.0
% of Correct Crisis Entry	–	–	0.0	0.0	–	–	0.0	0.0
% of Correct Post-Crisis	–	–	33.3	33.3	100.0	100.0	25.0	0.0
Dynamic-Recursive Out-of-Sample Forecasts								
% of Correct Tranquil	92.9	92.8	98.8	96.3	95.2	93.5	100.0	100.0
% of Correct Crisis Entry	–	–	0.0	0.0	–	–	0.0	33.3
% of Correct Post-Crisis	–	–	33.3	33.3	100.0	100.0	50.0	25.0

This detailed discussion of the statistical significance of the effects of the proposed indicators on the likelihood of experiencing sovereign debt problems, though important for policy makers, is not sufficient to conclude whether the estimated models can act as effective EWSs. Therefore, we next turn to testing their ability to provide forewarning signals of approaching crises.

6.7.2 Forecasting Accuracy

We start our analysis of the predictive performance of the estimated multinomial models by testing the accuracy of their in-sample forecasts. The results of this test is depicted in the upper panel of Table 6.13 for the models using a 1- and a 2-year lag of the signalling indicators.

According to this table, the estimated models are better in predicting tranquil and post-crisis periods than in forewarning an approaching debt crisis. In particular, the models are able to correctly predict more than 90% of the tranquil periods in Latin America and Africa, and about 100% in Asia and developed countries, even two years in advance. Slightly lower hit rates are achieved with respect to the post-crisis episodes. However, with respect to the more important hit rate of crisis entry periods, the models do not seem adequate, especially when using a 2-year lag. Only 50% of the episodes are forewarned in Africa and in developed countries, 20% in Latin America, and two-third in Asia.

The figures look much better, though, using a 1-year lag, where all crisis entry periods are correctly signalled in South-East Asia, and 80% in Africa. With respect to Latin America, and consistent with our previous conclusion, the multinomial logit estimation does not emerge as an appropriate method to construct an EWS for this region, having a hit rate of 50%, which does not improve over a random guess. As mentioned before, this is due to the fact that the situation in these countries tends to get worse after the crisis onset year and persist for prolonged periods.

Although the in-sample forecasts are important for evaluating the performance of EWSs, yet the more relevant test for policy makers is that of the out-of-sample forecasts. Therefore, the middle and the lower panels of Table 6.13 demonstrate, respectively, the results of applying the regular and the dynamic-recursive out-of-sample forecasting techniques to the constructed EWSs. The figures in these two panels imply that, even when using the dynamic-recursive forecasting technique, the multinomial dependent variable is not a proper quantification of sovereign debt crises. In fact, only one out of the three crises that occurred in the developed countries is correctly forewarned, while none of those that hit the region of Latin America are signalled even one year in advance.

6.8 EWS Evaluation and Conclusion

The main objective of this study is to identify the most appropriate technique that can be used to construct accurate EWSs for financial crises. It is, therefore, imperative to compare between the forecasting performance of the different applied econometric methods. Accordingly, Table 6.14 summarises the results of the accuracy measures of all the models we use to provide early warning signals for sovereign debt crises. These accuracy measures are calculated in accordance with the three evaluation criteria discussed in section 3.4. The upper panel of this table focuses on the in-sample forecasting performance of the different models using a 1- and a 2-year lag, while the lower panel depicts the (dynamic-recursive) out-of-sample performance.

Starting with the in-sample performance of the models that use the first lag of the signalling indicators, the multinomial logit appears more accurate in South-East Asia, being able to forewarn correctly all crisis onsets in this region. On the other hand, the binary logit model outperforms that of the multinomial in the other three regions. Particularly, in developed countries it correctly predicted all onsets, in Latin America it forewarned 12 out of the 15 crises, and in Africa and the Middle East 5 out of the 6 onsets. In developed countries, the multinomial logit only predicted one of the onsets, and, although it has the same hit rate as the binary logit in Africa, its lower AUC score reflects its weaker performance.

Since the dynamic signal approach uses a fixed 2-year crisis window, its forecasts can only be compared to the parametric models that use the second lags of the indicators. In this respect, the results in Table 6.14 show that in South-East Asia, where all three methods predicted correctly two of the three crisis onsets over the in-sample period, but the multinomial model outperforms that of the binary logit slightly and that of the signal approach significantly in terms of the other two evaluation criteria. On the other hand, in developed countries, the binary logit model prevails above the other two with respect to all assessment measures, although it has the same hit rate as the dynamic signal approach.

Table 6.14: Evaluating the Performance of Debt Crises EWSs

		S-E Asia			Latin America			Africa			Developed		
		SA	BL	ML	SA	BL	ML	SA	BL	ML	SA	BL	ML
In-Sample Performance	*Models using 1-year lag*												
	Detected Onsets	–	2	3	–	12	9	–	5	5	–	2	1
	Total Onsets	–	3	3	–	15	15	–	6	6	–	2	2
	% of Correct Onsets	–	66.7	**100.0**	–	**80.0**	60.0	–	**83.3**	83.3	–	**100.0**	50.0
	Area under ROC	–	0.98	1.00	–	0.98	0.96	–	0.97	0.96	–	1.00	1.00
	QPS (Brier Score)	–	0.03	0.01	–	0.05	0.08	–	0.07	0.07	–	0.00	0.01
	Models using 2-years lag												
	Detected Onsets	2	2	2	13	8	3	6	3	3	2	2	1
	Total Onsets	3	3	3	15	15	15	6	6	6	2	2	2
	% of Correct Onsets	66.7	66.7	**66.7**	**86.7**	53.3	20.0	**100.0**	50.0	50.0	100.0	**100.0**	50.0
	Area under ROC	0.58	0.95	0.97	0.64	**0.97**	0.96	0.75	**0.96**	0.92	0.86	1.00	1.00
	QPS (Brier Score)	0.11	0.04	0.02	0.26	**0.07**	0.08	0.20	**0.08**	0.10	0.03	0.00	0.00
Out-of-Sample Performance	*Models using 1-year lag*												
	Detected Onsets	–	0	0	–	1	0	–	0	0	–	1	0
	Total Onsets	–	0	0	–	1	1	–	0	0	–	3	3
	Percent Onsets	–	–	–	–	**100.0**	0.0	–	–	–	–	**33.3**	0.0
	Models using 2-years lag												
	Detected Onsets	0	0	0	1	1	0	0	0	0	2	2	1
	Total Onsets	0	0	0	1	1	1	0	0	0	3	3	3
	Percent Onsets	–	–	–	100.0	**100.0**	0.0	–	–	–	66.7	**66.7**	33.3

Note: SA denotes Signal Extraction Approach, BL Binary Logit models, ML Multinomial Logit models

With respect to Latin America and Africa, the dynamic signal approach is able to forewarn 87% of the crisis entry periods in the former region and 100% in the latter. However, this relatively high hit rate comes at the expense of a high false alarm rate, which is apparent from the lower AUC and the higher QPS measures. Thus, although the signal approach performs best according to the percentage of correct onsets, the latter two criteria recommend the binary logit model instead, despite of its much lower (almost half) hit rates.

Finally, we investigate the out-of-sample performance of our constructed EWSs to evaluate formally their effectiveness from a policy makers' perspective. Accordingly, the lower panel of Table 6.14 demonstrates that two years in advance, both the binary logit model and the dynamic signal approach correctly forecast the one out-of-sample crisis that occurred in Latin America and two out of the three crisis episodes in the advanced world. Nevertheless, as in the case of the in-sample results, the percentage of false alarms generated by the signal approach are double the ones issued by the binary logit model. This can be evidenced by comparing the figures in the lower (dynamic-recursive) panel of Table 6.10 to that of Table 6.6. The multinomial logit models, however, continue to fall behind the other two methods as in the case of the in-sample forecasts.

Consequently, we can conclude that the dynamic signal approach can be used to construct a more sensitive warning system of sovereign debt problems in the different country regions relative to the other two methods. Therefore, it is especially recommended for policy makers in the countries that are prone to debt crises (e.g. in Latin America), as it provides more accurate predictions of approaching distress periods. However, more reliable but less accurate signals are provided by the EWS that applies the regional binary logit models. With significantly reduced likelihood of issuing false alarms, this method can be recommended for countries with a more resilient government sector and sustainable sovereign debt, which is mainly the case of developed countries.

Last Chapter: Following our thorough investigation of the different methods that can be used to model EWSs for the three different types of financial crises (namely currency, banking, and sovereign debt) in both developed and developing countries, we proceed in the next and final chapter to provide more in-depth discussions, conclusions and recommendations in accordance with our main research objectives detailed in section 1.3.

Chapter 7

Summary, Conclusions and Recommendations

The opening statement of the October 2008 IMF World Economic Outlook (WEO)[1] read:

> "The world economy is now entering a major downturn in the face of the most dangerous shock in mature financial markets since the 1930s . . . The major advanced economies are already in or close to recession . . . The emerging and developing economies are also slowing, in many cases to rates well below trend . . . The immediate policy challenge is to stabilise global financial markets, while nursing economies through a global downturn and keeping inflation under control."

By the end of 2010, the IMF reported that the financial systems were still impaired, recoveries were very sluggish, and that social challenges were mounting up. They advised that "fiscal adjustment needs to start in earnest in 2011. Specific plans to cut future budget deficits are urgently needed now to create new room for fiscal policy manoeuvre"[2]. Nonetheless, the situation at the end of 2011 and the beginning of 2012 grew worse, especially in Europe. Therefore, the IMF staff argued: "The global economy is in a dangerous new phase. Global activity has weakened and become more uneven, confidence has fallen sharply recently, and downside risks are growing . . . The structural problems

[1]WEO (2008, October), Financial Stress, Downturns, and Recoveries.
Retrieved from https://www.imf.org/external/pubs/ft/weo/2008/02

[2]WEO (2010, October), Recovery, Risk, and Rebalancing.
Retrieved from https://www.imf.org/external/pubs/ft/weo/2010/02

facing the crisis-hit advanced economies have proven even more intractable than expected, and the process of devising and implementing reforms even more complicated"[1].

In light of these statements over the course of the recent global financial crisis, and considering the devastating national and international economic, and possibly social and political, effects of any such crises, it has become increasingly important to put serious efforts into constructing a financial monitoring tool that can forewarn the build-up of financial turmoil. The primary stimulus of constructing EWSs for financial crises is to provide policy makers with some lead time to take corrective actions that would help avert, or at least mitigate, the damages of an approaching crisis. Since the end of the 1990s, the IMF staff, along with extensive efforts from academia, has been systematically attempting to develop a framework for such EWSs using several econometric methods.

