How Useful Are Regime-Switching Models In Banking Crises Identification?

Tai-kuang Ho*

Graduate Institute of International Economics, National Chung Cheng University

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Abstract

We employ a regime-switching approach to the identification of banking crises. This approach reduces the arbitrariness in crisis identification by endogenizing the choices of crisis threshold and crisis duration. Using a sample of 47 countries, we show that this approach also subject to several same problems as the common procedures. The method is sample-dependent, tends to invent much more crises, and is less robust to different model specifications. We conclude that a bind application of regime switching model to crisis identification is questionable.

Key words: Markov-switching model, choice of crisis threshold, banking crises identification

JEL codes: C25, C49, G21

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* Department of Economics and Graduate Institute of International Economics, National Chung Cheng University, 160 San-Hsing, Min-Hsiung, Chia-Yi, 621 Taiwan, Tel: +00-886-5-2720411 ext. 34111, Fax: +00-886-5-2720816, E-mail: ecdtkh@ccu.edu.tw

1. Introduction

Financial crises in the last decade have stimulated research on the determinants financial crises. International institutions such as IMF and World Bank also sponsor research on financial crises. One approach to the systematic investigation of banking crises is to employ logit or probit model. Specifically, researchers estimate a logit or probit regression. On the left hand side of the regression is a binary variable that takes a value of one when there is a crisis and takes a value of zero when no crisis occurs. On the right hand side of the regression are explanatory variables such as domestic macro disturbances, external shocks, and institutional factors. For such exercise to be meaningful and useful for policy implication, one has to make sure that the left hand side variable, that is, the dependent binary variable, is correctly specified.

Existing literature uses market events to identify banking crises, that is, the dependent variable of the logit regression. The events method, however, has several shortcomings. For instance, it tends to identify crises too late, cannot identify the crises that are successfully fend off by the government measures, and most importantly, the crises dates are subject to arbitrariness (von Hagen and Ho, 2003). Recognizing these shortcomings, von Hagen and Ho (2003) develop a quantitative approach to the identification of banking crises. They define banking a crisis as situations in which there is excess demand for central bank reserves in the money markets. They construct an *index of money market pressure* that is able to reflect this excess demand. Periods in which the index exceeds a predetermined threshold are defined as banking crises. Similar research strategy along this line includes Kibritcioglu (2002) and Hawkins and Klau (2000).

A difficult problem remains: the choice of crisis threshold. Literature in the currency crises, following Eichengreen, Rose, and Wyplosz (1994, 1995, 1996), construct an index of speculative pressure to identify periods of currency attacks. Crisis threshold is defined as 2 standard deviations above the mean. For such practice to be meaningful, one has to assume that the index is normally distributed so that the criterion classifies the 2.5% upper-tail of the index distribution as crises. However, the index of speculative pressure, like most financial return data, is more likely to be fat-tailed and has the characteristics of volatility cluster. Therefore the assumption of normality is rarely met. Furthermore, the index differs from country to country so that a same threshold (2 standard deviations above the mean) actually classifies different proportion of distribution as crisis periods in different countries. In practice, different researchers choose different thresholds, with no justification for their choices. To avoid this problem, von Hagen and Ho (2003) pool the index and choose the 98.5 percentile as the crisis threshold. Caramazza, Ricci, and Salgado (2000) use a similar method in the context of currency crises and define a set of percentage (5 percent) of all observations as crises. This method is also ad hoc, and the percentage does not have a correspondent statistic meaning such as p-value because the method involves no inference of the true distribution. Since the crisis threshold depends on the sample moments, adding new data or changing periods covered that changes the sample moments can affect the identification of crises. Edison (2003), for instance, has documented such *case of disappearing crises*.

Since much crisis episodes tend to bunch together, researchers usually define a window of time of fixed length such that all episodes in which the indices across the threshold within that window are said to belong to the same crises. The purpose is to avoid counting the same crisis more than once if the subsequent crises are simply the continuations of the previous one. In the context of currency crises, such window implied that only one currency crisis is allowed within the window interval. In the context of banking crises, the window width implicitly defines the duration of a banking crisis. Demirgüc-Kunt and Detragiache (1998) impose a similar window on their logit regression to eliminate observations following a crisis in order to avoid the endogenous problem. Since probit/ logit models assume independence across observations, imposing a window actually introduces an artificial serial correlation as clearly pointed out in Abiad (2003).

One possibility to avoid the above-mentioned shortcomings in crisis identification is to endogenize the choice of crisis threshold, and let the data tell us the evolution of the states. That is what we try to do in this paper. We do this by using Markov switching model (MSM). MSM has advantages over the previous procedure. First, MSM endogenizes the choice of both crisis threshold and crisis duration and thus reduces the arbitrariness in crisis identification. Second, is allows each endogenously determined crisis duration to vary. This is an improvement over the ad hoc choice of window width, which implicitly imposes a same duration for all crises. We assume that there are two states in the financial market: a tranquil state and a crisis state. The two states differ in that the crisis state has higher and more volatile index value than the tranquil state. The economy transits from one state to the other according to a constant or time-varying transition probability. MSM has been extensively applied to the identification of business cycle turning points (Hamilton 1989, Hamilton and Raj 2002). A growing literature employs MSM to identify currency crises. For instance, Martinez-Peria (2002) uses MSM to identify speculative attacks on European Monetary System (EMS) during the period of 1979-1993, and to assess factors contributing to EMS vulnerability.

Abiad (2003) conducts similar exercises for five Asian countries. So far the author knows MSM has not been applied to the research on banking crises.

We structure the paper as follows. We begin with a brief discussion of the index of money market pressure and the data sources employed. This is followed up by the application of regime switching models in banking crises identification. We point out several problems with this method, and report a comparison of different rules for classifying crises. The final section represents several conditional logit estimates and discusses the factors contributing to banking crises.

2. An Index of Money Market Pressure and Data Sources

Our approach to the identification of banking crises is different from existing literature, which relies mainly on market events to determine the crisis dates. We build an index of money market pressure (IMMP) that reflects excess demand for liquidity in the money market.[1] We define the reserves to bank deposits ratio as the ratio of total reserves held by the banking system to total deposits. The index of money market pressure is calculated as the weighted average of changes in this ratio $\Delta\gamma$ and changes in the real short-term interest rates Δr. In a banking crisis, this index should increase either because the central bank injects additional reserves to the banking system, or because there are runs on deposits, or because excess demand for bank reserves bids up the interest rates. The index is expressed as

$$\text{IMMP} = \Delta\gamma/\sigma(\Delta\gamma) + \Delta r/\sigma(\Delta r)$$

In von Hagen and Ho (2003), we define banking crises as periods in which the index exceeds its country-specific 98.5 percentile. A window width of 8 quarters is imposed to avoid counting the same crisis more than once. In this paper, we discard such practice and let the regime-switching model to determine the crisis periods as well as crisis duration.

To compute the index, we use quarterly data provided by the IMF International Financial Statistics CD-ROM. Our sample covers 47 countries over the period 1980-2001.[2] Total deposits of non-banks with deposit money banks are calculated as the sum of demand deposits (line 24), time and saving deposits (line 25), and foreign liabilities (line 26c). We use borrowed reserves, defined as credit from monetary authorities to financial institutions (line 26g), as a proxy for reserves aggregate. Nominal interest rates are taken from money market

1 For details of the index of money market pressure, please refer to von Hagen and Ho (2003).

2 Countries included in the sample are Austria, Burundi, Chile, Cyprus, Denmark, Ecuador, Egypt, El Salvador, Finland, France, Germany, Greece, Guatemala, Honduras, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Kenya, Korea, Mexico, Nepal, Netherlands, New Zealand, Niger, Nigeria, Papua New Guinea, Peru, Portugal, Senegal, Seychelles, South Africa, Spain, Sri Lanka, Swaziland, Sweden, Switzerland, Thailand, Togo, Turkey, Uganda, United States, Uruguay, and Venezuela.

rates (line 60b). Inflation rates are calculated from consumer price index (line 64). Figure 1 reports the index of money market pressure for the 47 countries.

3. Markov-switching Models

We present two types of Markov switching models. The first one is a simple MSM as follows:

$$\mathrm{IMMP}_t = \beta_{S_t} + e_{S_t}, \quad e_{S_t} \sim N\left(0, \sigma_{S_t}^2\right)$$
$$\beta_{S_t} = \beta_1(1 - S_t) + \beta_2 S_t$$
$$\sigma_{S_t}^2 = \sigma_1^2(1 - S_t) + \sigma_2^2 S_t$$
$$S_t = 1,2$$

The two regimes differ in their means and variances. We expect that crisis periods may have a larger mean and a larger variance than the tranquil periods. The simple MSM is rather restricted because it assumes constant mean and constant variance in each regime. It serves only as a benchmark here. A more realistic setup should allow autocorrelation in IMMP, varying conditional mean and variance, and takes volatility cluster commonly found in most financial data into consideration. Therefore, our second specification is a GARCH (1,1) regime-switching model. We choose a GARCH (1,1) specification because literature finds that an order of (1,1) suffices to describe most financial data (Gray, 1996).

$$\mathrm{IMMP}_t = \mu_{i,t} + \varepsilon_{i,t} = \alpha_i + \beta_i \mathrm{IMMP}_{t-1} + \varepsilon_{i,t}, \quad i = 1,2$$
$$\varepsilon_{i,t} = \sqrt{h_{i,t}}\, z_t, \quad z_t \sim i.i.d.(0,1)$$
$$h_{i,t} = w_i + a_i \varepsilon_{t-1}^2 + b_i h_{t-1}$$
$$h_t = E\left[\mathrm{IMMP}_t^2 \mid \Phi_{t-1}\right] - E\left[\mathrm{IMMP}_t \mid \Phi_{t-1}\right]^2$$
$$\varepsilon_t = \mathrm{IMMP}_t - E\left[\mathrm{IMMP}_t \mid \Phi_{t-1}\right]$$

Our GARCH MSM specification follows Gray (1996). We do not follow the SWARCH model of Hamilton and Susmel (1994) because the SWARCH model requires that the conditional variances in the two regimes to be proportional to each other. Gray's model offers much more flexibility than the SWARCH model. A transition probability governs the evolution of states in both the simple and GARCH MSM.

$$\Pr\left[S_t = 1 \mid S_{t-1} = 1\right] = P$$
$$\Pr\left[S_t = 2 \mid S_{t-1} = 2\right] = Q$$

We follow the procedure of Kim and Nelson (2000) to estimate the model parameters.[3] Kim's smoothing algorithm is employed to calculate the smoothed probability. We use grid search to start the estimation. The final estimate is the one with highest likelihood value.

