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Working Paper

On crisis models: An alternative crisis definition

Research Notes, No. 01-1

Provided in Cooperation with:

Deutsche Bank Research, Frankfurt am Main

Suggested Citation: Eliasson, Ann-Charlotte; Kreuter, Christof (2001) : On crisis models: An alternative crisis definition, Research Notes, No. 01-1, Deutsche Bank Research, Frankfurt a. M.

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May 21, 2001

Research Notes in Economics & Statistics

On crisis models: An alternative crisis definition

In this paper we question the consensus of using a binary crisis definition for empirical crisis models. We believe that the most severe shortcomings of the crisis models today are in the crisis definition rather than the explanatory variables. We present a crisis model that is specified for a continuous crisis definition especially designed to describe extreme exchange-rate and interest-rate events in emerging markets. The crisis variable successfully portrays the crises of the 1990s and the estimated models perform excellently in explaining these events.

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On crisis models:

An alternative crisis definition

Ann-Charlotte Eliasson and Christof J. Kreuter*

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Abstract

In this paper we question the consensus of using a binary crisis definition for empirical crisis models. We believe that the most severe shortcomings of the crisis models today are in the crisis definition rather than the explanatory variables. We present a crisis model that is specified for a continuous crisis definition especially designed to describe extreme exchange-rate and interest-rate events in emerging markets. The crisis variable successfully portrays the crises of the 1990s and the estimated models perform excellently in explaining these events.

Keywords: Financial crises, risk model, panel data, emerging markets.

JEL Codes: C33, F21, F31

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1. Introduction

During the last couple of years there has been a surge of different crisis models aiming at describing currency crises of the past but also at providing a warning ahead of future crises, see e.g. Berg *et al.* (1999), Kaminsky *et al.* (1998). Estimating a crisis model is not a straightforward task and one of the main difficulties is how to define the actual crisis variable. The goal is often to describe large, out-of-the-ordinary exchange-rate and sometimes interest-rate changes¹. Since that is a difficult concept to quantify, a binary crisis definition is typically applied. However, transforming a continuous variable into a dummy variable implies a huge loss of information. It will also complicate the actual modelling since the number of crisis observations after this transformation often is very small. Moreover, creating a dummy crisis variable usually involves picking an arbitrary threshold, characterising the observations exceeding this limit as crisis observations and the ones that do not as quiet periods. There are many reasons why this may not be optimal and the difficulties in choosing the “right” threshold value are obvious. Considering this, it is surprising that the majority of relevant contributions in the literature today focuses on the explanatory variables rather than questioning the dichotomous crisis definition. Unlike these studies, we believe that the main limitation of the crisis models today lies in the binary crisis definition rather than the explanatory variables, and hence that a different approach is called for.

In this paper we will present a model developed to describe currency crises of the 1990s. It is specified for a continuous crisis definition that consists of large, out-of-the-ordinary exchange-rate and interest-rate events. The crisis definition is based on three separate components: exchange-rate depreciation, large increases in the real interest rate or a high level of the real interest rate compared with its long-term mean. The explanatory variables have been transformed into ratios and/or changes in order to achieve mean-reverting relationships, making usual econometric testing procedures valid. In this paper we will present two panel-data models: Asia and Latin America, each consisting of five countries in the respective region. The crisis variable successfully portrays the crisis periods that occurred in these regions during the 1990s. The explanatory power of the models is generally high and the Type I (probability of sending a false warning) and Type II (probability of missing a crisis) errors are satisfactory.

The outline of the paper is as follows. Section 2 (Background) starts by reviewing two very popular empirical crisis models in some detail. In the latter part of Section 2 the explanatory variables that will be used in this study are set out. The construction of the continuous crisis

definition and the modelling procedure can be found in Section 3. Section 4 presents the results of the models when estimated for the two panels Asia and Latin America. The paper concludes with some final remarks in Section 5.