However, the forecasting performance of these warning systems was not satisfactory, especially in predicting out-of-sample crisis incidents. This made Abiad (2003) argue that, no matter how sophisticated is the EWS, it will not be able to forecast crises with a high degree of accuracy. Berg *et al.* (2005) reinforced this view that EWSs are not sufficiently accurate to be solely used to forecast impending crises. Thus, the general conclusion in the literature was that such systems are no more than useful supplements to more informed country analyses, and as a means of summarising information in an objective manner. Furthermore, the challenge of designing an effective EWS escalated even further when the pre-2008 models failed to foresee the severity and international span of the current global crisis.

In the aftermath of the 2008 crisis onset, several studies attempted to develop new econometric techniques to model more accurate EWSs of the different types of financial crises. Consequently, this study investigates in detail the performance of these new methods in practice. We distinguish three types of crises that require attention when constructing a forewarning system, namely currency, banking and sovereign debt crises.

[1]WEO (2011, September), Slowing Growth, Rising Risks.
Retrieved from https://www.imf.org/external/pubs/ft/weo/2011/02

Hence, a separate EWS is developed for each type, while taking into account the possibility of being preceded by another crisis type, which is referred to in the literature as "twin" or "triple" crises. Moreover, we develop a new more powerful forecasting technique to improve the out-of-sample predictive power of the constructed EWS. Our results are shown to be very accurate compared to the ones found in the previous literature, which confirms the usefulness of our EWS in forewarning financial crises in the different regions of the world.

7.1 Contributions to EWS Literature

In accordance with the research objective to construct more effective EWSs for each of the three different types of financial crises in both developed and developing country regions, we design our models in a way to close several gaps in the literature.

7.1.1 Main Contributions

The literature review discussed in Chapter 2 identified three main gaps in modelling EWSs for each type of financial crisis. Our study addresses each of these gaps as follows:

Regional Heterogeneity

In the previous literature, the developed and emerging countries were frequently pooled together into a single dataset when modelling the EWS. Only few studies have focused on either type of economy, a particular region (especially South-East Asia in the aftermath of the 1997 crisis), or a specific country. However, no study (to the best of our knowledge) has investigated the possibility of signalling indicator differences between developed and developing countries.

Due to their inherent distinctiveness with respect to the structure of the economy, vulnerability to shocks, extent of integration into the global financial system, degree of dependence on other economies, institutional effectiveness and policy responses, it is fairly reasonable to expect the variables that can act as signalling indicators for financial crises to be different across both types of economies. Our study goes even deeper into analysing and identifying the crises leading indicators in each country region separately. Keeping regional differences in mind when constructing EWSs came as a recommendation of Kamin *et al.* (2001) for future research.

For this purpose, we divide the world into five different regions (developed countries, Latin America, Eastern and Central Europe, South and East Asia, Africa and the Middle East), and construct a separate EWS for each region. Comparing the collective predictions of the regional models to a global model that incorporates all countries together, as well as a collective model that pools all emerging countries together, the results show that the separate regional models outperform the other two significantly in terms of the forecasting performance.

Cross-Evaluation of the New Econometric Techniques

Traditionally, the two most common approaches used to model EWSs for financial crises were the discrete-dependent-variable models (binary logit / probit), suggested by Frankel and Rose (1996) and Demirguc-Kunt and Detragiache (1998), and the static signal extraction approach developed by Kaminsky *et al.* (1998). However, the poor predictive performance of both models in forecasting approaching financial crises stimulated further research to modify these models (or develop new ones) in order to improve the effectiveness of the EWS. In this respect, Bussiere and Fratzscher (2006) suggested the use of multinomial logit regression models to overcome the problem of "post-crisis bias" inherent in the binary version of the models. On the other hand, Casu *et al.* (2012) developed a more dynamic version of the signal extraction approach to make the model more fit for different time periods and across various country samples.

Nonetheless, the performance of these newly developed econometric techniques was only tested in particular conditions or in specific country regions. We extend the application of these three models (binary vs. multinomial logit regression models vs. dynamic signal approach) and examine their performance in predicting currency, banking, and sovereign debt crises in the different developed and developing country regions.

Furthermore, we suggest an alternative improvement to the binary logit model to overcome the post-crisis bias and still avoid falling into an endogeneity problem. Namely, our binary models treat the entire period a country spent in any type of financial crises as individual crisis episodes. As opposed to the standard conduct in the literature of dropping post-crisis observations, our specification enables us to retain and use all the information available in the dataset, investigate ongoing crises rather than just new ones, and evaluate the effectiveness of the constructed EWS in predicting the onset as well as the length of impending crises.

In addition, we address another important issue in the literature with respect to the "simplicity vs. complexity" issue of the regression models used to construct the EWS. In the previous literature, there was no general agreement as to the optimal level of model sophistication to deal with unobservable country and/or time heterogeneities. Some used pooled regressions, some fixed-effects or random-effects models, and others more complex mixed and time-varying specifications. Yet, no study has cross-evaluated their performance in fitting crisis models or in providing forewarning signals of approaching crises, save for Fuertes and Kalotychou (2006) who thoroughly investigated this issue in the case of debt crises in developing economies. We extend this analysis to the other two crisis types (currency and banking) and in every country region (advanced and emerging).

Finally, it is surprising to find in the literature that relatively few studies have analysed and tested the out-of-sample performance of their constructed EWSs. In fact, of those who did examine their models in a holdout period of their sample, most authors have only reported predicted probabilities (rather than compared their generated signals to actual crisis events) or some scoring rule (e.g. QPS), but not accuracy measures. Accordingly, in addition to the QPS scoring rule, we also report for each estimated model a set of accuracy measures to evaluate its in- as well as out-of-sample predictions. Moreover, when choosing the in-sample cut-off probability required to calculate the accuracy measures (which is then applied to the holdout period), we select the one that maximises Youden's J-statistic while, at the same time, keeps the false alarm rate within a 10% range. In contrast to the more common criterion used in the literature, namely minimising the $NTSR$ or some other loss function, Savona and Vezzoli (2015) showed that the J-statistic is more robust to the extreme values of Type I and Type II errors.

Dynamic-Recursive Forecasting Technique

The limited number of studies that did report out-of-sample forecast results tended to use a regular forecasting technique. According to this technique, the EWS model is estimated once over the in-sample period, and then the estimates are used to provide forecasts over the entire holdout period, which usually extends over a short period of 2-3 years.

In order to generate more accurate forecasts over a longer horizon, we develop a new more powerful *dynamic-recursive forecasting technique*. Using this method, the models are estimated several times, each time adding one further out-of-sample observation (thus recursive) along with the predicted probability of the previous period (thus dynamic), and generating a 1-step-ahead forecast. By feeding the model with new information as they become available over time and incorporating the previous predictions when making new ones, the predictive power of the parametric EWSs (using binary or multinomial logit) are improved significantly.

7.1.2 More Specific Contributions in Each Crisis Type

In addition to these three main contributions that are applied to the construction of EWSs for each of the three types of financial crises, we add a few other improvements to the modelling process that are specific to each type. These could be outlined as follows:

EWS for Currency Crises

In order to capture both successful and unsuccessful speculative attacks on a domestic currency, we prefer to use the full version of the EMP index when specifying the currency crisis dependent variable. Unlike the more frequently used index that only incorporates changes in the exchange rate and foreign exchange reserves, the full model also includes changes in the interest rate. Furthermore, for robustness checks, we attempt other different specifications of the EMP index that are suggested in the previous literature. In particular, we construct the EMP index without the interest rate component, by considering each component separately (as suggested by Zhang, 2001) with and without the interest rate component, and by calculating the weights using a rolling standard deviation of each component instead of the more commonly used fixed in-sample weights.

Additionally, when converting the EMP index into a binary response variable of currency crisis incidents, the major bulk of the literature has arbitrarily set the threshold to two or three standard deviations, while few studies used more peculiar levels, such as 1.5, 2.5 and 0.75. To avoid such non-systematic practice, we attempt different specifications of the EMP threshold level and choose the one that is found to provide the best fit of the well-known currency crisis episodes which occurred in the sampled countries, and to give the most accurate in-sample forecasts.

With respect to the proposed variables that can act as signalling indicators of currency crises, our models include variables that reflect possible contagion from other countries (third generation model), as well as several forward-looking variables that are expected to cause self-fulfilling prophecies (second generation model), in addition to the usual macroeconomic fundamentals (first generation model) considered by all the EWSs in the previous studies. Moreover, we also consider variables that can capture possible spillover from the other domestic sectors (fiscal and banking), and thus lead to a situation of 'twin' or even 'triple' crises.

Finally, we apply the dynamic signal approach when modelling the non-parametric EWS for currency crises in the different country regions (developed and emerging). Although the more traditional static version of the signal extraction approach is very popular in the literature, the dynamic version was never used before in the context of EWS for currency crises.

EWS for Banking Crises

Turning to the banking crisis forewarning system, we prefer to use a quarterly frequency of the data rather than the annual frequency used in the previous literature to avoid the problem of "crude crises timing" pointed out by Barrell *et al.* (2010). This quarterly frequency was rarely considered before due to the lack of available data on several important signalling indicators, and the lack of consensus in the financial economic literature regarding the most suitable way to define the beginning and the end of a banking crisis. To overcome the latter problem, we use the recently developed databases by the IMF and the WB to specify when each of the sampled crisis incidents started and ended. As for the former drawback, it was necessary to reduce the time period covered in our sample to one that spans from 1998-2012 only due to the non-availability of some of the indicators at the higher frequency.

When constructing the EWS for banking crises, we consider, in addition to the regularly used macroeconomic and financial variables, several indicators that reflect the possibility of twin crises (currency or debt), spillover from the real estate sector, and contagion from other countries. Moreover, our models incorporate a number of consolidated bank balance-sheet variables as predictors of banking sector distress, as these were rarely assessed by previous studies, but were recently found by Barrell *et al.* (2010) to have a significant effect on the probability of an approaching banking crisis.

Although the dynamic signal approach, suggested by Casu *et al.* (2012), was developed and tested for banking crises, it was only applied on a pool of OECD countries. Therefore, we extend its application and evaluate its performance on all five regions, developed and developing. Accordingly, we test the authors' argument that the dynamic version enables the results of the signal approach to be more globally applicable and across different time periods.