Martinez-Peria (2002) and Abiad (2003) have employed a time-varying transition probability. This has the advantage that factors contributing to the transition from tranquil to crisis period can be simultaneously determined in a consistent framework. We do not adopt this approach due to several reasons. Unlike currency crises, factors determining the probability of banking crises are mostly of low (annual) frequency. Accommodating these variables in the model would greatly reduce the number of observations available for estimate.[4] Besides, it is well known that estimates of regime switching model become unstable when more variables are included. Failure of convergence and singularity problem would prevail. This is not good for a large sample study like ours. Our approach here assumes a constant transition probability, and uses the MSM simply to identify the dates of banking crises. We then use conditional logit regression in the following-up step to investigate the factors determining the transition from tranquil to crisis state.

4. Empirical Results

4.1. First Impression

Figure 2 represents the smoothed probability of crisis state for the 47 countries. We follow the common practice and define periods in which the smoothed probability exceeds one half as crisis periods. Table 1 reports the crisis dates identified by the simple MSM. Smoothed probability of the crisis state and the crisis periods identified by the GARCH MSM are represented in Figure 3 and Table 2, respectively.

Before going further, it is worth a while to take a clear look at what the regime-switching model has identified. We compare the MSM with five other rules for classifying crises. Table 4 reports the comparison. The <u>2 STDEV</u> approach refers to the practice of Eichengreen, Rose, and Wyplosz (1994, 1995, 1996), which defines the crisis threshold as two standard deviations above the mean. The <u>Pooled</u> approach refers to the practice of von Hagen and Ho (2003), which simply sorts the index and defines a set of percentage of all observations as crises. The <u>Bootstrap</u> method uses 5000 resample to find the critical p-value. For instance, <u>Bootstrap 1.5%</u> means that crisis threshold is defined as the 98.5 percentile of the

3 The procedure is sometimes called quasi-maximum likelihood estimates (QMLE). The programs are written in EVIEWS language and can be requested from the author.
4 In other words, that would leave us with only 22 annual observations (1980-2001) to estimate 12 parameters in GARCH (1,1) MSM.

bootstrapped distribution. Crises identified by the events method are compiled from Caprio and Klingebiel (2002, 2003). The last classifying rule for comparison is Hadi's method for outlier detection. Outliers refer to observations that do not conform to the majority pattern. They are more distant from the sample center than the non-outliers. In practice, outliers can greatly twist the metric of distance due to the masking and swamping problems. Hadi (1992, 1994) proposes a procedure that involves using robust distance metric that is less contaminated by the outliers themselves. The implementation is easy and is readily available in STATA program. Engel and Hakkio (1996) have employed this method in the context of EMS exchange rates distribution. Since outliers could be above the mean or below the mean, we restrict outliers to only those above the mean. Table 3 represents the banking crises identified by Hadi's method.

Table 4 tells us several things. First, the simple MSM can replicate the majority of crisis quarters identified by the 2-standard-deviation method and the pooled method. For instance, 100 of the 114 crisis quarters identified by the 2-standard-deviation method coincide with the simple MSM. A similar degree of coincidence also happens to the pooled method. Second, regime-switching model tends to identify much more crises than the common procedures. The simple MSM identifies 1364 crisis quarters, while the 2-standard-deviation method identifies only 114 crisis quarters, and the pooled 2.5% method identifies only 94 crisis quarters. Third, the bootstrap method identifies as many as crisis periods as MSM method, and the crisis periods of the two methods has only roughly 50 percent coincidence. Fourth, GARCH MSM identifies less crisis periods (585 quarters) than the simple MSM (1364 quarters). Only roughly 40 percent of the crisis quarters identified by the GARCH MSM has a correspondence in the simple MSM. An analogous signal-to-noise ratio has a value of only 1.4, indicating that the two sets of crisis dates are quite different. This implies that the specification of MSM significantly influences the results of crisis identification.

Like common procedures, crises identification of the regime-switching model is sample-dependent, too. Hsu and Kuan (2001) employ a bivariate regime-switching model to study Taiwan's business cycles. They find that when confined to a sub-sample of 1990-1999, the model is successful in identifying the business cycles turning points in the 1990s. However, Markov switching model based on the full sample from 1979 to 1999 fails to identify any cycle in the 1990s. This is because that Taiwan's economy grew rapidly before 1990 but much slower afterwards. The Markov switching model classifies all the growth rates in 1990s into the low growth state when the full sample is considered, even though Taiwan's economy still experienced some ups and downs during this period. This is similar to the case of disappearing crises that Edison (2003) has documented.

A more serious problem of MSM is the case of *inventing crises*. Figure 4 illustrates two contrasting examples: Austria and Italy. In terms of money market pressure, Austria has a sound banking system, and the index never exceeds a value of 3. Study using events method also classifies Austria as a country that has never experienced any banking crisis. In contrast, Italian banking system was under great tension during the 1992 EMS crisis. The money market pressure surges up to a scale of 7. The MSM has successfully identifies this tension, in which the smoothed probability of the crisis state is over one half during 1992Q1-1993Q4. But when applying the MSM to Austria, we find many crises that are simply counterfactual. The smoothed probability of crisis state exceeds one half in almost half of the sample, and it identifies six banking crises in the Austria. This happens because the intrinsic built-in mechanism in the Markov switching models classifies each sample point into different states based on the relative level of the index. For country like Austria that has small index value, but whose index has up and down pattern, the regime-switching model will perform badly in crisis identification. In such case, the high (low) mean state dose not necessarily corresponds to what we mean about crisis (tranquil) period. The above discussion implies that a blind application of regime-switching model to crisis identification is dangerous. The approach is suitable only for countries whose index has obvious outliers, such as Italy. This may be a reason why in currency crisis literature, regime switching model has been applied to only a limited countries such as the Asian countries subject to the 1997 Asian financial crisis, and the European countries subject to the 1992 EMS crisis.

4.2. Eliminate Inadequate Sample Countries

Therefore, we discard those sample countries for which the Hadi's method detects no outliers. This leaves us with 19 sample countries: Chile, Denmark, Ireland, Israel, Italy, Jamaica, Kenya, Korea, Mexico, Niger, Peru, Seychelles, Sri Lanka, Swaziland, Sweden, Turkey, Uganda, United States, and Uruguay.

Table 6 reports the estimated results of GARCH (1,1) switching model for selected countries. The transition probabilities from crisis to crisis state are extremely low. This is because the number of crisis periods is far less than the tranquil periods. For instance, the transition probability (P; Q) for France is (0.98; 0.11), meaning that the expected duration of crisis and tranquil state are 50 and 1.1 quarters, respectively. Except for Italy, the crisis state has a higher conditional mean than the tranquil state, and IMMP in crisis state is more persistent than the tranquil state ($\alpha_2 > \alpha_1$ and $\beta_2 > \beta_1$). However, the GARCH effects are not obvious, because coefficients of conditional volatility (ϖ, a, b) are not significant and are near zero. A more complete analysis should include Hansen's specification test and independent switching test, which are not conducted in this paper.

4.3. A Brief Literature Review

Caprio and Klingebiel (1996) examine the causes of systematic banking crises using a database covering 86 episodes of insolvency in 69 countries. They define systematic banking problems as the cases in which the net worth of the banking system has been almost eliminated. They find that crisis countries have experienced greater volatility in output, inflation, and terms of trade. In 75 percent of the crisis countries the terms of trade fell by more than 10 percent in the years preceding the crisis. They do not find strong link between credit growth and bank insolvency, but they agree that excessive credit growth might be a primary factor behind the Latin American crises as Gavin and Hausman (1996) claim. As for microeconomic factors, they find that deficient bank management, poor supervision, and political interference are the primary causes of bank insolvency.

Honohan (1997) discusses three patterns of systematic financial failures: those due to endogenous macroeconomic boom and bust cycle, those due to poor management and other microeconomic deficiencies, and those due to government permeation. In a sample of 24 mostly developing countries, He finds that those countries having macroeconomic epidemics tend to have higher loan-to-deposit ratio, foreign borrowing to deposits ratio, and growth rate of real bank credit than the control group. Countries having experienced banking crises due to government permeation tend to have higher share of reserves to deposits (indicating bank has less discretion over the use of fund), government share of lending, and central bank refinancing of bank lending than the control group.

The above papers provide a first screen of the possible causes of systematic banking crises. A common deficient of these papers is that they involve little econometric work, and their conclusions are drawn from limited observations. Demirgüc-Kunt and Detragiache (1998) is the first econometric analysis on the determinants of systematic banking crises. Using a sample of 45-65 countries that include 31 crisis episodes, they find that low GDP growth, high real interest rate, and high inflation significantly increase the probability of a banking crisis. The presence of explicit deposits insurance increases bank fragility. Countries having better quality of law enforcement tend to experience less banking problems. They find that terms of trade shocks and rapid credit growth have only weak effects on the probability of a banking crisis. Government fiscal deficit and depreciation of the nominal exchange rate do not have an independent effect.

A shortage of Demirgüc-Kunt and Detragiache (1998) is that they use almost exclusively contemporaneous explanatory variables, and therefore, makes the direction of causality subject to ambiguity. To remedy this problem, Hardy and Pazarbasioglu (1999) employ both coincident and leading indicators in their econometric analysis. They control for regional differences and differentiate between full-fledged banking crises and banking distress. Likewise, they find banking crises to be strongly associated with a contemporaneous fall in real GDP growth and a rises in real interest rate. In additional, variables such as inflation, credit growth, real effective exchange rate, and banks' gross foreign liabilities display a "boom and bust" pattern, with a large positive coefficient two years before the crisis and a large negative coefficient in the crisis or pre-crisis year. Explanatory variables such as real gross fixed capital formation, the current account balance, reserve money, credit from monetary authorities, banks' reserves, banks' net foreign assets, and foreign exchange reserves relative to imports or deposits are not significant.