2. Background

Today there are many excellent reviews on crisis models and the theories behind them, see e.g. Berg *et al.* (1999), Kaminsky *et al.* (1998), which is why we refrain from the exercise in this paper. There are however two papers that have had a major impact on the empirical model literature, and in the first part of this section we would like to present both methods in some detail.

2.1 Two empirical studies

In the first study, Kaminsky, Lizondo and Reinhart (1998), construct an early-warning system using a signal model approach. This is a bilateral set-up where all indicators are compared, one at a time, with a crisis index. The idea behind the model is that the indicators behave differently on the verge of a crisis. Therefore, when an observation exceeds a specific threshold, the indicator sends a signal. The more indicators that are signalling, the higher is the probability of a crisis. The target period is set at 24 months. A currency crisis is defined as a sharp depreciation of the currency, a large decline in international reserves or a combination of the two. An index is created and periods when the index is above its mean by more than three standard deviations are defined as crisis periods. This amounts to a binary crisis definition with sample-dependent or time-varying thresholds. Optimal thresholds are estimated for each country, maximising the correct signals and minimising the false. Hence, the explanatory variables are also transformed into dummy variables depending on whether they are signalling or not. The percentage of correct signals to the percentage of false signals will give an indication of the accuracy of each indicator. The model is applied to 20 countries using monthly data from 1970 to 1995 and shows 76 crises during this period. An advantage of the signalling model is that it is well suited for finding vulnerabilities in an economy since it immediately shows up the variable that causes the weakness. However, the information from each indicator is treated in an inefficient way since all are transformed into dummies. This implies that signals are equally strong regardless of whether an indicator just passes the threshold or exceeds it by a large margin. Moreover, the method ignores correlation between the explanatory variables. This can affect the optimal thresholds when constructing a composite leading indicator.

In the second paper Frankel and Rose (1996) estimate a probit model with the aim of characterising currency crashes. They define a currency crash as “a large change of the nominal exchange rate that is also a substantial increase in the rate of change of nominal depreciation”. The depreciation rate is set at 25%, but has to exceed the previous year's depreciation level by at least 10% as well. A dummy crisis variable is constructed according to that rule. A variety of external, internal and foreign macroeconomic factors are considered as explanatory variables and the estimation is done with a multivariate probit model. The model is specified for over one hundred developing countries, covering annual data from 1970 to 1992. The result of the model suggests that some of the indicators are useful in describing currency crashes, but the overall explanatory power is quite low (the pseudo R^2 measure was around 20% for all specifications). There are many advantages in using a probit model rather than the signalling model. In particular, the probit model considers the significance of all variables simultaneously, making it easy to check the explanatory power of new variables. Moreover, the result of a probit model is easily interpreted as the probability of a crisis. A disadvantage is that the contribution of a particular variable is less easily identified since the result depends on all variables included. The same applies to logit and other limited dependent regressions.

Both studies have had a strong influence on the empirical crisis model literature, where a different set of explanatory variables has often been suggested or perhaps other variables have been used in the actual crisis definition. However, the main characteristics of a binary crisis definition has been kept, see e.g. Berg *et al.* (1999), Goldstein *et al.* (2000), Detragiache and Spilimbergo (2001).

2.2 Explanatory variables

The consensus regarding currency crises is that a broad variety of indicators are of importance even though the actual choice of which indicators to include differs between the studies. After carefully analysing the causes of different crises as well as reviewing the literature, we selected a set of 12 variables. The variables have been transformed into ratios and/or changes in order to achieve mean-reverting relationships, making usual econometric testing procedures applicable. The variables are: return on equity market (real, local currency), domestic credit to GDP, private credit (% change mom), M2 to bank reserves, M2 to foreign exchange reserves, industrial production (% change yoy), exports (deviation from 12-month trend), short-term debt to foreign exchange reserves, foreign liabilities to foreign assets within the banking

sector, and a contagion variable. The contagion variable is estimated as the average of the crises indices for all countries included in the model, lagged one period. Moreover, the real interest rate (3 months), the real effective exchange rate, REER for short, (cumulative return, 9 months) and changes in the crisis index are also included, all lagged one period. None of the variables is controversial and we refer to Berg *et al.* (1999) and/or Kaminsky *et al.* (1998) for the theoretical background on why these variables may be informative as indicators.