EWS for Sovereign Debt Crises

Regarding the construction of an EWS for sovereign debt crises, our study contributes to the financial economic literature by modelling a separate EWS for developed countries, which was not considered before. Particularly, only two very recent articles by Jedidi (2013) and Savona and Vezzoli (2015) have pooled some developed countries in their main sample of emerging economies. Furthermore, we test the applicability and the performance of the dynamic signal approach, which was originally developed for modelling EWSs for banking crises, in the case of sovereign debt crises.

Moreover, we propose a definition of debt crises that complements the conventional definition. It is common practice in the literature to consider the event of receiving a loan from the IMF in excess of 100% of the country quota as a debt crisis incident. However, this definition does not capture the fact that a certain country may obtain successive credit from the IMF as an extensive financial rescue scheme without having either amount exceeding 100% of its quota. In order to reflect this latter case, and in an attempt to more accurately date debt crises, we also consider the event of obtaining cumulative credit from the IMF in excess of 200% of the quota as a crisis incident.

Another issue that was rarely considered in the previous EWSs for debt crises is the possibility of being preceded by another type of financial crisis that hit the economy. Sovereign debt crises were only separately addressed in seclusion of currency or banking crises. However, Reinhart and Rogoff (2011) and Balteanu and Erce (2014) have pointed out the significant links between the three types of financial crises and recommended future research to take them into account. Therefore, we examine the inclusion, and test the predictive performance, of several variables that reflect the likelihood of spillover from the foreign exchange market and the domestic banking sector when modelling our EWS.

7.2 Key Results on Crises Signalling Indicators

We apply three econometric methods to construct EWSs for each type of financial crisis (currency, banking, and sovereign debt), namely the dynamic signal extraction approach, the binary and the multinomial logit regression models. First, we attempt to identify the most statistically significant explanatory variables that can act as leading indicators for each crisis type in the five different country regions. These indicators are then used to provide in- and out-of-sample forecasts of approaching crises. The evaluation of these forecasts is summarised in section 7.3.

7.2.1 Signalling Indicators of Currency Crises

The dataset used to model EWS for currency crises consists of monthly observations over the period 1994-2012. The sub-sample of 1994-2008 is used for estimation and examining the in-sample predictions, while the four-year period 2009-2012 is held back to evaluate the out-of-sample forecasts of each estimated model. The panel covers 10 (non-Eurozone) developed countries and 15 emerging economies from South-East Asia, Latin America, Eastern and Central Europe, and Africa and the Middle East.

The results of the three econometric methods consistently identified the full version of the EMP index using fixed in-sample component weights as the most accurate specification of the currency crisis dependent variable. Furthermore, the optimal threshold to convert the EMP index into a binary crisis series is found to be three standard deviations away from the in-sample mean. This specification provides the best fit of the currency crisis episodes in all country regions.

With respect to the signalling indicators of approaching currency crashes, the constructed EWS shows that in developed countries the overvaluation of the real exchange rate has the major leading role. Since the advanced economies tend to have more freely floating exchange rates than do developing counties, marked fluctuations in their foreign exchange market were also found to be reliable alarming signals by Edison (2003), Frankel and Saravelos (2012) and Gourinchas and Obstfeld (2012). This is not the case, however, with respect to developing countries that rely more on hard pegs or pegged-float regimes. In addition, and using similar reasoning, the stock market deterioration appears to reflect the slowdown of the economic activity in developed economies and growing uncertainty perceptions of investors, which was also noted by Edison (2003) and Lang (2013).

The expansion of domestic credit, and decreased bank profitability (as measured by falling lending-to-deposit interest rates) also marks the periods preceding developed currency crashes. This signifies spillover from the banking sector to the foreign exchange market, and thus the increased likelihood of twin currency-banking crises. This result is in-line with the most recent literature, which found that banking distresses tend to increase the likelihood of currency crises (refer for example to Lang, 2013; Babecky *et al.*, 2014). On the other hand, and contrary to previous findings in emerging economies (Kaminsky *et al.*, 1998), increased public debt is usually associated with tranquil periods for the advanced world.

The banking sector appears to be a significant contributor to currency problems in Latin America and Eastern Europe as well, which was confirmed by Kamin (1999) and Karahoca *et al.* (2013), while rising public debt tends to precede crashes in Africa and the Middle East only. On the other hand, our findings confirm the results of earlier studies which suggested that the erosion of foreign exchange reserves is an alarming indicator in all emerging economies (Burkarta and Coudert, 2002; Kumar *et al.*, 2003; Comelli, 2013).

Moreover, in South-East Asia and Latin America, the current account balance, the rate of inflation, and the GDP growth rate are all significant indicators of currency crises as also concluded by Kamin (1999), Krznar (2004) and Comelli (2013). Yet, the negative impact of the rate of inflation on the likelihood of a currency crash implies that it is associated with a growing economy (demand-pull inflation) rather than loose monetary policy. In addition, the instability of the political arena seems to put further pressure on the domestic currency of the Latin American economies, whereas stronger links to developed economies' stock markets can help to fend off regional capital flight. These factors were not considered before in Latin America, and very rarely in emerging countries in general.

With respect to Eastern Europe, the deviation of the exchange rate from its trend (refer also to Karahoca *et al.*, 2013), a deteriorating current account balance (refer also to Takahashi, 2012), and contagion from neighbouring countries are among the significant indicators of currency crashes. The latter factor was only considered by Kumar *et al.* (2003), who also recommended its inclusion in further research. Finally, in Africa and the Middle East and consistent with the findings of Candelon *et al.* (2012) and Lang (2013), a shrinking term spread tends to reflect worsening future economic prospects, and easily reversible portfolio inflows increase the likelihood of currency crises. This supports the notion of "self-fulfilling" crises, contrasting with the earlier results of Kaminsky (2006) that most currency crises are preceded by weak economic fundamentals only.

7.2.2 Signalling Indicators of Banking Crises

To model EWS for banking crises, we rely on a quarterly frequency of the data over the period 1998-2012 for 30 developed and developing countries. For the purpose of estimation, only the sub-sample 1998-2007 is considered, while leaving out the observations that reflect the 2008-2012 global financial crisis to evaluate the out-of-sample forecasting performance of the EWS.

The estimation results show that, in contrast to Bongini *et al.* (2002) but consistent with Barrell *et al.* (2010) and Caggiano *et al.* (2014), the consolidated bank balance-sheet variables appear to be playing the major role in explaining an approaching banking crisis, especially in developing countries. Particularly, increases in the capital-assets ratio (which signals government injections to bailout banks), the erosion of bank liquidity, and the fall of the z-score are highly significant indicators in all emerging economies. On the other hand, bank asset quality is only relevant in Latin America, while increased acquisition of credit from the central bank are important in Eastern Europe, Africa and the Middle East. In advanced economies, a rising ratio of non-performing loans and the rapid growth of bank assets at the expense of liquidity are among the major signalling indicators as well.

In addition to the balance-sheet variables, several macroeconomic indicators seem to play an equally important role in explaining the occurrence of banking distress in developed countries. The results show that, in-line with Davis and Karim (2008b) and Casu *et al.* (2012), a slowdown in the growth of real GDP and an increasing current account deficit raise the probability of a crises. However, while Wong *et al.* (2010) found that increasing money supply reflects macroeconomic misalignment in emerging economies, our findings report that in developed countries the injection of liquidity (growth of M2) can help prevent banking sector problems from growing into a systemic crisis. Furthermore, directing credit to a financially distressed government to cover its budget deficit and/or payback public debt leaves banks with a lower amount of funds to grant to private borrowers with lower creditworthiness, and thus reduces the likelihood of defaults. This is again incongruous with the previous results in developing countries, where Ahec-Sonje (2002) found that an indebted government contributes to banking sector distress.

Focusing on emerging economies, our models show that the more traditional first-generation macroeconomic variables tend to lose their significance once the balance-sheet variables are accounted for in the EWS. Nevertheless, the results outline the importance of third-generation variables that reflect possible spillovers and contagion from other countries or domestic markets. More specifically, in Eastern Europe, Africa and the Middle East, as well as in developed countries, banking crises are usually preceded by crashes in the real estate market (falling property prices), especially if fuelled by rapid credit growth.

The significance of these variables as leading indicators of banking crises was also pointed out by Wong *et al.* (2010) and Babecky *et al.* (2014).

Furthermore, domestic banking crises are usually preceded by crises in financially interlinked economies in these regions as well, which was also previously noted by Barrell *et al.* (2010). On the other hand, while banking crisis contagion is only marginally significant in South-East Asia, the overvaluation of the real exchange rate (which drains the foreign reserves of the central bank) appears to play an important role, which provides evidence that currency crashes can further damage an already distressed banking sector (Duttagupta and Cashin, 2008; Singh, 2011). Moreover, consistent with Ahec-Sonje (2002), a growing stock of external debt increases the likelihood of an impending banking crisis in South-East Asia.

7.2.3 Signalling Indicators of Sovereign Debt Crises

The panel data considered in the sample of sovereign debt crises consists of 38 advanced and emerging economies during the period 1980-2012 on an annual basis. To be able to cover a long time span, we do not include countries from Eastern and Central Europe, as their data is only available from 1995, and they have only experienced a very limited number of sovereign debt crises. Accordingly, in addition to the advanced economies, the sampled emerging countries are divided into three regions only: South-East Asia, Latin America, and Africa and the Middle East. Furthermore, the time period is divided into two subsets, where the observations over the years 1980-2005 are used for model estimation and the evaluation of in-sample forecasts, while those of 2006-2012 are used for testing the predictive performance of the EWS.

We find that the variables suggested by the economic theory are able to provide a good measure of the likelihood of an approaching debt crisis. Particularly, the estimation results of the three econometric techniques utilised to design EWSs for sovereign debt crises show that the debt exposure variables (ratio of external debt to GDP and credit acquired from the IMF) are significant indicators in all country regions, which was also previously reported by Peter (2002), Lausev *et al.* (2011) and Jedidi (2013). However, the multinomial logit model shows that the IMF credit is, surprisingly, low before crisis onsets and high afterwards in the case of emerging countries, but is high before and after for more advanced economies. A probable explanation of this phenomenon is that developed countries have easier and quicker access to IMF funds. This distinction is not apparent when using the binomial logit model (refer also to Fuertes and Kalotychou, 2006) that combines the crisis and post-crisis periods together, as the positive effect dominates the negative.

Another general finding that is consistent among all the regions is that governments, in both developed and emerging countries alike, tend to keep their expenditures low around the times of crises. That is, public spending are increased only during tranquil times when the finances are available and there is no serious threat of compounding unsustainable debt. However, Lausev *et al.* (2011) found that increasing government expenditures raise the likelihood of sovereign defaults in Eastern European countries, which were not included in our sample.