4.4. Conditional Logit Regression

Research on financial crises using panel binary choice model rarely controls for country-fixed effects. In logit regression, controlling for fixed effects would require omitting the sample countries that have experienced no crises during the sample period. This would imply a loss of a large amount of available information (Demirgüc-Kunt and Detragiache, 1998). However, neglecting the fixed effects implies disregarding the possibility that the dependent variable may change cross-country independently of the explanatory variables. Simply adding country dummies in the panel logit is not an adequate method to control for country-fixed effects. For a fixed number of observation T, the number of country dummies increases with the number of cross-sectional units N, so that the country-intercept terms cannot be consistently estimated for a fixed number of observations. This is known as the incidental parameters problem (Baltagi, 1995). The usual solution to this incidental parameters problem is to find a sufficient statistics for country-intercept terms that does not depends on the slope terms. For the logit model, a minimum sufficient statistics for country-intercept terms is $\sum_{t=1}^{T} y_{it}$. Chamberlain (1980) proposes the conditional logit model that maximizes the conditional likelihood function $L_c = \prod_{i=1}^{N} \Pr\left(y_{i1}, \ldots, y_{iT} \middle/ \sum_{t=1}^{T} y_{it} \right)$ instead of the unconditional likelihood function $L=\prod_{i=1}^{N}\prod_{t=1}^{T}\left(F_{it}\right)^{y_{it}}\left(1-F_{it}\right)^{1-y_{it}}$. We follow Chamberlain (1980) and estimate a conditional logit model for banking crises.

4.5. Determinants of Banking Crises

In this section, we estimate two regressions, one with smoothed probability of crisis state as dependent variable, and one with binary crisis dummy as dependent variable. Our choice of explanatory variables is guided by existing literature and data availability. For a detailed discussion, see Demirgüc-Kunt and Detragiache (1998) and von Hagen and Ho (2003). Table 7 lists the variables and their sources.

Table 8 reports the estimated results when using smoothed probability as dependent variable. This is simply a fixed-effect OLS regression with a continuous dependent variable. A problem with such panel regression is that the predicted value is not confined between zero and one. Also as showed in Figure 3, smoothed probabilities tend to have low value in most periods, and we may be more interested in periods with high crisis probabilities. Table 9 reports the estimated results for conditional logit model, where the binary dependent variable is obtained by a dichotomy of the smoothed probability. This help to focus on periods with high crisis probabilities. The following discussion will focus on Table 9.

The sample consists of 305 quarterly observations, including 100 crisis quarters. Thus the rate of incidences of banking crises in the sample is about 30 percent. Table 9 presents six specifications of the model. The first specification includes only macroeconomic variables as explanatory variables. The second specification includes macroeconomic and financial variables. The third specification includes additional institutional variables. The fourth specification adds the events crisis dummy. The fifth specification includes interaction effects. The last specification retains only those significant variables.

Only two of the ten macroeconomic factors are significant: real exchange rate overvaluation and the ratio of budget surplus to GDP. A decline in real GDP growth and nominal depreciation increase the probability of banking crises, but the effects are not significant. Crises are strongly associated with over-valued exchange rates. The coefficients on real interest rate and inflation rate have a positive sign as expected, but in no case are they significant. Government budget deficits increase the probability of banking crises. The effects of monetary base growth and domestic credit growth are negligible.

Turning to financial variables, we find that coefficient on ratio of domestic credit to GDP is not significant. Liquidity of a banking system, approximated by ratio of bank cash and reserves to bank assets, is significant and reduces the probability of banking crisis. This implies that liquidity in banking system can serve as buffer against external shocks. As for institutional variables, we find that the coefficient on GDP per capita is negative and significant, indicating less developed countries in our sample tend to experience more crises. Financial liberalization and existence of explicit deposits insurance scheme have only negligible effects. The coefficient on Freedom House country rating is negative and significant, meaning that countries having good governance and institutional quality tend to have fewer crises. The OECD dummy indicates that the introduction of Basle capital requirement starting in 1993 did cause money market tensions in OECD countries. Finally, the events crisis dummy and all the interactive terms are not significant.

Table 11 compares our results with other research. The discrepancy is large. Factors identified by existing literature to have significant effects on banking crises, such as GDP slowdown, high interest rate, high inflation and credit boom, are not found to be important in this paper. The only common finding is that over-values exchange rate increases the likelihood of banking crises. To see where the discrepancy comes from, we estimate another conditional logit regression, but with the set of dependent variable identified by using the Hadi's outlier detection method. Table 10 represents the results. Now the results are more similar to the existing literature. For instance, variables such as decline in GDP, overvaluation, high inflation, domestic credit to GDP ratio, and existence of deposits insurance scheme are strongly associated with banking crises. We conclude that different crises periods identified by the regime-switching model accounts for a large proportion of this discrepancy.

5. Conclusion

Summed up, using regime-switching models to the identification of banking crises is not very promising. MSM endogenizes the crisis threshold and thus reduces the arbitrariness involved in setting crisis threshold and exclusion window. However, crisis identification of MSM is sample-dependent and has the problem of inventing far more crises than it actually has. The specification of the model significantly influences the crisis identification, and so far there is no commonly accepted criterion for selecting competing specifications. In a strict sense, the method does not allow the data to tell us freely what they are. In fact, the built-in mechanism already instructs what the data should tell us. More importantly, the MSM are specified to characterize regime means. The approach implicitly assumes that the observations are distributed surrounding two different means. However, crises are more like outliers (extreme values) of a given distribution. This also means that the high mean-value state does not necessarily correspond to what we mean by crisis state, and the low-value mean state does not correspond to what we mean by tranquil state. An increasing literature employs GARCH switching model to the identification of currency crises (Brunetti, Mariano, Scotti and Tan, 2003). However, whether there are really GARCH effects in the speculative pressure index (or money market pressure in our case) is questionable. Furthermore, even with a cautious application, we suspect the crises identified by the MSM are not reliable. This can explain why factors contributing to banking crises in our sample have a great discrepancy with existing research. We call for cautions in applying the regime-switching method to crisis identification.

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Figure 1: Index of money market pressure for 47 sample countries