The model developed in this paper is purely quantitative, hence no qualitative variables such as political uncertainty or security issues are considered. This does not imply that we find qualitative variables superfluous, it is rather that there exists no objective quantitative measure for them. Constructing a historical series capturing qualitative events (knowing the outcome of all uncertainties) usually results in a bias. Because of this, we decided to exclude qualitative indicators in this paper.

3. Methodology

The idea behind the model presented in this paper is different from the approach followed in other crisis models. The usual starting point is to decide on a threshold value and to construct a binary crisis variable accordingly. After that, the modellers embark on the difficult task of describing the discrete crisis variable with a set of continuous explanatory variables. The resulting models often have low explanatory power even in-sample. In this paper we start by constructing a continuous crisis definition based on extreme observations, hence no arbitrary threshold is necessary. After that a logit model is estimated. Finally, we define what we view as a crisis and evaluate the model according to that. The advantage of this approach is threefold. First, a continuous crisis definition is more informative on the actual crisis development than a binary crisis definition. Second, continuous explanatory variables are applied to describe a continuous crisis definition. This improves the fit of the model and, hence, provides more information on the influence of each explanatory variable. Third, if the model is applied as an early-warning tool the Type I and Type II errors can be used to decide on an optimal crisis limit, i.e. it is possible to decide on an optimal threshold value for the crisis indicator; if the value is exceeded this constitutes a warning. The threshold is optimised regarding to the number of mistakes on the basis of our “knowledge” the number of false warnings (Type I) and missed crisis (Type II), see Section 5.

3.1 Continuous crisis definition

In order to achieve a continuous crisis indicator we need to transform the series in question with a nonlinear transformation function. The transformation function has to be continuous and, for simplicity of interpretation, bounded. In the following we derive a transformation function from data. Note that depending on the properties of the crisis indicator and the model, other transmission functions might also be appropriate, in line with our general idea.

The continuous crisis definition is created in a five-step procedure. We will go through all the steps using foreign exchange-rate returns, i.e. the percentage change in the exchange rate, as an example. However, each of the variables included in the crisis definition: foreign exchange returns, real interest-rate increases and the level of real interest rates compared with the long-term mean have been transformed in the same way.

In the *first step* we project the exchange-rate returns of the countries included in the study² into one single histogram. A Gaussian distribution is fitted to the observed distribution in the *second step*. The two distributions can be found in Figure 1, where positive figures indicate depreciation and negative figures appreciation. There is a distinct peak in the neighbourhood of zero implying that a majority of the exchange-rate returns are small and close to zero. The long tails mirror the extreme observations. When considering exchange-rate returns it is only *depreciation* that is of interest for our study and, hence, the focus in this example will be on the observations of the right-hand tail. The Gaussian distribution is then subtracted from the integrated return distribution. This will isolate the crisis observations.

In the *third step* the density function of an extreme value distribution is fitted to the crisis observations.

We parameterise with:

$$f(y) = \alpha * \exp(-1/((y - \mu)/\gamma)^\sigma) / ((y - \mu)/\gamma)^{(\sigma + 1)} \quad (1)$$

where α , μ , σ and γ are parameters that are optimised with respect to the fit. Equation (1) is not the only function that can be used for this purpose. Many functions would do, as long as they describe the data well. The extreme values and the fitted density function for the exchange-rate returns can be found in Figure 2. Integrating over this yields the cumulative density function that is bounded between zero and unity. This gives us a nonlinear

transformation function that can be applied to the crisis observations, creating a continuous crisis definition that is bounded between zero and unity. In Figure 3 the nonlinear transformation function for exchange-rate returns conditioned on the 10 countries² is displayed. We find that according to the figure a crisis stance equal to 0.80 amounts to an exchange-rate depreciation of 7.5% and, a crisis stance of 0.90 corresponds to a depreciation level of 12.5%. As mentioned above, other construction methods for the transformation function might be applied, e.g. using the structural form of a logit function or a Gaussian function (see also neural networks and fuzzy logic systems).