In addition to these variables and in-line with the previous literature on emerging countries in general, rising FDI inflows (Lausev *et al.*, 2011), current account improvements (Peter, 2002), and growth of national savings tend to signal a decreased need for external credit, and thus less pressure on government debt in Latin America. As for the countries in Africa and the Middle East, inflation causes external debt servicing to be more expensive, the overvaluation of the domestic currency drains the required foreign reserves to service maturing sovereign debts, and trade openness seems to be doing more harm than good by making the African economies more vulnerable to foreign shocks. These results are also consistent with those found by Fuertes and Kalotychou (2006), Manasse and Roubini (2009) and Savona and Vezzoli (2015).

With respect to South-East Asia, the accumulation of foreign reserves increases the ability of the government to service its external obligations (as also reported by Jedidi, 2013), whereas banking sector distress and increased pressure on the real exchange rate tend to contribute to debt problems, leading to twin or even triple crises. The link between the three types of financial crisis is complex and still requires further analysis; yet, it was evidenced several times in the literature that debt crises tend to be associated with currency and banking crises (Manasse *et al.*, 2003; Reinhart and Rogoff, 2011). Finally, in developed countries, the rate of real GDP growth (refer also to Peter, 2002; Savona and Vezzoli, 2015), the ratio of national savings to nominal GDP, and the banking sector variables (domestic credit and bank assets growth) have a major influence on the likelihood of debt crises.

7.3 Evaluation of EWS Predictive Power

The main purpose of this study is to build forewarning systems that can provide accurate in- and, more importantly, out-of-sample forecasts of each of the three types of financial crises. Accordingly, after identifying the key signalling indicators of currency, banking, and sovereign debt crises, we now proceed to discuss the results of the constructed EWSs in terms of their predictive performance in-line with our main contributions.

7.3.1 Regional Heterogeneity

Although the perception of leading indicator differences across the various country regions is not new in the literature of constructing EWSs for financial crises, as it was recently suggested by Caggiano *et al.* (2014) in the context of banking crises and by Kamin *et al.* (2001) and Candelon *et al.* (2012) for currency crises, it was thus far not formally tested. Notwithstanding, it is readily noticeable from our estimation results discussed in section 7.2 that the leading indicators of financial crises vary to a great extent from one region to another. A variable (or even a set of variables) that can act as a significant indicator of approaching crises in one region could be irrelevant, or at least not so important, in another. Thus, there appears to be regional heterogeneity with respect to the signalling indicators of the different types of financial crises.

This primary conclusion is rather plausible given the relatively distinct nature and symptoms of several noted crises that occurred in particular regions in the recent history; for example the European currency crisis in 1991/92, the Latin American debt crisis of 1994, the Asian financial crisis of 1997/98, and finally the recent financial crisis of 2008 which hit almost all the developed world. More formally, the goodness-of-fit measures of the estimated binary and multinomial logit models support this conclusion, where the McFadden's R^2, the log-likelihood ratio, and the BIC criterion all favour each of the regional regressions over the global one using either the pooled, the fixed-effects or the random-effects method of estimation. This result signifies the paramount need for developing and monitoring a separate EWS in each region.

In addition, the apparent regional heterogeneity is further confirmed by comparing the predictive power of the global models to that of the regional one. The results of the EWS of each of the three types of crises indicate that the regional models have a significantly higher hit rate (given the same range of false alarms) than the global model, as well as the collective model that incorporates all emerging economies, using any of the three proposed econometric methods. Particularly, in the case of currency crises, the global logit model correctly predicts 70% of the total crisis incidents that occurred in-sample, whereas the average hit rate of the regional models is 90-100%, while keeping the false alarm rate below 10%. The same range of 90-100% correctly predicted crises is also found with respect to the regional EWSs for banking crises and for sovereign defaults, but the global models' hit rate is slightly below the 90%. These differences in the forecasts between the global and the regional models are also reported by the dynamic signal approach and the multinomial logit regressions.

7.3.2 Simplicity vs. Complexity

The analysis of whether controlling for unobservable differences across countries and over time can enable the EWS to provide more accurate forecasts of financial crises was only addressed in the context of sovereign defaults. In this regard, Savona and Vezzoli (2015) found that simple models tend to outperform more complex ones in terms of forecast accuracy using a regression tree. A more extensive investigation was conducted by Fuertes and Kalotychou (2006), who considered nine different binary logit specifications that range from a simple pooled regression to a random coefficients model. Their results show that the more complex models that allow for both country and time variation tend to generate poor forecasts, while the model that assumes full homogeneity develops a more effective EWS of sovereign debt crises.

Our results with respect to the other two crisis types (currency and banking) and in every country region (advanced and emerging) further support this notion that simplicity outperforms complexity in predictive power, although the latter provides a better fit of the data using all goodness-of-fit measures. In fact, the panel fixed-effects logit regressions of the EWS for currency crises have in-sample hit rates that stand below 70% in the different regions, the random-effects models below 40%, while the simple pooled regressions are able to correctly predict 90-100% of the crisis episodes. In the case of banking crises, where the regional pooled models have sensitivity of 90%, both the fixed- and the random-effects models could not even improve over a random guess of 50%. Likewise, the hit rates of the pooled models developed for sovereign debt crises are all well above 90%, whereas the fixed- and random-effects have an average hit rate of around 70%.

Since the panel fixed-effects do not improve over the pooled regional models, the regional heterogeneity of the different crises indicators seem to be more important than country-specific ones when it comes to generating accurate predictions. That is, despite the existence of country differences, which is reflected in the better fitting ability of the fixed-effects models, they either do not change much over the period of the forecasts or the effects of their change on the likelihood of experiencing new crises does not weaken the effectiveness of EWS based on simple pooled models.

Furthermore, due to increased financial integration, trade links, and globalisation effects across the countries, the simple pooled regional models are found to outperform the models that account for country-specific heterogeneity; as the former take these interlinks into consideration when forecasting, while the latter forecast the probability of a financial crisis in an individual country in isolation of the similar economies in its region.

Testing Regional Financial Development

To investigate these arguments further, we test whether countries in any specific region tend to have similar characteristics, which makes pooling them into a regional model plausible. Accordingly, we conduct a *Discriminant Analysis* of the countries' state of financial development using the K-nearest neighbour algorithm. That is, we investigate whether countries in the same region have a similar degree of development and structure of their financial sector which is distinct from the countries of the other regions. For this purpose we use the "Financial Development Index" calculated and reported by the World Economic Forum[1] (WEF).

This index is designed to reflect the degree of depth and efficiency in providing financial services in the different countries on a scale from one to seven. It encompasses over 120 indicators and their respective interactions, which can be categorised in the following seven groups[2]:

1. Institutional Environment: degree of financial sector liberalisation, corporate governance, legal and regulatory issues, and contract enforcement
2. Business Environment: reflects human capital, taxes, infrastructure, and costs of doing business

[1]The data for the index are extracted from the Financial Development Reports from 2008-2012, which are available for more than 60 countries on: http://www.weforum.org/

[2]Refer to Appendix A of the Financial Development Reports for a detailed structure of the index and a list of all indicators.

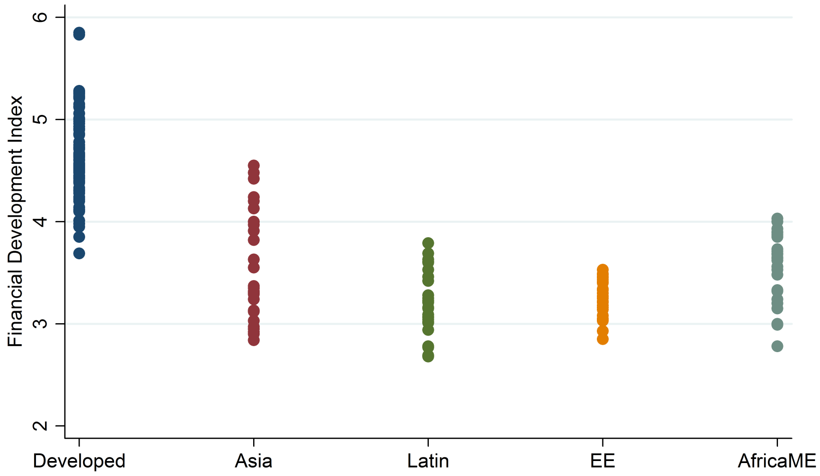

Figure 7.1: Financial Development Index by Country Region

3. Financial Stability: captures the risk of currency crises, systemic banking crises, and sovereign debt crises
4. Banking Financial Services: measures size, efficiency, and financial information disclosure
5. Non-banking Financial Services: includes IPO and M&A activity, insurance, and securitisation
6. Financial Markets: encompasses foreign exchange and derivatives markets, and equity and bond market development
7. Financial Access: evaluates access by individuals and businesses to different financial services

It can be noted from the scatter plot of the overall index illustrated in Figure 7.1 and its descriptive statistics in the first column of Table 7.1 that the financial sector of the countries in the different regions has a distinct structure and degree of development. For example, the index in the developed countries rarely falls below 4 and has a mean of 4.65, while in Latin America, Eastern Europe and Africa and the Middle East it does not rise above 4. The index scores of countries in South-East Asia seem to lie somewhere between developed and other emerging economies. Although they have a slightly lower average overall score than Africa and the Middle East (3.55 compared to 3.62), they exhibit greater dispersion. On the other hand, Eastern European countries have the smallest variation in the score of their financial development index, which is also the lowest amongst all emerging regions.

Taking a closer look at the means and standard deviations depicted in Table 7.1 and the kernel densities[1] illustrated in Figure 7.2 for each of the seven index components in every region, we can conclude that advanced countries, naturally, have the most developed financial systems and the highest scores in all seven index components. According to the WEF reports, they exhibit consistent strengths across the institutional and business environments, having top ranking in auditing and accounting standards, excellent protection of property rights, a highly effective judicial system, and high quality infrastructure within a liberalised financial system.

As for the emerging regions, South-East Asia and Africa and the Middle East tend to have more developed financial systems than countries in Latin America and Eastern Europe. Particularly, the financial systems in Africa and the Middle East are the most stable in the emerging countries, with a financial stability score that is nearly as high as that in developed economies, a very low frequency of banking crises, high bank capital ratios, low effective exchange rate volatility, and relatively good manageability of public debt. Countries in South-East Asia have relatively high scores for their banking system across size, efficiency and financial disclosure, as well as for their non-bank financial institutions compared to other emerging regions. Furthermore, their financial markets (particularly foreign exchange and derivatives) are more developed than the other emerging counterparts. However, their business and institutional environments show room for development due to their inhospitable tax regimes and relatively poor contract enforcement.