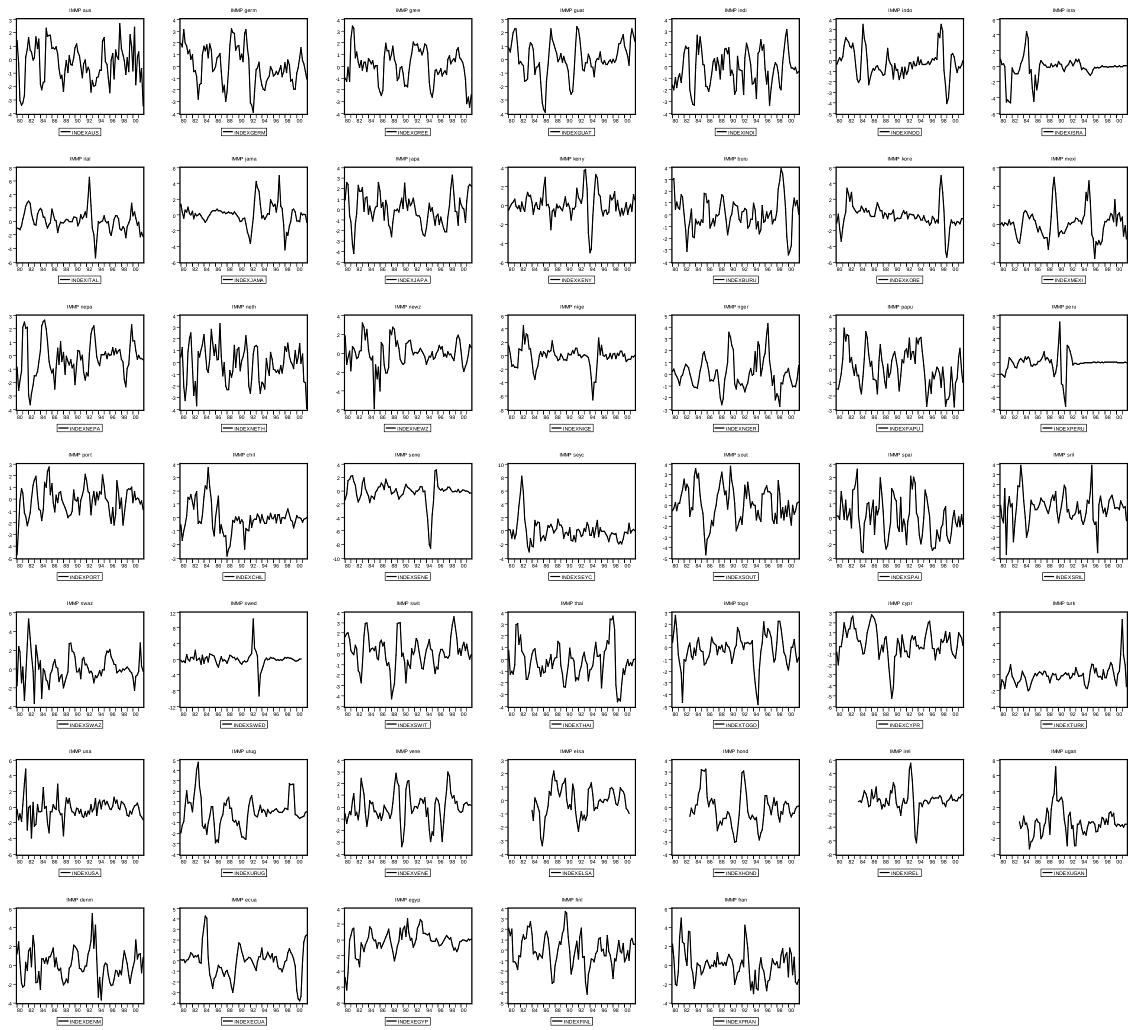

Figure 2: Smoothed probability, simple Markov-switching model

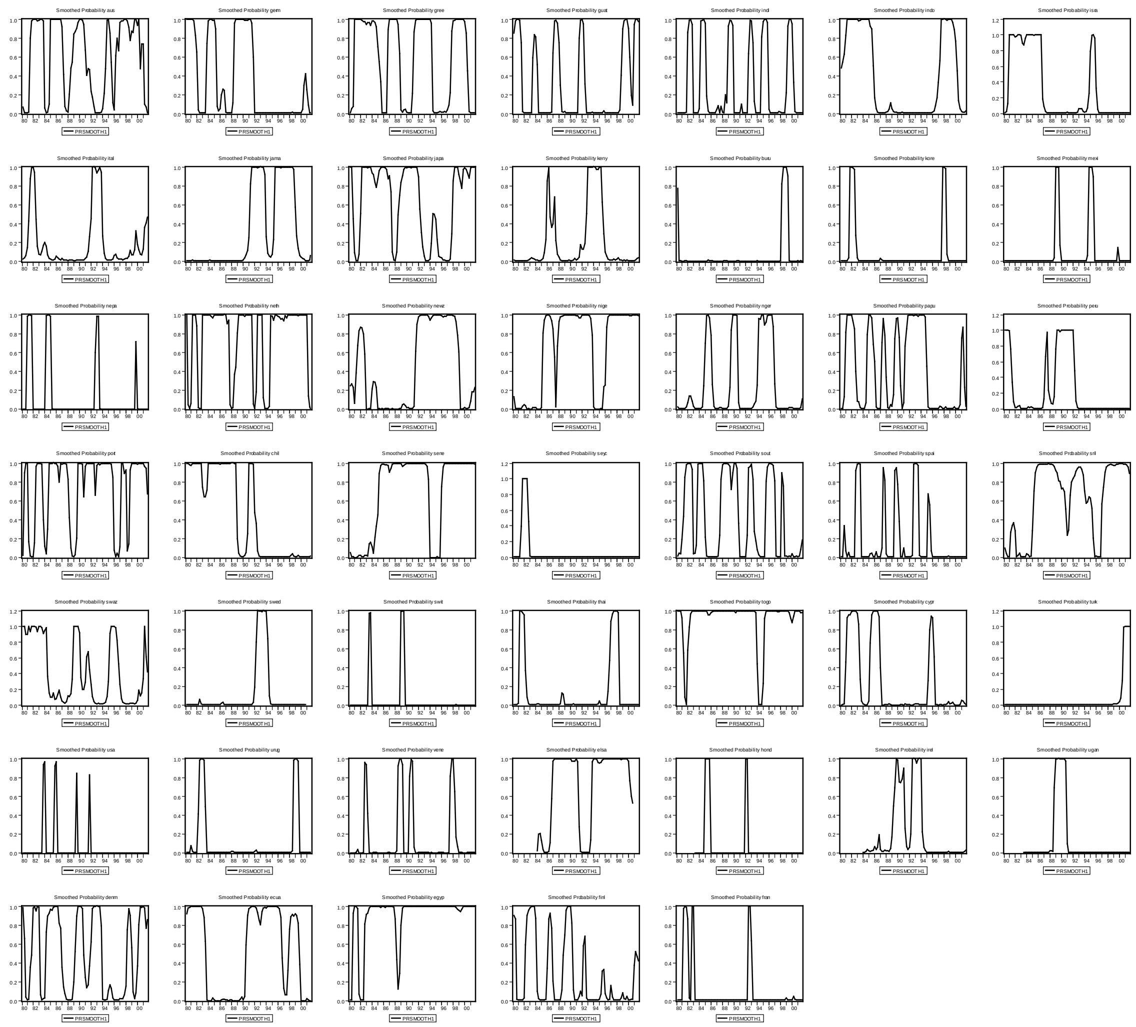

Figure 3: Smoothed probability, GARCH (1,1) Markov-switching model

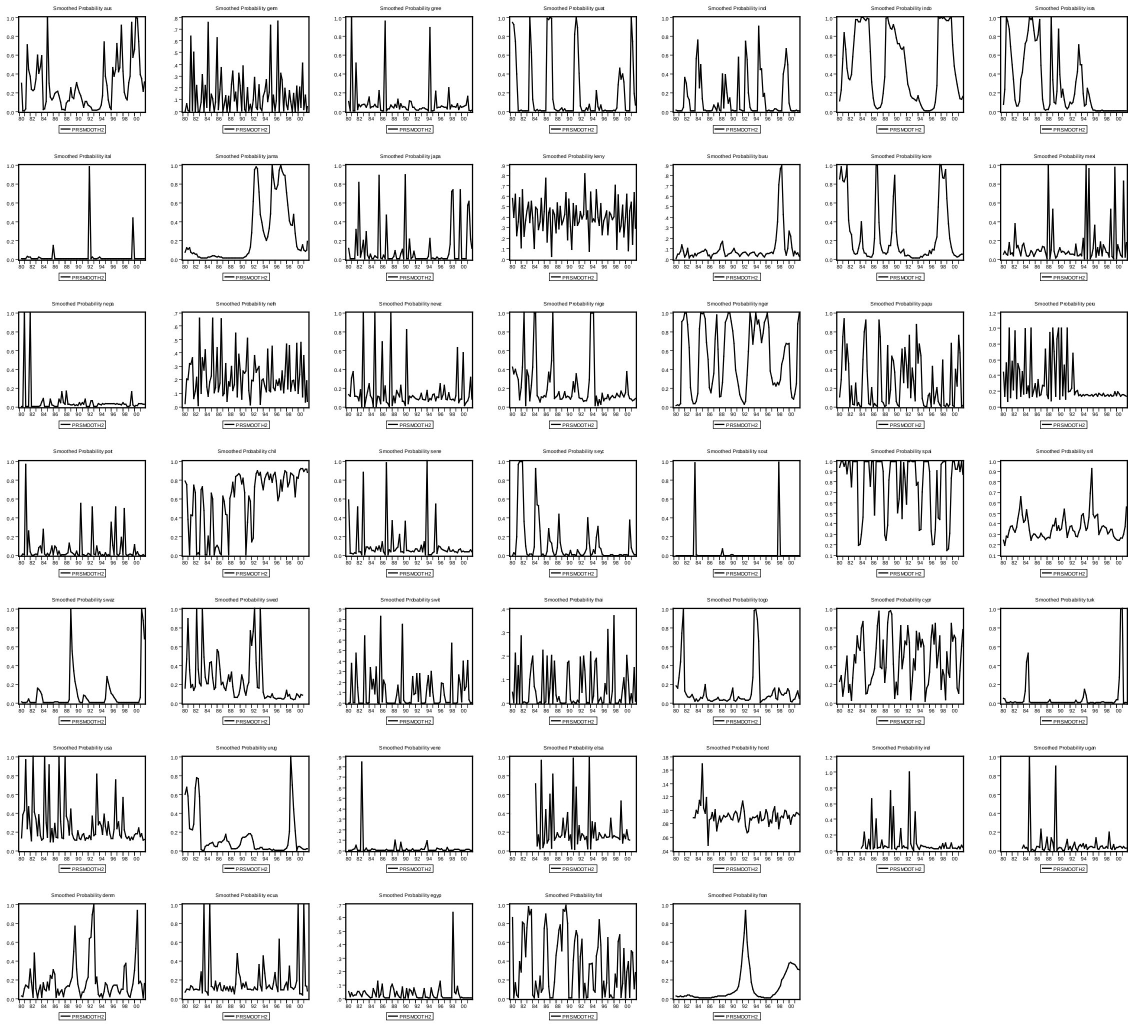

Figure 4: An illustration, Austria and Italy, Simple Markov-switching model

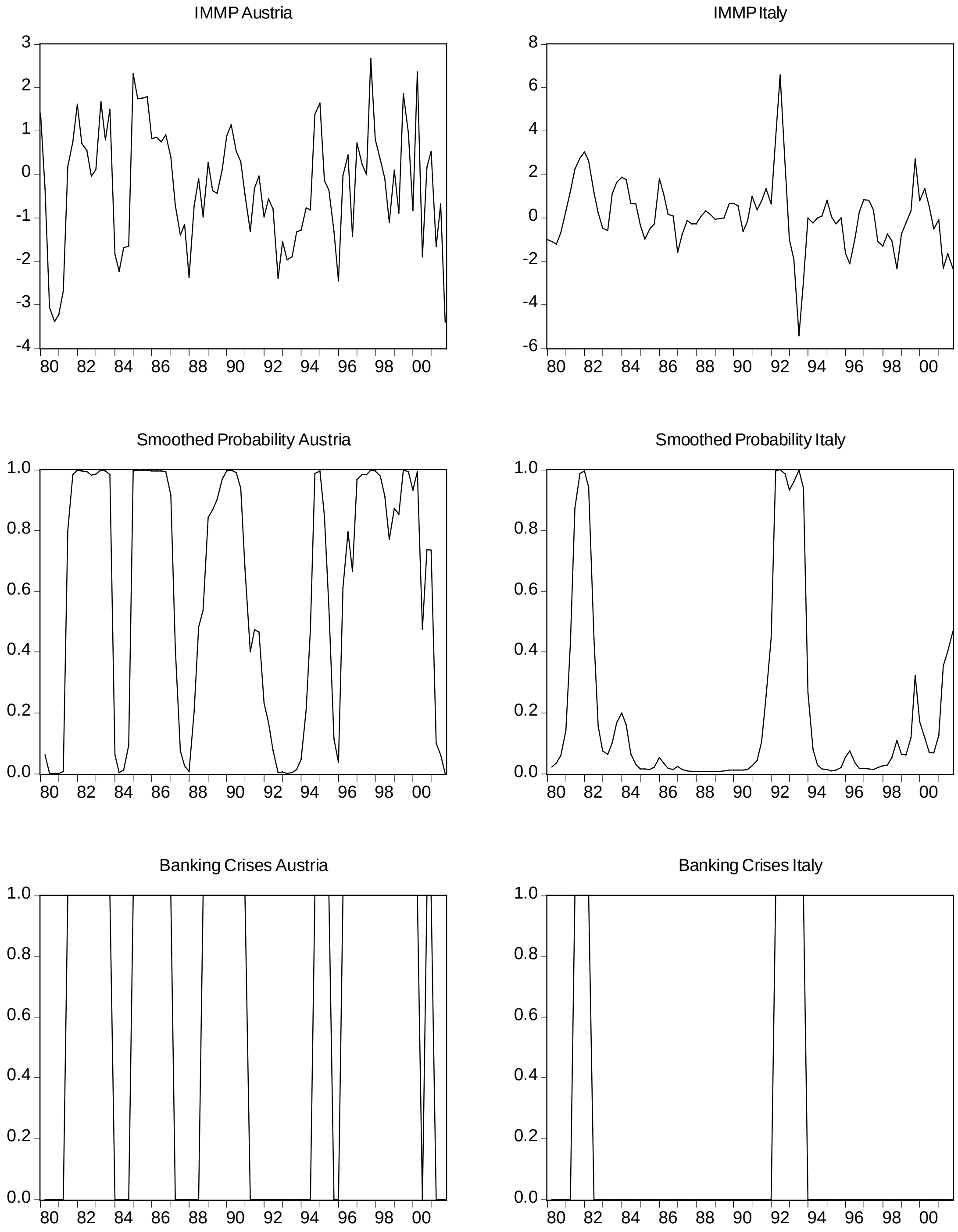

Table 1: Banking crisis dates, simple Markov-switching model

Country	Identified Banking Crisis
Austria	1981Q3~1983Q4; 1985Q1~1987Q1; 1988Q4~1991Q1; 1994Q4~1995Q3; 1996Q2~2000Q2; 2000Q4~2001Q1
Burundi	1980Q2~1980Q2; 1998Q2~1999Q2
Chile	1980Q2~1988Q4; 1991Q1~1991Q4
Cyprus	1981Q2~1983Q2; 1985Q2~1986Q4; 1995Q3~1996Q2
Denmark	1980Q2~1980Q3; 1982Q1~1983Q1; 1984Q2~1986Q4; 1989Q2~1990Q3; 1992Q1~1993Q4; 1998Q2~1999Q1; 2000Q2~2001Q4
Ecuador	1980Q2~1983Q3; 1990Q3~1996Q3; 1998Q1~1999Q3
Egypt	1980Q4~1981Q3; 1982Q4~1988Q1; 1989Q1~2001Q4
El Salvador	1986Q4~1991Q2; 1993Q4~2000Q4
Finland	1980Q2~1980Q3; 1982Q2~1984Q1; 1986Q2~1986Q4; 1989Q1~1990Q2; 1992Q2~1992Q3; 2001Q2~2001Q2
France	1981Q2~1982Q1; 1982Q4~1983Q1; 1992Q3~1993Q1
Germany	1980Q2~1982Q1; 1983Q4~1985Q2; 1988Q3~1991Q4
Greece	1981Q1~1985Q2; 1986Q4~1988Q4; 1991Q2~1994Q2; 1997Q4~2000Q2
Guatemala	1980Q2~1981Q3; 1983Q3~1984Q2; 1987Q1~1988Q1; 1991Q3~1992Q2; 1999Q1~2000Q2; 2001Q1~2001Q4
Honduras	1985Q1~1985Q4; 1992Q1~1992Q2
India	1982Q1~1982Q4; 1984Q2~1985Q1; 1989Q1~1989Q4; 1992Q3~1993Q2; 1994Q4~1995Q4; 1999Q2~2000Q1
Indonesia	1980Q3~1985Q4; 1997Q2~2000Q1
Ireland	1989Q3~1991Q1; 1992Q3~1994Q1
Israel	1981Q1~1986Q3; 1995Q1~1995Q4
Italy	1981Q3~1982Q2; 1992Q2~1993Q4
Jamaica	1991Q2~1993Q4; 1995Q3~1999Q1
Japan	1980Q2~1980Q3; 1982Q1~1987Q2; 1988Q4~1992Q2; 1994Q3~1994Q3; 1998Q1~2001Q4
Kenya	1986Q1~1986Q2; 1987Q2~1987Q2; 1992Q4~1995Q3
Korea	1981Q4~1982Q3; 1997Q4~1998Q2
Mexico	1989Q1~1989Q3; 1994Q4~1995Q3
Nepal	1981Q1~1981Q4; 1984Q2~1985Q1; 1992Q4~1993Q2; 1999Q4~1999Q4
Netherlands	1980Q2~1980Q2; 1981Q2~1982Q1; 1983Q1~1987Q3; 1989Q1~1991Q3; 1992Q3~1993Q2; 1994Q4~2001Q1
New Zealand	1981Q3~1982Q4; 1991Q3~1999Q1
Niger	1985Q2~1987Q2; 1987Q4~1993Q4; 1996Q2~2001Q4
Nigeria	1985Q1~1986Q1; 1989Q3~1990Q3; 1994Q2~1996Q4
Papua New Guinea	1981Q1~1982Q3; 1984Q4~1986Q1; 1987Q2~1987Q4; 1989Q3~1990Q2; 1991Q2~1994Q4; 2001Q1~2001Q2
Peru	1980Q2~1981Q2; 1987Q2~1987Q3; 1989Q1~1992Q1
Portugal	1980Q3~1981Q1; 1982Q3~1983Q3; 1984Q4~1988Q1; 1989Q4~1995Q4; 1997Q2~1998Q1; 1998Q4~2001Q4
Senegal	1985Q2~1993Q4; 1996Q1~2001Q4
Seychelles	1981Q4~1982Q3
South Africa	1981Q3~1982Q4; 1983Q4~1984Q4; 1987Q4~1990Q3; 1992Q3~1993Q2; 1995Q3~1997Q1; 1998Q2~1998Q3
Spain	1982Q4~1983Q3; 1987Q3~1987Q4; 1989Q3~1990Q1; 1992Q4~1993Q3; 1995Q2~1995Q3
Sri Lanka	1985Q2~1990Q4; 1991Q3~1995Q2; 1997Q1~2001Q4
Swaziland	1980Q2~1984Q2; 1989Q1~1990Q1; 1991Q2~1991Q3; 1995Q2~1996Q4; 2001Q2~2001Q3

Sweden	1992Q2~1994Q2
Switzerland	1983Q3~1983Q4; 1989Q1~1989Q3
Thailand	1981Q2~1982Q1; 1997Q1~1998Q2
Togo	1980Q2~1981Q2; 1982Q1~1993Q4; 1995Q2~2001Q4