In *step four* the three components of the crisis definition, i.e. exchange-rate returns, real interest-rate increases and the level of real interest rates compared with the long-term mean, are combined with a maximum function. The crisis definition will adopt the value of the strongest signalling variable for each point in time, creating a prudent measure.

The crisis variable is still characterised by oscillations between crisis and no-crisis observations during periods when there are recurring crises. In *the fifth step*, a modified exponentially weighted moving average smoothing method is applied³. The filter is especially developed to keep the extreme values and the sharp increases from normal to crisis times, while smoothing the return-to-normal period exponentially, see Figure 4. This implies that it will take a little longer for the economy to return to “normal”, capturing the turbulence during the aftermath of a crisis. It will also prevent sharp swings between months when, for example, January and March have high crisis index observations and February is quiet. Instead we will get a smooth downturn in February between the high January and March observations. This is a desired feature for a descriptive model.

3.2. Estimation procedure

A multinomial logit model is chosen for the estimations because of the continuous and bounded crisis definition. Regional fixed-effect panel data models are estimated for five countries in Latin America and Asia, respectively. By using panel-data models we increase the number of observations for each parameter estimate as well as reduce the estimation bias and problems of data multicollinearity, see Hsiao (1986). The models are specified for 1990:1 to 2000:12 using Deutsche Bank Research in-house data for the indicators and Eviews 4⁴ for estimations. Data from the 1970s and 1980s are not considered in the study, since the functioning of the emerging-markets financial world of the 1990s is different from that of the 1980s and 1970s. In the 1990s there was, for example, a surge of financial instruments and

many emerging markets gave up a currency peg in favour of free floating. Industrial countries are also excluded. The run-up to a crisis, as well as the actual crisis period is likely to be dissimilar for countries at different levels of development: this is why we decided to consider only emerging markets in this paper.

The general-to-specific approach is applied in choosing which explanatory variables should enter the model, see Hendry (1995). This implies that all indicators are included initially and that the non-significant ones are excluded one at a time, using the z statistics as guidance.

4. Results

4.1 Asia

The fixed-effect panel-data model for Asia is specified for Indonesia, Korea, Malaysia, the Philippines and Thailand and the results can be found in Table 1. Since the estimated coefficients of a logit model refer to their impact on the logit rather than on the crisis definition variable, the marginal contribution of each indicator, evaluated at the mean of the data, is given in the first column. In the second column the z statistics, for the hypothesis of no effect, are shown. We find that many indicators appear to be influential in explaining the crisis periods in Asia. Excluding the ones that do not enter significantly we are left with 10 variables, all entering with the expected sign except for the REER. It turns out that a crisis in Asia is more likely when there is an increase in domestic credit to GDP, in M2 to FX reserves, in M2 to banking reserves, in short-term debt to FX reserves or a high real interest rate in the previous month, a positive change in the crisis index in the previous month and when the crisis index increases in the other countries (the contagion variable). A crisis is also more likely when there is a decrease in industrial production or in the REER. The negative sign of the REER is puzzling. It might be due to the fact that it enters with only one month lag. Other studies have shown that the REER is very informative as an early-warning indicator, indicating an overvalued currency, when the warning window is set for two years, see e.g. Goldstein *et al.* (2000). In this case, the REER is already turning negative before the crisis kicks in, and hence the negative sign.