On the other hand, the Eastern European economies deliver a strong performance in the business environment component with low regulatory burden, solid information technology infrastructure, contract enforcement, and the quality of human capital. Nevertheless, they have the lowest scores in terms of capital availability and access, and their

[1]Kernel Density is a non-parametric technique for visualising the underlying distribution of a continuous variable. It can be viewed as a smoothed histogram, since histograms are inherently discrete and are thus more appropriate for displaying discrete variables.

Table 7.1: Summary Statistics of the Financial Development Index and its Components

	Overall Index	Institutional Environment	Business Environment	Financial Stability	Banking Services	Non-Banking Services	Financial Markets	Financial Access
Developed	4.65	5.65	5.47	4.87	4.65	3.34	4.05	4.52
	(0.42)	(0.40)	(0.36)	(0.61)	(0.53)	(1.21)	(0.89)	(0.91)
S-E Asia	3.55	4.05	4.09	4.45	3.67	2.75	2.38	3.42
	(0.54)	(0.64)	(0.77)	(0.53)	(0.86)	(0.99)	(0.67)	(0.87)
Latin America	3.24	3.87	4.11	4.50	3.12	2.14	1.67	3.30
	(0.30)	(0.52)	(0.36)	(0.75)	(0.50)	(0.56)	(0.43)	(0.58)
E-Europe	3.25	3.89	4.52	4.12	3.05	2.02	1.88	3.26
	(0.17)	(0.46)	(0.18)	(0.67)	(0.61)	(0.93)	(0.36)	(0.42)
AfricaME	3.62	4.29	4.46	4.74	3.68	1.90	2.54	3.74
	(0.33)	(0.56)	(0.55)	(0.72)	(0.44)	(0.43)	(0.92)	(0.85)
Global	3.91	4.68	4.77	4.62	3.89	2.66	2.89	3.87
	(0.73)	(0.95)	(0.75)	(0.69)	(0.88)	(1.14)	(1.24)	(0.96)

Note: Numbers within parentheses represent standard deviations.

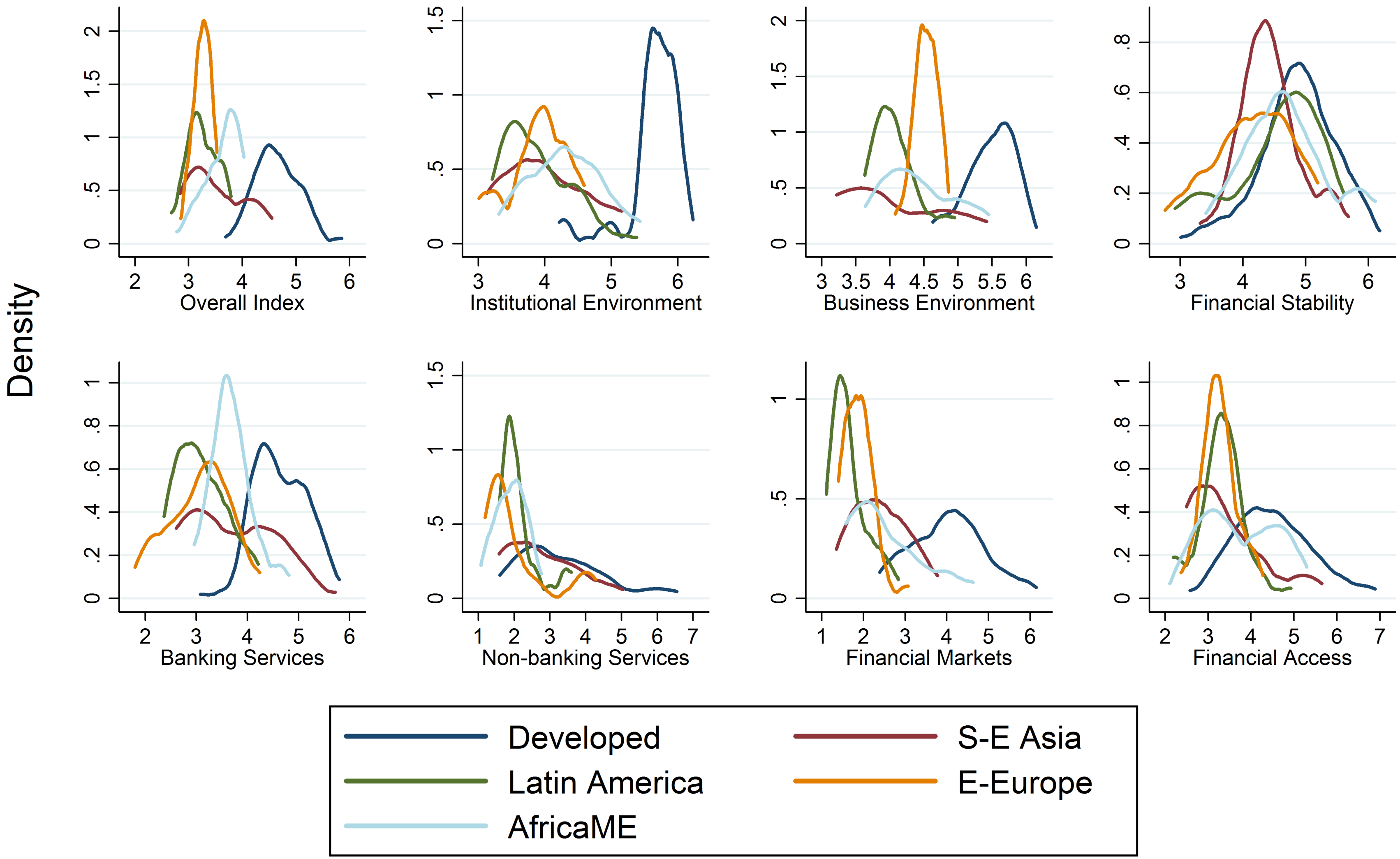

Figure 7.2: Financial Development Index Components by Region

institutional environment is generally weak, characterised by relatively poor protection of property rights, and lax auditing and accounting standards. With respect to the financial sector in Latin American countries, it appears as the least developed among the emerging regions. It ranked last for its institutional environment, due to weak protection of property rights, highly burdensome government regulation and an ineffective political environment. Furthermore, the business environment is also poor with relatively weak auditing and accounting standards and poor corporate governance. Latin America scored low marks for the size and depth of its financial markets and capital access, but it has a relatively stronger scores for its non-bank financial institutions compared to other developing countries.

Table 7.2: Results of the Discriminant Analysis

True \ Class	Developed	Asia	Latin	E-Europe	AfricaME	Total
Developed	**79**	8	0	0	2	89
Asia	0	**27**	0	2	1	30
Latin	0	1	**25**	6	3	35
E-Europe	0	0	2	**29**	2	33
AfricaME	0	2	1	0	**29**	32
Total	79	38	28	37	37	219

With respect to the results of the discriminant analysis, Table 7.2 shows that 80-90% of the countries are classified correctly into their true regions using the nearest-neighbour algorithm on the basis of their financial development index. This method classifies each country into the group with the observations that have the smallest Euclidean distance[1] to that specific country. Hence, these results support our previous findings and can partially explain the superiority of the pooled regional models over the panel fixed-effects.

Consequently, these findings have important implications for policy makers in the context of forecasting future crises. The fact that simple pooled regional models have dominant predictive power over more complex specifications suggests that policy makers

[1]Euclidean distance $= \sqrt{\sum_{i=1}^{k}(x_i - z_i)^2}$

should not only assess and monitor the health of their own economy and financial system, but also that of other countries in the same region as well. Furthermore, in order to make more accurate predictions of the vulnerability of the domestic economy, it is crucial to take into particular consideration the economic and financial conditions of countries with close trade and/or financial links, or with similar structure and degree of financial development.

7.3.3 Dynamic-Recursive Forecasting Technique

From a policy maker's perspective, the real challenge for the EWSs is their ability to provide accurate out-of-sample forecasts for the holdout period over which the estimated models had no information. However, the major bulk of the studies that considered the construction of EWSs for financial crises have not subjected their models to this challenge. Therefore, we carry out an extensive out-of-sample forecast horse-race between all our proposed methods in each of the three types of financial crises for every country region.

To facilitate comparison with the limited number of papers that did report out-of-sample measures of their models, we first apply the regular forecasting technique, where the model is estimated once and then used to provide forecasts over the entire holdout period. Then, we improve on these results by applying our novel dynamic-recursive forecasting technique, which continuously updates the EWS every period with the new information as it becomes available and the lag of the previously predicted probabilities. The results show that our dynamic-recursive forecasting technique improves substantially over the regular out-of-sample forecasts in all the considered cases.

More specifically, in the case of currency crises, the regular technique is unable to predict the crisis episode in South-East Asia and only 50% of the episodes in Africa and the Middle East, while in developed countries the false alarm rate is relatively high (around 30%). Using the dynamic-recursive technique, *all* the incidents in South-East

Asia, Latin America, and developed countries are forewarned even six months in advance without issuing more than 15% false alarms. In Africa and the Middle East, almost 80% of the incidents are correctly predicted.

Regarding the banking crisis EWS, the results show an average of 50-70% chance of correctly signalling an approaching crisis using the regular forecast. However, the dynamic-recursive forecasting technique is able to predict about 85-90% of the recent global financial crisis incidents. Likewise, none of the four sovereign defaults that occurred in Latin America are forewarned using the regular technique, while in developed countries, only 70% are correctly predicted. These findings improve substantially when applying the dynamic-recursive forecasting technique, proving the superiority of this method. In Latin America and Africa, *all* crisis incidents are correctly signalled two years *ex-ante*. Moreover, the estimated model in developed countries is able to foresee three quarters of the sovereign distress periods that occurred in Greece, Portugal and Ireland.

7.3.4 The Final Verdict

After recognising from the results of the empirical analysis that the predictive performance of the EWSs is significantly improved when using simple pooled models that account for the regional heterogeneity of the signalling indicators and using the dynamic-recursive forecasting technique to generate out-of-sample forecasts, it only remains to identify the econometric model that can construct the most effective EWS with the most accurate forecasts. For this purpose we apply three evaluation criteria, namely the QPS as a scoring rule, the AUC as a sensitivity measure, and the percentage of correctly predicted crisis onsets over the specified crisis window.