Turkey	2000Q4~2001Q4
Uganda	1988Q4~1990Q4
United States	1983Q4~1984Q1; 1985Q4~1986Q1; 1989Q3~1989Q3; 1991Q4~1991Q4
Uruguay	1982Q3~1983Q2; 1998Q4~1999Q3
Venezuela	1982Q4~1983Q1; 1988Q3~1989Q2; 1990Q3~1991Q1; 1997Q3~1998Q2

Table 2: Banking crisis dates, GARCH (1,1) Markov-switching model

Country	Identified Banking Crisis
Austria	1981Q3~1981Q3; 1983Q2~1983Q2; 1984Q1~1984Q1; 1985Q1~1985Q1; 1994Q4~1994Q4; 1997Q1~1997Q1; 1997Q4~1997Q4; 1999Q3~2000Q4
Burundi	1998Q2~1998Q4
Chile	1980Q3~1980Q4; 1982Q1~1982Q2; 1983Q2~1983Q3; 1985Q1~1985Q2; 1987Q1~1987Q2; 1988Q2~1990Q4; 1991Q3~1991Q4; 1992Q3~2001Q4
Cyprus	1983Q1~1983Q1; 1983Q3~1984Q4; 1986Q4~1987Q2; 1988Q1~1988Q1; 1988Q4~1989Q3; 1991Q1~1991Q1; 1991Q4~1992Q3; 1993Q4~1995Q1; 1996Q2~1997Q1; 1997Q3~1997Q4; 1999Q1~1999Q1; 1999Q4~2000Q3; 2001Q3~2001Q4
Denmark	1989Q4~1989Q4; 1992Q2~1993Q1; 2000Q2~2000Q3
Ecuador	1983Q4~1983Q4; 1984Q4~1984Q4; 1996Q4~1996Q4; 2000Q1~2000Q1; 2001Q1~2001Q1
Egypt	1998Q3~1998Q3
El Salvador	1984Q3~1984Q3; 1985Q3~1985Q3; 1987Q1~1987Q1; 1987Q3~1987Q3; 1991Q1~1991Q1; 1991Q3~1991Q3; 1993Q4~1993Q4; 1999Q2~1999Q2
Finland	1980Q3~1980Q3; 1982Q2~1982Q3; 1983Q1~1983Q4; 1986Q1~1986Q3; 1988Q2~1990Q1; 1991Q2~1991Q4; 1992Q3~1992Q3; 1995Q2~1995Q4; 1997Q1~1997Q1; 1998Q4~1999Q1; 1999Q4~1999Q4; 2001Q1~2001Q1
France	1992Q1~1992Q4
Germany	1981Q3~1981Q3; 1982Q1~1982Q1; 1984Q3~1984Q3; 1986Q1~1986Q1; 1995Q2~1995Q2; 1996Q3~1996Q3
Greece	1981Q1~1981Q1; 1981Q4~1981Q4; 1986Q4~1986Q4; 1994Q3~1994Q3
Guatemala	1980Q3~1981Q1; 1983Q3~1983Q4; 1986Q3~1987Q2; 1991Q2~1991Q4; 2001Q1~2001Q2
Honduras	
India	1984Q1~1984Q2; 1991Q2~1991Q2; 1992Q3~1992Q4; 1994Q4~1994Q4; 1999Q3~1999Q3
Indonesia	1981Q1~1981Q3; 1982Q4~1985Q4; 1988Q3~1991Q4; 1997Q3~2000Q1
Ireland	1986Q1~1986Q1; 1989Q2~1989Q2; 1989Q4~1989Q4; 1992Q3~1992Q3
Israel	1981Q1~1981Q4; 1984Q1~1986Q4; 1988Q4~1988Q4; 1990Q1~1993Q3
Italy	1992Q2~1992Q2
Jamaica	1992Q2~1993Q2; 1995Q3~1998Q2
Japan	1982Q2~1982Q2; 1985Q4~1985Q4; 1990Q2~1990Q2; 1998Q2~1998Q3; 1999Q4~1999Q4; 2001Q1~2001Q2
Kenya	1980Q3~1980Q3; 1981Q1~1981Q1; 1981Q4~1981Q4; 1982Q2~1982Q2; 1983Q2~1983Q2; 1983Q4~1983Q4; 1985Q3~1985Q3; 1986Q2~1986Q2; 1988Q2~1988Q2; 1988Q4~1988Q4; 1989Q4~1989Q4; 1990Q2~1990Q2; 1991Q1~1991Q1; 1991Q3~1991Q3; 1993Q1~1993Q1; 1994Q1~1994Q1; 1995Q1~1995Q1; 1995Q4~1995Q4; 1998Q2~1998Q2; 1998Q4~1998Q4; 1999Q3~1999Q3; 2000Q2~2000Q2; 2001Q1~2001Q1; 2001Q3~2001Q3
Korea	1980Q3~1981Q4; 1986Q4~1987Q1; 1989Q4~1990Q1; 1997Q3~1999Q1
Mexico	1988Q2~1988Q2; 1989Q1~1989Q1; 1994Q4~1994Q4; 1995Q2~1995Q2; 1999Q1~1999Q1; 1999Q4~1999Q4; 2001Q2~2001Q2
Nepal	1981Q1~1981Q1; 1982Q1~1982Q1
Netherlands	1983Q1~1983Q1; 1985Q2~1985Q2; 1986Q4~1986Q4; 1989Q2~1989Q2; 1991Q2~1991Q2
New Zealand	1983Q1~1983Q1; 1985Q1~1985Q1; 1986Q2~1986Q2; 1987Q4~1987Q4; 1990Q3~1990Q3; 1999Q2~1999Q2; 2000Q2~2000Q2
Niger	1982Q3~1982Q3; 1984Q2~1984Q3; 1987Q3~1987Q3; 1994Q1~1994Q3
Nigeria	1981Q3~1982Q4; 1984Q3~1986Q1; 1987Q2~1987Q4; 1988Q4~1990Q3;