There are no universally accepted goodness-of-fit measures for logit models and in Table 1 the adjusted R^2 and standard error for each of the countries in the panel are shown in the two right-hand columns. The adjusted R^2 estimated for a multinomial logit model cannot be interpreted as it is in a linear model, but it will still give an indication of the fit since the crisis

definition is not dichotomous. The limitation of using the adjusted R^2 as a goodness-of-fit measure for usual logit models is due to the traditionally binary characteristics of the dependent variable rather than its boundedness. However, given the continuous crisis definition it will still give us some information of the fit of the model. The crisis variables along with the fitted values for all models in the Asia panel are displayed in Figures 5-9.

In Figure 5 the crisis variable (solid line) is presented along with the fitted values (dashed) for Indonesia. It appears as if both the crisis variable and the fitted model capture the Asian crisis in 1997/98, while the model is incapable of describing the financial market deterioration in 1999. The latter was due to uncertainty about the political outlook and security, and given that no qualitative variables are included as indicators (see Section 2.2), it is not surprising that the model fails to capture it. Korea is presented in Figure 6 and the model is successful in describing the Asian crisis and the subsequent turbulence. This is also the case for the Philippines and Thailand (see Figures 8 and 9). Malaysia, on the other hand, was also affected by the Asian crisis but the model cannot depict that (Figure 7). This suggests that Malaysia was a victim of contagion rather than of deteriorating fundamentals. Besides the Asian crisis there have been some, but not too frequent, periods of high exchange rates and/or interest rates for all countries in the sample and generally the model appears to be able to illustrate these events as well.

4.2 Latin America

The Latin American panel data model is specified for Brazil, Chile, Colombia, Mexico and Peru. The results of the model estimates can be found in Table 2. As in the Asian model, the marginal contribution of the indicators is presented in the first column and the z statistics are presented in the second. The two right-hand columns show the adjusted R^2 and standard error for each of the countries in the panel, respectively. Many indicators appear to be influential in explaining the crisis periods in the Latin American countries as well. After excluding the ones that did not enter significantly we are left with ten indicators. Four of the indicators enter with unexpected signs while six enter with expected. According to the results in Table 2 a crisis in the Latin American countries is more likely when there is an increase in private credit (% mom), short-term debt to FX reserves, an increase in the change in the crisis index (previous period) or an increase in the crisis index (previous period) in the other countries (the contagion variable). A crisis is also more likely when the REER is decreasing, the industrial production is decreasing or the return on equity market is going down. However, a decrease in domestic credit to GDP, M2 to FX reserves and M2 to banking reserves increases the

probability of a crisis. The signs of these indicators are unexpected since one usually talks about high increases in these variables being dangerous for the economy. On the other hand, a sharp decrease in these variables would tighten the liquidity situation for an economy, especially if it was at a low level to begin with. Hence, a sharp decrease in these variables might very well increase the probability of a crisis.

In Latin America there were quite a few crisis episodes during the 1990s originated both at home and as a result of contagion from other countries and regions, such as Russia and Asia. In Brazil the hyper inflation period at the beginning of the sample, is captured by a crisis index close to unity (see Figure 10). In 1997 the crisis variable increases due to contagion from the Asian crisis, in 1998 due to the Russian crisis, and then in January 1999, due to its own devaluation crisis. The estimated model follows the crisis variable closely when it comes to the crisis observations but not during the “quiet times”. During these periods the crisis variable often is in the neighbourhood of zero while the model estimates are systematically above (Figure 10). In Mexico both the crisis variable and the model portray the crisis of 1994/95 (see Figure 11) as well as some turbulence around 1997/98 which may have been due to Asian or Russian contagion and, in 1999, the situation in Brazil. The crisis variable in Colombia (Figure 12) was strongly affected by the Mexican crisis, but this was not captured by the model. Hence it appears as if it was a victim of contagion rather than domestic vulnerability. The contagion variable yields a small increase in the crisis index, but with a lag. The currency turbulence in the later part of the 1990s is adequately described except for the events in 1999, which was a result of uncertainty about the political outlook and security problems in combination with contagion from Brazil. In Peru (Figure 13), the crisis of the early 1990s is described by both the crisis variable and the estimated model, but the contagion from Mexico in 1995 is not depicted by the model though it strongly affects the crisis index. For Chile on the other hand, the economic situation has been more calm and this is shown both in the crisis definition, that never equals unity, and in the model estimates (Figure 14).