The results of these criteria show that, with respect to the EWS for currency crises, the dynamic signal approach outperforms both versions of logit models in all regions, being able to provide early warning signals of almost all new crises that occurred in the in-sample period, but at a higher rate of false alarms. In the holdout period, on the other hand, the binary logit model (using the dynamic-recursive forecasting technique) outperforms the multinomial model, while the dynamic signal approach has the same predictive power but at a higher false alarm rate.

In the case of the EWS for banking crises, the binary logit model outperforms the other two techniques in the in-sample. However, the predictive performance of the dynamic signal approach stands out significantly above that of the other two in the holdout period but at the expense of a much higher false alarm rate. Regarding the EWS for sovereign defaults, in the in-sample, the multinomial logit appears slightly more accurate than the binary logit in South-East Asia, but the latter prevails in the other regions, with same hit rates as the dynamic signal approach but at lower false alarms. As for the out-of-sample performance, both the binary logit model and the dynamic signal approach correctly forecast most of the out-of-sample crises, but the false alarms generated by the signal approach are double the ones issued by the binary logit model. The multinomial logit models, on the other hand, fall behind the other two in the holdout period of all regions.

Thus, in conclusion, the results signify that the performance of the multinomial logit models is generally lower than that of the binary models and the dynamic signal approach. This is contrary to the findings of Bussiere and Fratzscher (2006) and Caggiano *et al.* (2014) who found that the multinomial logit models provide better forecasts. However, these authors only compared the practice of dropping post-crisis episodes with specifying a three-state dependent variable. Therefore, our results support the notion that specifying post-crisis periods as individual crisis episodes, rather than a separate regime or dropping them altogether, can improve the effectiveness of the EWS in forewarning crisis onsets as well as duration.

On the other hand, however, the choice between the binary logit and the non-parametric method is not as straight forward. Rather, it involves a trade-off between the accuracy of the forecasts in terms of lower missed crises or false alarms, where the binary logit outperforms the dynamic signal approach by issuing fewer false alarms, while the latter dominates in missing fewer crises. Therefore, it was noted by Fuertes and Kalotychou

(2007) that the policy makers' preference between both types of errors would influence the optimal choice of the EWS methodology.

A conservative policy maker, who does not wish to incur large expenses to defend the domestic currency, bail out banks, or address sovereign problems when there may actually be no serious threats to the financial systems, would prefer the EWS based on the *simple regional binary logit model* with its more reliable but relatively less accurate signals. With its significantly reduced likelihood of issuing false alarms, this method can also be recommended for countries with relatively more sustainable sovereign debt, healthy banking sectors, and stronger domestic currency. This is usually the case of developed countries.

Conversely, the *dynamic signal approach* can be used to construct a more sensitive warning system of financial crises in the different country regions. Therefore, it is recommended for more cautions policy makers, especially in the countries that are more prone to a certain type(s) of financial crises (e.g. debt crises in Latin America), as it provides more accurate predictions of approaching distress periods. Furthermore, it may be preferred by policy makers if their purpose is to avoid a financial crisis at all costs and keeping their economy sound and healthy at all times by continually correcting imbalances as they develop. Such policy makers bear in mind that false alarms are not always true forecast errors, but signals of approaching crises just beyond the specified crisis window or of potential crises that were avoided by policy corrections. A further advantage of the signal extraction approach over the logit models is its ability to identify the set of individual indicators that are issuing signals. Thus, Kaminsky *et al.* (1998) argued that they can provide information to the policy makers about the source and the symptoms of the financial or macroeconomic weaknesses that underlie the probability of an approaching crisis.

7.4 Recommendations

In consequence, a number of recommendations can be highlighted to construct effective EWSs for the three types of financial crises in the various country regions in order to help policy makers derive proper and timely policy adjustment paths that may reduce the likelihood of an impending crisis. Ideally, this financial monitoring tool could be used for surveillance, crisis prevention, and crisis resolution. However, it is important to note, as argued by Bussiere and Fratzscher (2006), that the EWS cannot replace the sound judgement of the policy makers, but they play an important complementary role as a neutral and objective measure of vulnerability.

In general, however, the results of our empirical analyses highlight a number of points that require special attention from policy makers aiming to keep their economies sound and healthy, by correcting weaknesses and vulnerabilities before they lead to a financial crisis. First, when constructing an EWS for any type of financial crisis, policy makers are advised to consider the economic and financial conditions of the regional economies, as well as in countries with close trade and financial links to allow for the possibility of contagion. Second, it is important to closely monitor interrelated sectors within the domestic economy, as weaknesses in one sector can have adverse effects on the other sectors, creating a snowball effect that could eventually trigger twin, or even triple, financial crises. Finally, the estimation of the likelihood of an approaching crisis should be updated at least once every six months for currency and banking crises, and once every year for sovereign debt crises, as the probability of such crises depends on the build-up of new vulnerabilities, as well as the corrective actions undertaken by policy makers.

On the other hand, several more specific recommendations can be highlighted with respect to the choice of the signalling indicators used and the econometric methodology applied to construct more accurate EWS for financial crises. These are outlined in the following sections.

7.4.1 Signalling Indicators

Our models show that, in addition to the traditional first-generation macroeconomic variables, it is crucial for the construction of effective EWSs to also take into account second-generation indicators that have a forward-looking perspective, and that reflect (domestic and international) investors' anticipations of the country's future economic prospects and the soundness of its foreign exchange market, banking sector, and sovereign debt position.

In this respect, we propose several possible extensions to our work. Future research may consider other forward-looking variables that can capture self-fulfilling crises. For example, micro-level company and bank data (e.g. accounting ratios) may be able to capture idiosyncratic problems before they escalate into macro-level weaknesses in the banking system. However, one must be cautious when dealing with micro-level data to minimise the possibility of measurement and aggregation errors. In the context of currency crashes, and depending on data availability, one may consider investigating the role of standard financial derivatives (e.g. forwards, futures, options, swaps) that reflect investors' future expectations. Furthermore, credit default swaps, sovereign bond spreads, and other variables that can be used to assess sovereign credit ratings may shed some light on perceived future sovereign risk.

In addition to second-generation indicators, our results show that the inclusion of third-generation variables, that express the possibility of contagion from neighbouring countries and spillovers from one type of crisis to another, improves the performance of EWSs. Accordingly, this finding may encourage further investigation as to the inclusion of variables that can reflect other channels of contagion and spillover than the ones employed here (i.e. equity market contagion using correlation of stock price indices, and dummies for crises in other countries). The most prominent alternative channels of contagion are mainly real and banking system interdependencies. The former can be assessed using variables that reflect trade linkages across countries. With respect to the latter, Fratzscher (2003) noted that crises are more likely to spread across banking systems that have a common lender that refused to roll over loans or extend new funds, or by the decision of investors to withdraw their funds from potentially weak banks. Accordingly, constructing a measurement index that can reflect the degree of competition for bank funds across countries, and monitoring the correlation of banking stock price indices, can be viewed as possible extensions of our work.

However, in the context of sovereign debt crises, the annual frequency of the data impedes the use of same-year information on defaulting sovereigns in assessing the possibility of contagion to the other economies. As for the construction of EWS for currency crises, a mechanism is required to assess the effects of weak economic fundamentals in one Euro-zone country on the entire bloc, so as to be able to construct an EWS for attacks on the Euro.

Furthermore, because of the differences in the origin, severity and timing of crises, as well as the evolving nature and the growing interlinks of the financial markets between the national economies, it is possible that the indicators found useful now may not necessarily continue to be so in the future. Newer crises may emerge from newer characteristics and relations. Therefore, the process of identifying leading indicators should be dynamic in nature, allowing for a constant assessment of the need for new indicators. For that, the timely availability of high frequency data (especially in developing economies), along with their compilation on sound statistical bases, is crucial for the design of effective EWSs.

7.4.2 Econometric Technique

We evidence that the simple pooled logit regression models that account for regional heterogeneity, the entire period a country spent in a certain type of financial crisis, and that the use of our dynamic-recursive forecasting technique are able to construct significantly more accurate EWSs than the multinomial logit regressions, the general practice of dropping post-crisis periods, the tradition regular forecasting technique, and models that account for country-specific heterogeneity. Furthermore, the newly developed dynamic signal extraction approach outperforms the more conventional static version.

Nevertheless, the continuous monitoring of how close the leading indicators are fluctuating around their threshold values is also crucial for policy actions rather than waiting for them to cross these pre-specified thresholds. In addition, it would be ideal to construct a generic warning system for all types of financial crises that has the ability to recognise the exact type of crisis (exchange rate, banking, or sovereign debt) being predicted, instead of having a separate model for each type.

Another area of possible improvement is to find a more intuitive way to group countries into regions when considering separate regional models, going beyond the traditional geographical segmentation. Noting that, for example, we need to leave out Japan when considering South-East Asia, or Israel when considering the Middle East, defining regions in a way that can group countries with similar characteristics together could be an area of future research. For this purpose, criteria such as the degree of financial development (e.g. using the WEF financial development index) or macroeconomic similarity (e.g. an index that combines real exchange rate misalignment, current account balance, trade patterns, credit boom, fiscal balance, and GDP growth rate) could be used as a guide for regional segmentation.

A final important aspect that deserves attention in the literature of EWSs is to explicitly evaluate the economic, social, and political value of the generated forecasts once they become public. That is, whether and how these forecasts affect the behaviour and the decision-making process of (domestic and international) investors, government officials, and policy makers. Although this entails the full articulation of the decision environment of such forecast users, it could shed some light on the true nature of the presumed false alarms generated by the forewarning models, and thus complete the picture of the usefulness of the construction of EWSs for financial crises.