	1993Q1~1996Q3; 1999Q1~2000Q1; 2001Q3~2001Q4
Papua New Guinea	1981Q1~1981Q2; 1981Q4~1981Q4; 1984Q3~1985Q1; 1987Q2~1987Q3; 1988Q4~1988Q4; 1989Q3~1989Q3; 1991Q2~1991Q2; 1991Q4~1991Q4; 1992Q3~1992Q3; 1993Q4~1993Q4; 1994Q2~1994Q3; 1999Q4~1999Q4; 2001Q1~2001Q2
Peru	1981Q1~1981Q1; 1981Q3~1981Q3; 1982Q1~1982Q1; 1982Q3~1982Q3; 1983Q1~1983Q1; 1984Q2~1984Q2; 1985Q2~1985Q2; 1987Q4~1987Q4; 1988Q3~1988Q3; 1989Q1~1989Q2; 1989Q4~1990Q1; 1990Q3~1990Q3; 1991Q1~1991Q1; 1991Q3~1991Q3; 1992Q3~1992Q3
Portugal	1981Q2~1981Q2; 1990Q4~1990Q4; 1992Q4~1992Q4; 1996Q4~1996Q4
Senegal	1980Q3~1980Q3; 1982Q1~1982Q1; 1983Q1~1983Q1; 1987Q1~1987Q1; 1994Q1~1994Q1; 1995Q3~1995Q3
Seychelles	1981Q3~1982Q2; 1984Q3~1985Q1
South Africa	1983Q4~1983Q4; 1998Q2~1998Q2
Spain	1980Q3~1983Q3; 1984Q4~1986Q2; 1986Q4~1988Q1; 1989Q1~1991Q1; 1991Q3~1994Q1; 1994Q4~1996Q1; 1997Q2~1997Q2; 1998Q1~1998Q4; 1999Q4~2001Q4
Sri Lanka	1983Q2~1983Q3; 1984Q3~1984Q3; 1991Q1~1991Q1; 1994Q2~1994Q2; 1995Q3~1995Q4; 2001Q4~2001Q4
Swaziland	1989Q1~1989Q2; 2001Q2~2001Q4
Sweden	1981Q1~1981Q1; 1982Q3~1982Q3; 1983Q3~1983Q3; 1986Q1~1986Q2; 1991Q4~1992Q3; 1993Q3~1993Q3
Switzerland	1983Q2~1983Q2; 1986Q1~1986Q1; 1989Q4~1989Q4; 1998Q2~1998Q2
Thailand	
Togo	1981Q3~1981Q4; 1994Q1~1994Q4
Turkey	1984Q4~1984Q4; 2000Q4~2001Q1
Uganda	1985Q1~1985Q1; 1989Q3~1989Q3
United States	1981Q2~1981Q2; 1982Q3~1982Q3; 1984Q3~1984Q3; 1985Q2~1985Q2; 1987Q1~1987Q1; 1988Q1~1988Q1; 1993Q3~1993Q3; 1996Q4~1996Q4; 1998Q1~1998Q1
Uruguay	1980Q3~1981Q1; 1982Q2~1983Q1; 1998Q4~1999Q1
Venezuela	1982Q4~1982Q4

Table 3: Banking crisis dates, Hadi's outlier detection method

	5% significance level	10% significance level
Country	Date of Banking Crisis	Date of Banking Crisis
Chile	1984Q4~1984Q4	1984Q4~1984Q4
Denmark	1993Q1~1993Q1	
Ireland	1989Q4~1989Q4 1992Q3~1993Q1	1992Q3~1992Q4
Israel	1984Q2~1984Q4	1984Q2~1984Q4
Italy	1992Q3~1992Q3	1992Q3~1992Q3
Jamaica	1993Q1~1993Q2 1997Q1~1997Q1	1993Q1~1993Q1 1997Q1~1997Q1
Kenya	1986Q2~1986Q2 1993Q1~1993Q2 1995Q1~1995Q2	
Korea	1981Q4~1982Q1 1982Q3~1982Q3 1997Q4~1998Q2	1981Q4~1982Q1 1982Q3~1982Q3 1997Q4~1998Q2
Mexico	1989Q2~1989Q2 1995Q2~1995Q2	
Niger	1982Q3~1982Q3	
Peru	1987Q3~1987Q3 1990Q1~1990Q2 1991Q3~1992Q1	1987Q3~1987Q3 1990Q1~1990Q2 1991Q3~1992Q1
Seychelles	1981Q4~1982Q3	1981Q4~1982Q3
Sri Lanka	1983Q3~1983Q3 1995Q4~1995Q4	1983Q3~1983Q3 1995Q4~1995Q4
Swaziland	1982Q1~1982Q1	1982Q1~1982Q1
Sweden	1992Q3~1992Q4	1992Q3~1992Q3
Turkey	2001Q1~2001Q1	2001Q1~2001Q1
Uganda	1989Q3~1989Q3	1989Q3~1989Q3
United States	1981Q2~1981Q3 1987Q1~1987Q1	1981Q3~1981Q3
Uruguay	1983Q1~1983Q1	
	19 countries	14 countries

Table 4: Comparison of rules for classifying crises

		2 STDEV		Pooled 1.5%		Pooled 2.5%		Bootstrap 1.5%		Bootstrap 2.5%		Events	
		N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
MSM-linear	N	2647	14	2654	7	2648	13	2067	594	2040	621	2004	657
	Y	1264	100	1324	40	1283	81	511	853	495	869	945	419
Signal to noise ratio		2.7		2.6		2.6		3.0		3.0		1.2	

		2 STDEV		Pooled 1.5%		Pooled 2.5%		Bootstrap 1.5%		Bootstrap 2.5%		Events	
		N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
MSM-GARCH	N	3339	54	3368	25	3345	48	2274	1119	2233	1160	2491	902
	Y	526	59	563	22	539	46	272	313	270	315	415	170
Signal to noise ratio		3.8		3.3		3.5		2.0		2.0		1.1	

		Hadi 5%		Hadi 10%	
		N	Y	N	Y
MSM-linear	N	2658	3	2655	6
	Y	1335	29	1322	42
Signal to noise ratio		2.7		2.6	

		Hadi 5%		Hadi 10%	
		N	Y	N	Y
MSM-GARCH	N	3381	12	3376	17
	Y	565	20	554	31
Signal to noise ratio		4.4		4.6	

		MSM-GARCH	
		N	Y
MSM-linear	N	2297	329
	Y	1096	256
Signal to noise ratio		1.4	

		Hadi 5%		Hadi 10%	
		N	Y	N	Y
Pooled 1.5%	N	4007	18	3996	29
	Y	33	14	28	19
Signal to noise ratio		5.3		56.89	
Pooled 2.5%	N	3967	11	3960	18
	Y	73	21	64	30
Signal to noise ratio		36.3		39.3	

Table 5: Comparison of rules for classifying crises, adjusted sample

		2 STDEV		Pooled 1.5%		Pooled 2.5%		Bootstrap 1.5%		Bootstrap 2.5%		Events	
		N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
MSM-linear	N	1213	9	1219	3	1216	6	910	312	895	327	922	300
	Y	352	47	383	16	367	32	193	206	189	210	208	191
Signal to noise ratio		3.7		3.5		3.6		2.3		2.2		2.1	