We conclude that the crisis variable appears to be well behaved in that it captures the major exchange-rate and interest-rate events in both Asia and Latin America. Moreover, the models adequately describe the majority of these crisis events, except for the ones due to political or security issues.

5. Model evaluation and extensions

The crisis model presented in this paper can easily be extended to function as an early warning model. In that case the explanatory variables should preferably enter with some lags and the crisis definition should be revised according to what is to be warned against. However, viewing the model presented in this paper as an early-warning model, its in-sample accuracy can be evaluated by the Type I and Type II errors.

When dealing with early-warning models there is always a trade-off between warning too often – increasing the number of false warnings, or warning too seldom – missing a crisis. The first error is referred to as Type I and the second is called Type II. In order to assess the performance of the model we have to decide on threshold values for each of the variables included in the crisis definition. For this purpose, we arbitrarily decide that a crisis occurs when the currency depreciates more than 10% or when the interest rate increases more than 20%. The timeframe is one month. In Figure 15 the probability of a false warning (Type I error) is pictured by the solid line and, the probability of missing a crisis (Type II error) is given by the dashed. Both types of error are defined for all possible values of the crisis indicator and, in deciding when the model should send a warning, a 5% probability of missing a crisis is chosen. This amounts to sending a warning when the estimated crisis index exceeds the 0.35 line on the y-axis (crisis stance) and we can see that the number of false warnings (Type I) for that level is 36%, which is quite high. However, less strict crisis thresholds would result in fewer false warnings and so would a longer timeframe. Moreover, only two out of three variables of the crisis definition were included in the chosen crisis measure, increasing the Type I errors. The final threshold choice depends on which mistake is most costly. If the cost of missing a crisis is much higher than the cost of warning too often the results are perhaps tolerable. However, if the costs are equal the warning should be sent where the Type I and Type II lines cross.

After specifying the model, an adequate crisis level can be chosen depending on the needs of the modeller. Which level to pick depends on the purpose of the model and on the cost of warning too often (Type I error) compared with the cost of missing a crisis (Type II error). The advantage is that this can be decided in the final step.

6. Final remarks

In this paper we have presented a continuous crisis definition that successfully describes the crises of the 1990s together with a model that can explain the major peaks of this crisis definition. There are many advantages in using this methodology. The continuous crisis definition makes it possible to obtain more information on the economy before and during crisis periods. This could be valuable for future research evaluating economic theories on currency crises, for example. Another externality of this model, which was discussed in Section 5, is to create an early-warning system. The in-sample performance of the model will outperform its binary “competitors“ as we are using continuous variables to explain a continuous crisis definition. Moreover, no initial arbitrary crisis threshold is called for. Instead the threshold can be decided in the very final step, i.e. after estimating the models for the countries in question using the Type I and Type II errors. Another possible extension of the model would be to incorporate the political risk and/or to allow for long-term relationships as well, using the theory of cointegration.

The main objective of this paper is to question the consensus of using a binary crisis definition when developing a crisis model, rather than to present another model. We believe that the most serious shortcomings of the crisis models today lie in the crisis definition rather than in the explanatory variables. Methodological issues and the choice of indicators to be included are always important but the use of a dummy variable which equals zero in around 98% of the observations renders the methodological choices limited. We have suggested one alternative to the usual binary crisis variable and we hope that others will follow with new ideas on how to evade the dichotomous crisis specification.

Acknowledgements: The authors would like to thank Andrea Burgtorf, Ralf Hoffmann, Sara Johansson di Silva and Maria-Laura Lanzeni for useful comments. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of Deutsche Bank or of any other person associated with Deutsche Bank. The responsibility of any errors or shortcomings in this article remains ours.