Appendix A

List of Currency Crisis Neighbours

Country	Possible Crisis Contagion Countries
Developed Countries	
USA	Canada , Japan , South Korea , UK
Canada	USA , UK , Japan
Japan	USA , UK , South Korea , Russia
UK	USA , Canada , Japan , Sweden
Denmark	USA , UK , Norway , Sweden
Norway	UK , Sweden , Denmark , USA
Sweden	UK , USA , Norway , Denmark
Iceland	USA , UK , Canada
Australia	UK , New Zealand , Canada , USA
New Zealand	Australia , UK , USA , Japan
South-East Asia	
Indonesia	Japan , Philippines , South Korea , Thailand
Philippines	Japan , Indonesia , South Korea , Thailand
South Korea	Japan , Indonesia , Philippines , Thailand
Thailand	Japan , Indonesia , South Korea , Philippines
Latin America	
Argentina	Brazil , Mexico , Chile , USA
Brazil	USA , Argentina , Chile , Mexico
Mexico	USA , Argentina , Brazil , Chile
Chile	Brazil , Mexico , Argentina , USA
Eastern Europe	
Turkey	Russia , UK , South Korea , USA
Russia	USA , Japan , South Korea , UK
Bulgaria	UK , Russia , South Korea , Czech Rep.
Czech Rep.	Russia , Bulgaria , South Korea
Africa & Middle East	
Egypt	USA , Russia , Jordan , UK
Jordan	USA , Russia , Egypt , UK
South Africa	USA , UK , South Korea , Japan

Appendix B

Episodes of Banking Crises

Country	Comments
Developed Countries	
❖ **Non-EU** ❖	
United States of America	
Q2:2007-Q4:2010	During 2007, the US sub-prime mortgage market collapsed. Credit losses and asset write-downs got worse with accelerating mortgage foreclosures. By June 2008, sub-prime-related losses stood at around $400 billion. By end of 2008 and early 2009 mortgage giants Fannie Mae and Freddie Mac collapsed, and several huge investment banks failed including Bear Stearns, Lehman Brothers, Goldman Sachs, Merrill Lynch, and Morgan Stanley. The Federal Deposit Insurance Corporation closed more than 300 failed banks from 2008 to 2010.
Canada	
–	None
Japan	
Q4:1997-Q2:2002	At the end of 1998 banking system non-performing loans were estimated at 18% of GDP. In 2002 non-performing loans were 35% of total loans; with a total of 7 banks nationalised, 61 financial institutions closed and 28 institutions merged.
❖ **EU Countries** ❖	
United Kingdom	
Q4:2007-Q4:2011	In September 2007, Northern Rock experienced a bank run, and was nationalised in February 2008 following two unsuccessful bids to take it over. In April 2008, the Bank of England announced it would accept to swap mortgage-backed securities for government paper to aid banks in liquidity problems for a period of 1 year. September 2008 UK's Bradford and Bingley bank is nationalised. A bank rescue package totalling some £500 billion was undertaken in 2008-2009 to bailout failing banks.

Belgium	
Q2:2008-Q4:2012	Central Bank claims on financial institutions increased by 14.1%. Government raised the deposit insurance from 20,000 to 100,000 Euro. Two of the country's largest banks, Fortis and Dexia Bank Belgium, started to face severe problems, exacerbated by the financial problems hitting other banks around the world. By the end of 2008, Fortis was split into two parts. The Dutch part was nationalised, while the Belgian part was sold to the French bank BNP Paribas. Dexia group was dismantled, Dexia Bank Belgium was nationalised.
Finland	
Q3:1991-Q4:1994	One of the largest banks (Skopbank) was taken over by the Central Bank in September 1991. Savings banks badly affected; government took control of three banks that together accounted for 31% of system deposits.
France	
Q2:1994-Q3:1995	Credit Lyonnais experienced serious solvency problems, with losses totalling to about $10 billion.
Q4:2008-Q4:2011	In August 2007, the first French bank, BNP Paribas, announced the freeze of its three active investment funds assets for a total amount of 1.6 billion Euro. Over the first half of 2008, not knowing how all the banks were affected by the crisis, banks stopped to lend to each other. In October 2008, the government announced a 360 billion Euro rescue plan for the French banks. 40 billion Euro were injected to help recapitalise banks in difficulty (mainly BNP Paribas, Societe Generale and Credit Agricole) and a further 320 billion Euro to guarantee interbank lending. The government also rushed forward 11.5 billion Euro worth of credits and tax breaks for 2009.
Germany	
Q4:2008-Q4:2011	By October 2008, three of the largest German financial institutions (Deutsche Industriebank, Landesbank Sachsen, Hypo Real Estate Holding) had to be rescued from completely going bankrupt, and another large bank (West Landesbank) was taken over. The government undertook a bank bailout program of 480 billion Euro, 400 billion of which were earmarked for lending guarantees for banks, and the remaining 80 billion was used to recapitalise financial institutions and purchasing risky assets. In February 2009, the government had to inject about 200 billion Euro more capital as a second bank rescue package.

Italy	
Q4:1990-Q1:1995	58 banks, accounting for 11% of lending, were merged with other institutions.
Q4:2008-Q4:2012	Loan loss provisions of Italy's largest bank, UniCredit, totalled about 9.3 billion Euro. The government initiated a bailout program of 12 billion Euro to rescue banks in distress. In addition, Bank of Italy approved 3.9 billion Euro in loans to fund another large bank, the Monte dei Paschi di Siena. By 2012 the Italian banks have been absorbing 268 billion Euro of liquidity issued by the ECB by means of the long term financing operation programme.
Spain	
Q4:2008-Q4:2012	The credit ratings of several Spanish banks were downgraded, some to "junk" status. The Bankia bank, the country's largest mortgage lender, was nationalised and required a bailout of 23.5 billion Euro to cover losses from failed mortgages. The Spanish government had to shrink and restructure three major banks (Bankia, NCG Banco, Catalunya Banc) and sell a fourth (Banco de Valencia). By 2012, the country was unable to bailout its financial sector and had to apply for a 100 billion Euro rescue package from the European Stability Mechanism to recapitalise its banks. In addition, the Spanish banks borrowed 376 billion Euro from the ECB in July 2012.
Sweden	
Q2:1991-Q4:1994	Nordbanken and Gota Bank, accounting for 22% of banking system assets, were insolvent. Sparbanken Foresta, accounting for 24% of banking system assets, was intervened. Overall, 5 of the 6 largest banks,with more than 70% of banking system assets, experienced difficulties.
Q4:2008-Q4:2011	In October 2008, the government announced the state would guarantee all bank deposits and creditors of all 114 banks. Three of the largest banks (Nordbanken, Gotabanken, Carnegie) were granted financial support and were nationalised at a cost of $8.5 billion. In addition, the Swedish government undertook a $200 billion rescue plan to bailout the other financial institution, which amounted to about 4% of Sweden's GDP.
Greece	
Q3:1991-Q2:1995	Significant injections of public funds into specialised lending institutions.

Q4:2008-Q4:2012	In October 2008 the Greek government declared that it will guarantee bank deposits. As things became worse, the EU, ECB and IMF (collectively known as the Troika) launched a 110 billion Euro bailout loan for Greece in May 2010. One year later, in 2011, the Greek government secured an additional bank recapitalisation package worth 48 billion Euro, of which 24.4 billion were injected into the four biggest Greek banks (NBG, Eurobank, Alpha, Piraeus) that have each seen more than a fifth of their market capitalisation wiped out. In 2012 the Troika agreed to a second bailout package for Greece totalling 130 billion Euro, 58.2 billion of which were used to recapitalise Greek banks.
Portugal Q1:2010-Q4:2012	Throughout 2008 & 2009 Portuguese banks had been accumulating losses. By 2010, the largest listed lender, Banco Espirito Santo, with an average market share of 20.3% in Portugal collapsed. The central bank announced a 4.9 billion Euro rescue plan. However, the government required a further 78 billion Euro bailout loan from the EU and IMF in 2011 to recapitalise the distressed banks.
Denmark Q4:2008 -Q4:2012	After a housing bubble and bust, the Danish economy went into recession in 2008, followed by the collapse of Roskilde Bank, the tenth largest, and the takeover of EBH Bank, the sixth largest, by Denmark central bank. The combined profits of the Danish banking sector dropped by about 150% from late 2007 to 2009. The average loan impairments till 2011 equal to 26.6% of the annual revenue for Danske Bank, Denmark's biggest lender. Eleven banks have failed in Denmark over 2008-2011 and fifteen more were at risk of default, which represented about 3% of Denmark financial industry. In 2008, the government offered an unlimited guarantee on bank deposits, and set up a bank rescue fund worth 5 billion Euro. Another rescue package was initiated in 2009, amounting to 13.5 billion Euro.
Netherlands Q4:2008 -Q4:2012	The banks' unwillingness to lend to each other put healthy financial institutions at risk. The Dutch government provided 20 billion Euro to guarantee interbank lending in October 2008. In addition, the government operated a 200 billion Euro scheme to guarantee the banks issuance of medium-term debt paper between 2008 and 2011. The bank giants ING, SNS Reaal and Aegon were recapitalised for an amount of 14 billion Euro. In 2009, the Dutch government nationalised Fortis bank, as well as three other banking giants (ABN AMRO, ASR, SNS REAAL) by 2013.

Emerging Markets	
❖ **Latin America** ❖	
Argentina	
Q1:1995-Q4:1995	The Mexican devaluation led to a run on the banks, resulting in 18% decline in deposits between December 1994 and March 1995. Eight banks were suspended and three banks collapsed. Out of the 205 banks in existence as of end of 1994, 63 exited the market through mergers, absorptions, or liquidation.
Q2:2001-Q2:2003	In March 2001, bank runs started due to lack of public confidence in government policy actions. On February 4, 2002, bank assets were asymmetrically pesified, adversely affecting the solvency of the banking system. By August 2003, one bank was closed, three banks nationalised, and many other have reduced their staff and branches.
Brazil	
Q3:1994-Q1:1999	The "Plan Real" of July 1994 caused liabilities and assets of banks expanded rapidly. Loans to private sector grew by 60% during the first year of the plan.Central Bank raised interest rates and imposed credit restrictions. The financial situation of banks weakened as bad loans increased from 15.4% in June 1994 to 22.4% at end of 1995, and to 30% in October 1996. By the end of 1997 the Central Bank intervened in the administration of 43 financial institutions and closed down 17 small banks. Private banks returned to profitability in 1998, but public banks did not begin to recover until 1999.
Mexico	
Q4:1994-Q2:1997	Of 34 commercial banks in 1994, 9 were intervened and 11 participated in the recapitalisation program. The 9 intervened banks accounted for 19% of financial system assets and were deemed insolvent.
Paraguay	
Q2:1995-Q4:1998	In May 1995 the third and fourth largest banks could not meet clearing obligations and were intervened. Three more banks, with more than 15% of deposits, were closed during 1997 and 1998. Between 1995-1997, 15 out of the 19 locally-owned banks were either closed or absorbed by stronger institutions. By the end of 1998, over 80% of bank assets became foreign owned.
Q4:2001-Q4:2002	One of the largest banks was closed in end of 2001 and another became insolvent in 2002. Banks in the system continued to experience rising non-performing loans till late 2002.