		2 STDEV		Pooled 1.5%		Pooled 2.5%		Bootstrap 1.5%		Bootstrap 2.5%		Events	
		N	Y	N	Y	N	Y	N	Y	N	Y	N	Y
MSM-GARCH	N	1348	20	1360	8	1354	14	972	396	953	415	959	409
	Y	198	36	223	11	210	24	117	117	117	117	153	81
Signal to noise ratio		5.0		4.1		4.7		2.1		2.0		1.2	

		Hadi 5%		Hadi 10%	
		N	Y	N	Y
MSM-linear	N	1219	3	1216	6
	Y	370	29	357	42
Signal to noise ratio		3.9		3.9	

		Hadi 5%		Hadi 10%	
		N	Y	N	Y
MSM-GARCH	N	1356	12	1351	17
	Y	214	20	203	31
Signal to noise ratio		4.6		4.9	

		MSM-GARCH	
		N	Y
MSM-linear	N	1069	138
	Y	299	96
Signal to noise ratio		1.9	

		Hadi 5%		Hadi 10%	
		N	Y	N	Y
Pooled 1.5%	N	1603	18	1592	29
	Y	5	14	0	19
Signal to noise ratio		140.7		Infinity	
Pooled 2.5%	N	1591	11	1584	18
	Y	17	21	8	30
Signal to noise ratio		62.1		124.4	

Table 6: Estimated results of GARCH (1,1) switching model for selected countries

	France		Ireland		Italy		Mexico	
Parameters	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
α_1	-0.01	0.96	0.05	0.59	0.06	0.72	-0.01	0.92
α_2	3.84	0.00***	1.59	0.22	0.02	0.64	0.27	0.63
β_1	0.57	0.00***	0.57	0.00***	1.06	0.00***	0.76	0.00***
β_2	1.71	0.30	1.48	0.12	0.41	0.00***	1.73	0.01***
ϖ_1	0.00	0.99	0.00	1.00	0.63	0.89	0.02	0.99
ϖ_2	0.00	0.99	1.00	1.00	0.01	0.21	0.94	0.93
a_1	0.18	0.82	0.24	0.98	0.16	0.52	0.41	0.97
a_2	0.39	0.99	0.66	0.97	0.15	0.17	0.38	0.98
b_1	0.56	0.84	0.42	0.98	0.54	0.96	0.24	0.96
b_2	0.08	0.89	0.19	0.92	0.00	0.99	0.64	0.91
P	0.98	0.00***	0.92	0.00***	0.77	0.00***	0.83	0.00***
Q	0.11	0.74	0.00	0.92	0.58	0.58	0.04	0.69
Log likelihood	-130.22		-94.27		-115.46		-100.93	

GARCH (1,1) Switching Model

$$\mathrm{IMMP}_t = \mu_{i,t} + \varepsilon_{i,t} = \alpha_i + \beta_i \mathrm{IMMP}_{t-1} + \varepsilon_{i,t}, \quad i = 1,2$$

$$\varepsilon_{i,t} = \sqrt{h_{i,t}}\, z_t, \quad z_t \sim i.i.d.(0,1)$$

$$h_{i,t} = w_i + a_i \varepsilon_{t-1}^2 + b_i h_{t-1}$$

$$h_t = E\left[\mathrm{IMMP}_t^2 \mid \Phi_{t-1}\right] - E\left[\mathrm{IMMP}_t \mid \Phi_{t-1}\right]^2$$

$$\varepsilon_t = \mathrm{IMMP}_t - E\left[\mathrm{IMMP}_t \mid \Phi_{t-1}\right]$$

$$\Pr\left[S_t = 1 \mid S_{t-1} = 1\right] = P$$

$$\Pr\left[S_t = 2 \mid S_{t-1} = 2\right] = Q$$

Table 7: Explanatory variables and data sources

Variable Name	Definition	Sources
	MACROECONOMIC VARIABLES	
GROWTH (%)	Growth rate of real GDP	IFS line 99bvp or 99b.p
DEPRECIATION (%)	Changes of nominal exchange rates	IFS line RF
OVERRER (%)	Overvaluation of real exchange rate (An increase in number means a real depreciation)	Deviation from H-P filter (smoothing parameter=6.25)
RLINTEREST (%)	Real interest rates	Nominal interest rates are from IFS line 60b; Inflation rates are from IFS line 64
INFLATION (%)	Inflation rates	IFS line 64
SURPLUS/GDP (%)	Ratio of budget surplus to GDP	Surplus from IFS line 80; GDP from line 99b
DGROWTH (dummy)	Dummy for severe recession	GROWTH<-5%
DDGROWTH (dummy)	Dummy for severe recession	DGROWTH×GROWTH
DINFLATION (dummy)	Dummy for high inflation	INFLATION>20%
MBGRO (%)	Growth rate of monetary base	IFS line 14
CREDITGRO (%)	Growth rate of real domestic credit	IFS line 32d ÷ line 64
	FINANCIAL VARIABLES	
PRIVATE/GDP	Ratio of domestic credit to private sector to GDP	Domestic credit to private sector from IFS line 32d
CASH/BANK (%)	Ratio of bank liquid reserves to bank assets	Bank liquid reserves from IFS line 20; Bank assets from IFS line 21 plus lines 22a to 22f
	INSTITUTIONAL VARIABLES	
GDP/CAP (1000 dollars/person)	Real GDP per capita	Population is IFS line 99z
FL (dummy)	Dummy variable for financial liberalization	Demirgüc-Kunt and Detragiache (1998), Glick and Hutchison (2001)
DEPOSITEX (dummy)	Dummy variable for existence of explicit deposit insurance	Garcia (1999), Demirgüc-Kunt and Detragiache (2000)
FH	Indicator for governance and institutional quality	Freedom House country ratings for political freedoms and civil liberty
OECD (dummy)	Dummy variable that takes the value of one only in OECD countries and only in 1991-92.	OECD countries introduced the Basle capital requirements that were binding starting in 1993
DEVENT (dummy)	Crises identified by events method	Caprio and Klingebiel (2002, 2003)

Table 8: Fixed-effects panel regression, smoothed probability as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
MACROECONOMIC VARIABLES						
GROWTH (-1)	-0.0002	-0.0002	-0.0003	-0.0002	-0.0003	
	(-0.49)	(-0.48)	(-0.57)	(-0.45)	(-0.54)	
DEPRECIATION (-1)	0.0009**	0.0009**	0.0008*	0.0008*	0.0005	0.0005***
	(2.13)	(2.07)	(1.83)	(1.89)	(0.70)	(2.75)
OVERRER (-1)	-0.001	-0.001	-0.001	-0.001	-0.0005	-0.001*
	(-1.24)	(-1.19)	(-1.28)	(-1.17)	(-0.46)	(-1.79)
RLINTEREST (-1)	0.0002	0.0002	0.0001	0.0001	0.0002	
	(1.34)	(1.35)	(0.72)	(0.68)	(1.29)	
INFLATION (-1)	-0.00002	-0.00002	-0.00008	-0.00008	0.0004	
	(-0.11)	(-0.08)	(-0.36)	(-0.38)	(0.60)	
SURPLUS/GDP (-1)	-0.00001	-0.00001	-0.00001	-0.00001	-0.00	
	(-0.82)	(-0.82)	(-0.85)	(-0.65)	(-0.56)	
DDGROWTH (-1)	0.008	0.009	0.002	0.005	0.002	
	(1.24)	(1.24)	(0.23)	(0.66)	(0.28)	
DINFLATION (-1)	-0.03	-0.03	-0.02	-0.02	-0.03	
	(-1.15)	(-0.98)	(-0.57)	(-0.70)	(-0.96)	
MBGRO (-1)	-0.0006**	-0.0006**	-0.0005**	-0.0005**	-0.0006*	-0.0004***
	(-2.39)	(-2.32)	(-2.01)	(-2.09)	(-1.93)	(-2.60)
CREDITGRO (-1)	0.00002	0.00002	0.00003	0.0001	0.00003	
	(0.05)	(0.05)	(0.06)	(0.23)	(0.06)	
FINANCIAL VARIABLES						
PRIVATE/GDP (-1)		0.0001	-0.0002	-0.00008	-0.0002	
		(0.21)	(-0.34)	(-0.15)	(-0.30)	
CASH/BANK (-1)		-0.0001	0.00008	0.00001	-0.0001	
		(-0.14)	(0.08)	(0.01)	(-0.11)	
INSTITUTIONAL VARIABLES						
GDP/CAP (-1)			-0.006**	-0.006**	-0.006**	-0.007***
			(-2.58)	(-2.51)	(-2.46)	(-3.11)
FL (-1)			-0.03	-0.03	-0.03	-0.009
			(-0.97)	(-0.90)	(-0.94)	(-0.31)
DEPOSITEX (-1)			0.12***	0.11***	0.12***	0.11***
			(4.01)	(3.78)	(3.80)	(3.98)
FH (-1)			-0.02**	-0.03**	-0.03**	-0.02**
			(-2.20)	(-2.43)	(-2.58)	(-2.27)
OECD dummy						
OECD			0.009	-0.01	-0.01	
			(0.20)	(-0.22)	(-0.26)	
Events dummy						
DEVENT				0.05**	0.06**	-0.003
				(2.25)	(2.33)	(-1.07)
Interaction effect						
DEVENT*GROWTH					-0.005	
					(-1.47)	
DEVENT*DEPRECIATION					-0.00	
					(-0.02)	
DEVENT*OVERRER					0.001	
					(0.75)	
DEVENT*RLINTEREST					0.00	
					(0.02)	
DEVENT*INFLATION					-0.00007	
					(-0.25)	
Number of observations	305	305	305	305	299	348
Number of countries	17	17	17	17	17	19
AIC	-331.14	-327.21	-340.76	-344.43	-331.10	-373.94

Note: The sign "*", "**", and "***" indicate significance levels of 10, 5, and 1 percent respectively.

Table 9: Conditional Logit regression, crisis dummy as dependent variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
MACROECONOMIC VARIABLES						
GROWTH (-1)	-0.04	-0.04	-0.04	-0.04	-0.06	-0.06
	(-0.86)	(-0.72)	(-0.60)	(-0.72)	(-1.00)	(-1.21)
DEPRECIATION (-1)	0.0005	0.005	0.009	0.01	0.004	
	(0.04)	(0.34)	(0.57)	(0.73)	(0.25)	
OVERRER (-1)	-0.06**	-0.06**	-0.06**	-0.06**	-0.04	-0.05**
	(-2.28)	(-2.29)	(-2.41)	(-2.48)	(-1.45)	(-2.53)
RLINTEREST (-1)	0.009	0.01	0.004	0.001	0.008	
	(0.79)	(0.82)	(0.35)	(0.17)	(0.59)	
INFLATION (-1)	0.02	0.02	0.009	0.007	0.01	
	(1.52)	(1.36)	(0.56)	(0.44)	(0.74)	
SURPLUS/GDP (-1)	-0.001*	-0.0008	-0.0009	-0.0007	-0.001	-0.001*
	(-1.75)	(-0.66)	(-0.72)	(-0.63)	(-0.68)	(-1.88)
DDGROWTH (-1)	-0.08	-0.06	-0.09	-0.02	0.04	
	(-0.45)	(-0.31)	(-0.48)	(-0.08)	(0.17)	
DINFLATION (-1)	-0.91	-0.82	-0.59	-0.75	-0.60	
	(-1.56)	(-1.35)	(-0.95)	(-1.27)	(-0.93)	
MBGRO (-1)	-0.01	-0.01	-0.006	-0.006	-0.007	
	(-1.55)	(-1.41)	(-0.77)	(-0.79)	(-0.84)	
CREDITGRO (-1)	-0.007	-0.01	-0.009	-0.006	-0.008	
	(-0.78)	(-1.08)	(-0.88)	(-0.63)	(-0.68)	
FINANCIAL VARIABLES						
PRIVATE/GDP (-1)		-0.08	-0.07	-0.08	-0.09	
		(-0.92)	(-0.91)	(-1.03)	(-1.00)	
CASH/BANK (-1)		-0.05*	-0.05*	-0.05*	-0.04*	-0.03*
		(-1.78)	(-1.72)	(-1.83)	(-1.65)	(-1.70)
INSTITUTIONAL VARIABLES						
GDP/CAP (-1)			0.07*	-0.07	-0.08	-0.08**
			(1.68)	(-1.61)	(-1.64)	(-2.09)
FL (-1)			-0.59	-0.63	-0.79	
			(-1.00)	(-1.10)	(-1.32)	
DEPOSITEX (-1)			0.83	0.74	0.77	
			(1.45)	(1.28)	(1.29)	
FH (-1)			-0.25	-0.31	-0.34	-0.34*
			(-1.18)	(-1.44)	(-1.47)	(-1.69)
OECD dummy						
OECD			0.91	0.68	0.69	1.21*
			(1.31)	(0.96)	(0.92)	(1.70)
Events dummy						
DEVENT				0.85**	1.20**	
				(2.16)	(2.23)	
Interaction effect						
DEVENT*GROWTH					-0.07	-0.02
					(-0.99)	(-0.41)
DEVENT*DEPRECIATION					0.02	
					(0.81)	
DEVENT*OVERRER					-0.01	
					(-0.23)	
DEVENT*RLINTEREST					-0.01	
					(-0.97)	
DEVENT*INFLATION					-0.02	
					(-1.05)	
Number of crises	100	100	100	100	97	98
Number of observations	305	305	305	305	299	307

LR statistic	38.75***	46.01***	52.78***	57.56***	59.94***	36.02***
AIC	239.05	235.79	239.01	236.24	236.03	236.14
PREDICTION CLASSIFICATION (CUTOFF=50%)						
% Total correct	68	68	68	67	68	68
% Crises correct	2	2	2	1	3	1
% Non-crisis correct	100	100	100	100	100	100
PREDICTION CLASSIFICATION (CUTOFF=30%)						
% Total correct	68	68	68	68	68	68
% Crises correct	3	2	2	3	4	1
% Non-crisis correct	100	100	100	99	99	100

Table 10: Conditional Logit mode, crisis dummy as dependent variable, Hadi's method

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
MACROECONOMIC VARIABLES						
GROWTH (-1)	-0.08	-0.05	-0.04	-0.04	-0.12	-0.12*
	(-0.92)	(-0.58)	(-0.44)	(-0.47)	(-0.93)	(-1.95)
DEPRECIATION (-1)	-0.007	0.01	0.02	0.03	0.007	
	(-0.32)	(0.53)	(0.87)	(1.13)	(0.19)	
OVERRER (-1)	-0.08**	-0.11**	-0.15***	-0.14***	-0.10	-0.09**
	(-2.08)	(-2.50)	(-2.66)	(-2.92)	(-1.51)	(-2.56)
RLINTEREST (-1)	-0.02	-0.02	-0.03	-0.03	-0.01	
	(-0.91)	(-0.97)	(-0.97)	(-0.82)	(-1.63)	
INFLATION (-1)	0.01	0.005	-0.004	-0.01	0.005	
	(0.46)	(0.21)	(-0.16)	(-0.48)	(0.15)	
SURPLUS/GDP (-1)	0.0004	0.01	0.01	0.01**	-0.003	-0.0001
	(0.80)	(1.55)	(1.34)	(2.29)	(-0.62)	(-0.29)
DDGROWTH (-1)	-0.17	-0.21	-0.24	-0.14	0.18	
	(-0.89)	(-1.02)	(-1.07)	(-0.65)	(0.58)	
DINFLATION (-1)	1.25*	1.18	1.23	1.14	1.97**	1.60**
	(1.70)	(1.51)	(1.42)	(1.31)	(2.24)	(2.39)
MBGRO (-1)	0.0008	0.0007	0.004	0.007	0.007	
	(0.08)	(0.07)	(0.37)	(0.63)	(0.63)	
CREDITGRO (-1)	-0.001	-0.002	-0.001	-0.0007	-0.01	
	(-0.06)	(-0.10)	(-0.06)	(-0.04)	(-0.51)	
FINANCIAL VARIABLES						
PRIVATE/GDP (-1)		-2.66	-2.97	-2.73**	-0.50*	-0.15*
		(-1.44)	(-1.21)	(-1.97)	(-1.94)	(-1.66)
CASH/BANK (-1)		-0.06	-0.04	-0.04	-0.09	
		(-1.50)	(-0.90)	(-0.95)	(-1.50)	
INSTITUTIONAL VARIABLES						
GDP/CAP (-1)			-0.02	-0.03	-0.08	
			(-0.24)	(-0.37)	(-0.85)	
FL (-1)			-0.13	-0.34	-0.28	
			(-0.13)	(-0.33)	(-0.27)	
DEPOSITEX (-1)			2.12**	1.90*	2.24**	1.44**
			(2.05)	(1.73)	(2.04)	(1.96)
FH (-1)			0.34	0.30	0.21	
			(0.94)	(0.77)	(0.47)	
OECD dummy						
OECD			1.50	1.21	1.09	0.93
			(1.64)	(1.36)	(1.12)	(1.18)
Events dummy						
DEVENT				1.29**	1.33*	0.78
				(2.04)	(1.70)	(1.41)
Interaction effect						
DEVENT*GROWTH					0.02	0.05
					(0.13)	(0.78)
DEVENT*DEPRECIATION					0.11**	
					(2.08)	
DEVENT*OVERRER					-0.15	
					(-1.43)	
DEVENT*RLINTEREST					-0.03	
					(-1.49)	
DEVENT*INFLATION					-0.14**	
					(-2.51)	
Number of crises	27	27	27	27	26	27
Number of observations	306	306	306	306	300	308

LR statistic	30.23***	37.07***	47.36***	52.10***	65.29***	36.60***
AIC	123.85	121.00	120.72	117.98	108.68	113.68
PREDICTION CLASSIFICATION (CUTOFF=50%)						
% Total correct	91	92	92	92	92	92
% Crises correct	4	7	7	7	15	4
% Non-crisis correct	99	99	100	100	99	100
PREDICTION CLASSIFICATION (CUTOFF=30%)						
% Total correct	90	91	92	91	92	91
% Crises correct	4	7	19	15	27	11
% Non-crisis correct	99	99	98	98	99	99

Table 11: A summary of the existing results on the determinants of systematic banking crises

Study	Sample Coverage	Significant Variables		Non-significant Variables
		Macroeconomic factors	Microeconomic factors	Macroeconomic factors
Caprio and Klingebiel (1996)	86 crisis episodes	(1) Terms of trade drop (2) Recession (3) Inflation	(1) Deficient management (2) Poor supervision (3) Government intervention (4) Connected lending	(1) Credit growth
Goldstein and Turner (1996)	Literature review	(1) Terms of trade volatility (2) International interest rate volatility (3) Real exchange rates volatility (4) Fall in GDP Growth (5) Inflation	(1) Currency mismatch (2) Maturity mismatch (3) Financial liberalization (4) Government involvement (5) Weak accounting, disclosure and legal framework	
Honohan (1997)	24 countries, 18 crisis episodes	(1) High loan to deposit ratio (2) High foreign borrowing to deposits ratio (3) Credit growth	(1) High share of reserves to deposits (2) Central bank refinancing of bank lending	
Demirgüc-Kunt and Detragiache (1998)	45-65 countries, 31 crisis episodes	(1) Low GDP growth (2) High real interest rate (3) Inflation (4) Terms of trade shocks (5) Credit growth	(1) Deposit insurance (2) Rule of law	(1) Fiscal deficit (2) Exchange rate depreciation
Hardy and Pazarbasioglu (1999)	50 countries, 43 crisis episodes	(1) Fall in GDP growth (2) Inflation (3) Credit growth (4) Real exchange rate		(1) Gross fixed capital formation (2) Current account balance (3) Reserve money (4) Banks' reserves
This paper	19 countries	(1) Real exchange rate overvaluation (2) Ratio of budget surplus to GDP (3) Ratio of bank liquid reserves to bank assets (4) Real GDP per capita (5) Governance and institutional quality		(1) Real GDP growth (2) Nominal depreciation (3) Real interest rate (4) Inlfation (5) Monetary base growth (6) Real domestic credit growth