❖ South East Asia ❖

Indonesia	
Q4:1997-Q2:2002	Through May 2002, Bank Indonesia closed 70 banks and nationalised 13, of a total of 237. Official non-performing loans for the banking system were estimated at 65-75% of total loans at the peak of crisis and fell to about 12% in February 2002.
Philippines	
Q1:1998-Q4:2000	Since January 1998 one commercial bank, 7 of 88 thrifts, and 40 of 750 rural banks have been placed under receivership. Banking system non-performing loans reached 12% by November 1998, and were expected to reach 20% in 1999.
South Korea	
Q2:1997-Q4:1999	5 banks were forced to exit the market through "purchase and assumption formula" and 303 financial institutions shutdown (215 were credit unions); another 4 banks were nationalised. Banking system non-performing loans peaked between 30-40% and fell to about 3% by March 2002.
Malaysia	
Q3:1997-Q4:1999	The finance sector was restructured, where the number of institutions was reduced from 39 to 10 through mergers. The two largest finance companies were taken over by the Central Bank. Two banks, accounting for 14% of sector assets, were insolvent. Non-performing loans reached 35% of banking sector assets. By end of 1999 54 banks were merged into 10 groups.

❖ Middle East and Africa ❖

Egypt	
Q1:1991-Q1:1995	The four main public banks (Banque Misr, NBE, Banque du Caire, Bank of Alexandria) were given capital assistance.
Jordan	
–	None
South Africa	
–	None

❖ Eastern Europe ❖

Russia	
Q3:1998-Q2:1999	Nearly 720 banks, or 50% of those operating, were deemed insolvent, accounting for 32% of retail deposits.

Q4:2008-Q4:2009	In November 2008, nine banks went bankrupt and the Central Bank announced imminent insolvency of another 40 banks. Regional banks, heavily dependent on individual deposits, were under the risk bank runs. The government enabled deposit insurance at a cost of $3.5 billion to prevent Russian banks from going bankrupt. Central Bank extended unsecured stabilisation loans of $150 billion to Russian banks, which was later dubbed "soft re-nationalisation", to rescue 47 Russian banks which were bound to fail in September 2009. An additional $36 billion was required a few months later.
Bulgaria	
Q1:1996-Q2:1997	The bad loans made during 1991-1995 resulted in about 75% of banking system loans to be substandard by end of 1995. The public began to lose confidence in banks and initiated a bank run in early 1996, causing the negative net worth of the banking sector to amount to 13% of GDP. The government then stopped providing bailouts, prompting the closure of 19 banks accounting for one-third of sector assets. Surviving banks were recapitalised by 1997.
Turkey	
Q2:1994-Q4:1994	Three banks failed in April 1994.
Q4:2000-Q1:2002	In Nov 2000, two large banks were closed and 19 banks have been taken over by the Savings Deposit Insurance Fund.
Latvia	
Q4:1994-Q4:1997	Between 1995 and 1998 35 banks had their licenses revoked, were closed, or ceased operations. In 1995 the negative net worth of the banking system was estimated at about 7% of GDP, which decreased to 3% by 1998.
Q1/2009-Q3/2010	In 2008, global financial woes hit Parex Bank, the largest locally and independently owned bank in the Baltic states. After clients panicked and withdrew $120 million in November 2008 alone, the government had to nationalise the bank – a task that turned out to be beyond its financial abilities. In February 2009, the Latvian government asked the IMF and the EU for an emergency bailout loan of 7.5 billion Euros.

Source: Caprio and Klingebiel (2003); Laeven and Valencia (2008); Reinhart and Rogoff (2009); Laeven and Valencia (2012)

Appendix C

Debt Crisis Episodes

Country	Comments
Latin America	
Argentina	
1983-1992	Default on external debt started in 1983. Despite credits and loans from IMF, which reached 245% of country quota in 1988, the amount of principal and interest arrears exceeded 20% of total debt by 1992. About 30% of the sovereign debt was rescheduled in 1993.
2001-2005	Continuous credit from IMF to avoid default exceeded 500% of quota by 2001. Nevertheless, the country defaulted in 2002 and had to reschedule its debts by 2005. Several restructuring schemes were also undertaken to reduce the amount of outstanding debt during this period.
Brazil	
1983-1994	Brazil started to default on some of its external debt and required a loan from IMF as a rescue plan, which almost reached 300% of its quota. Increasing arrears required several debt rescheduling and buybacks in 1989. However, defaulting continued till 1994 when massive other rescheduling and restructuring of external debt became inevitable.
1999	Loans from IMF exceeded 200% of country quota.
2002-2003	IMF loans increased from 44% of quota in 2000 to more than 600% in 2003.
Mexico	
1982-1990	In 1982 Mexico started to default on its external obligations, but was rescued by continuous receipt of IMF loans which amounted to 400% of country quota by 1990. Furthermore, more than 40% of the sovereign debt was rescheduled, forgiven or bought back during this period.
1995-1996	IMF loans increased from 150% of quota in 1994 to more than 600% in 1996.
Chile	
1983-1990	In 1983 credit from the IMF reached 130% of country quota and increased to about 250% by 1986. Rescheduling of 20% of sovereign debt took place in 1990.

Paraguay	
1986-1990	Defaults on external obligations increased from about 5% of total debt in 1986 to 20% in 1990, which required the rescheduling of 16% of the outstanding debt and the restructuring of another 25%.
Dominican Republic	
1983-1999	In 1983 loans from IMF jumped to 200% of country quota and to continued to increase to about 250% in 1985. Nevertheless, arrears on external obligations exceeded 25% of total debts in 1990. In 1994, 10% of external debts were rescheduled and another 8% restructured. Yet, defaulting on principal and interest payments continued till 1999.
2003-2005	Dominican Republic was not able to meet its external obligations in 2003, which lead to the rescheduling of 20% of the outstanding debt in 2005, while loans from the IMF tripled over the same period, reaching 130% of its quota.
2010-2011	From 2009 till 2011 credits and loans from the IMF increased from 220% to about 400% of country quota.
Ecuador	
1983-1995	Despite credit from the IMF, which started in 1982 and peaked in 1985 at 260% of country quota, principal and interest arrears reached about 40% of total external debt by 1994. More than quarter of the outstanding debt was rescheduled in 1995.
1999-2000	Increasing principal arrears in 1999 required the rescheduling of 30% of the debt during 2000 and a further restructuring of another 28%.
Venezuela	
1989-1996	Increasing defaults on external debt repayment called for the rescheduling of over 50% while another 10% was forgiven in 1990. However, arrears continued till 1996.
Bolivia	
1980-1985	Increasing arrears since 1980 despite acquiring credit from the IMF, which peaked at 170% of quota in1982. By 1985 the arrears reached about 20% of the outstanding debt.
1986-1994	To prevent further failure to meet its external obligations, Bolivia acquired increasing credit from the IMF totalling to 200% of its quota, and engaged in several rescheduling schemes till 1993.
Peru	
1980-1997	Despite that the loans and credit from the IMF reached 270% of the country quota in 1983, it could not meet more than 50% of its debt servicing obligations over the entire period. In 1996 the debt was restructured; yet IMF loan remained above 150% till 1997.

	Panama
1983-1997	Loans from the IMF increased from 25% in 1980 to about 300% of quota in 1986, while interest and principal arrears continued to increase to about 60% of the outstanding debt in 1995. The debt was restructured by 1997.
	Costa Rica
1981-1991	Country acquired credit from the IMF of over 200% of its quota. However, a quarter of the external debt services was in arrears till 1991.

South and East Asia	
	Indonesia
1998-2003	During period 1998-2002 Indonesia was granted loans from the IMF of about 400% of its quota. Nevertheless, arrears on external obligations continued at over 10% of total debt till 2004.
	Philippines
1981-1990	During this period credits and loans from the IMF remained above 200% of country quota, until about 10% of the external debt was restructured in 1990.
	China
–	No significant external debt problems.
	India
–	No significant external debt problems.
	Malaysia
–	No significant external debt problems.
	Thailand
1981-1982	Loans from the IMF increased to 280% of country quota.
1997-1999	Loans from the IMF reached 400% of country quota.
	South Korea
1980-1982	Credit from the IMF increased to four times the quota of South Korea.
1997-1998	A massive rescue fund was granted by the IMF, which accounted to over 1500% of the country quota.
	Singapore
–	No significant external debt problems.

Middle East and Africa	
Egypt	
1980-1991	Principal and interest arrears continued to increase to more than 20% of outstanding debt in 1986. These defaults remained above 15% till 1990. In 1991, 35% of total debt was rescheduled.
Jordan	
1989-1994	Jordan defaulted on more than 10% of its sovereign debt, and in 1993 it had to engage in some debt rescheduling and restructuring schemes, although arrears continued into 1994.
South Africa	
1985-1989	Failure to meet about 50% of external debt obligations, which called for a rescheduling plan in 1987 and again in 1989.
Lebanon	
1985-1991	Arrears reached 12% of total debt outstanding during this period.
Morocco	
1981-1989	Loans from IMF reached about 400% of country quota. Defaults on more than 5% of external obligations continued until about 10% of external debt was rescheduled in 1990.
Tunisia	
1986-1991	A loan was acquired from the IMF amounting to 100% of country quota in 1986 to meet arrears on external obligations. Credit continued to flow from the IMF till it reached 150% in 1989 remained above 130% of country quota till 1991.
Algeria	
1990-1996	Rescheduling over 10% of debt principal, while loans from IMF exceeded 160% of country quota.
Nigeria	
1988-1999	Defaulting on debt repayment increased from 12% in 1988 to more than 60% of the outstanding amount due in 1999. Debt was rescheduled in 1989 and was restructured twice in 1992 and 1996.
Central Africa	
1981-2006	Arrears increased steadily from 11% of amount due in 1981 to more than 30% in 2005 and 2006.

Advanced Europe	
Greece	
2010-2012	Government debt increased to more than 160% of GDP in 2009, and credit from the IMF reached over 1700% of the quota of Greece by 2012.

Portugal	
1986	The IMF granted Portugal a loan that amounted to 150% of its quota.
2011-2012	A huge exceptional loan was granted from the IMF, which amounted to 1700% of the country quota in order to fend off the increasing government debt which reached 130% of the GDP of Portugal.
Spain	
_	No significant external debt problems.
Ireland	
2011-2012	The increasing public domestic and external debt exceeded 120% of GDP, which induced the IMF to grant Ireland a huge loan of 1300% of its quota.
Italy	
_	No significant external debt problems.
Belgium	
1992-1994	The public debt of Belgium increased to over 140% of its GDP during this period.
Sweden	
_	No significant external debt problems.
Germany	
_	No significant external debt problems.
UK	
_	No significant external debt problems.

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