References

- Berg, A., Borensztein, E., Milesi-Ferretti, G.M., Pattillo C., 1999. Anticipating balance of payment crisis. The role of early warning systems. IMF Occasional Paper 186.
- Detragiache E., Spilimbergo, A., 2001. Crisis and liquidity: evidence and interpretation. IMF Working paper, 2.
- Frankel, J., Rose, A., 1996. Currency crashes in emerging markets: An empirical treatment, *Journal of International Economics* 41, 351366.
- Goldstein, M., Kaminsky, G., Reinhart, C., 2000. Assessing Financial Vulnerability. An Early Warning System for Emerging Markets. Institute for Intern. Economics, Washington D.C.
- Hendry, D. F., 1995. *Dynamic Econometrics*. Oxford University Press, Oxford.
- Hsiao, C., 1986. *Analysis of Panel data*. Cambridge University Press, Cambridge.
- Kaminsky, G., Lizondo, S., Reinhart, C. 1998. Leading indicators of currency crises. IMF staff papers, Vol. 45, No 1.

Endnotes

¹Foreign exchange reserves are also included in the crisis definition in some studies. However, the surge of monetary instruments as well as non-crisis-driven extraordinary changes in FX reserves (e.g. maturing eurobonds) during the 1990s have made this variable unreliable.

²The countries included are Brazil, Chile, Colombia, Mexico, Peru for Latin America, and Indonesia, Malaysia, the Philippines, South Korea and Thailand.

³For details on this filter please contact the authors.

⁴Eviews 4 is a Quantitative Micro Software program. More information can be found at www.eviews.com.

Tables:**Table 1. Asia panel, 1990:3-2000:12**

Total observations 130

Total panel (unbalanced) observations 646

Estimation method: iterative least squares (Marquardt)

Variables	Marginal effects	Z statistic	Adjusted R²	Standard error
Intercept: Indonesia	-2.03	-14.65	0.48	0.22
Thailand	-2.62	-13.01	0.39	0.17
Korea	-2.12	-12.38	0.55	0.13
Malaysia	-2.64	-14.54	0.39	0.16
Philippines	-2.01	-14.29	0.23	0.20
Domestic credit to GDP	0.56	6.50		
% yoy industrial production	-0.29	-2.04		
M2 / foreign exchange reserves	2.71	10.95		
M2 / banking reserves	0.037	3.28		
3 months real interest rate (-1)	2.76	8.10		
Cumulative return on REER (9 months)	-0.018	-2.02		
Return on equity market (real, local currency)	-0.43	-4.20		
Short-term debt to FX reserves	0.11	6.43		
Change in crisis index (-1)	0.61	8.23		
Contagion(-1)	1.81	9.85		

Table 2. Latin American panel. 1990:3-2000:12

Total observations 130

Total panel (balanced) observations 650

Estimation method: iterative least squares (Marquardt)

Variables	Marginal effects	Z statistic	Adjusted R²	Standard error
Intercept: Brazil	-0.30	-5.17	0.70	0.22
Chile	-0.073	-0.73	0.29	0.17
Colombia	-0.44	-4.03	0.30	0.16
Mexico	-0.068	-7.49	0.53	0.17
Peru	-0.57	-5.43	0.67	0.18
% mom private credit	2.27	7.40		
Domestic credit to GDP	-0.12	-2.98		
% yoy industrial production	-0.24	-1.81		
M2 / foreign exchange reserves	-0.57	-4.49		
M2 / banking reserves	-0.10	-5.65		
Cumulative return on REER (9 months)	-0.032	-5.81		
Return on equity market (real, local currency)	-0.40	-3.51		
Short-term debt to FX reserves	0.22	7.81		
Change in crisis index (-1)	0.75	10.1		
Contagion(-1)	0.90	6.51		

Figures:

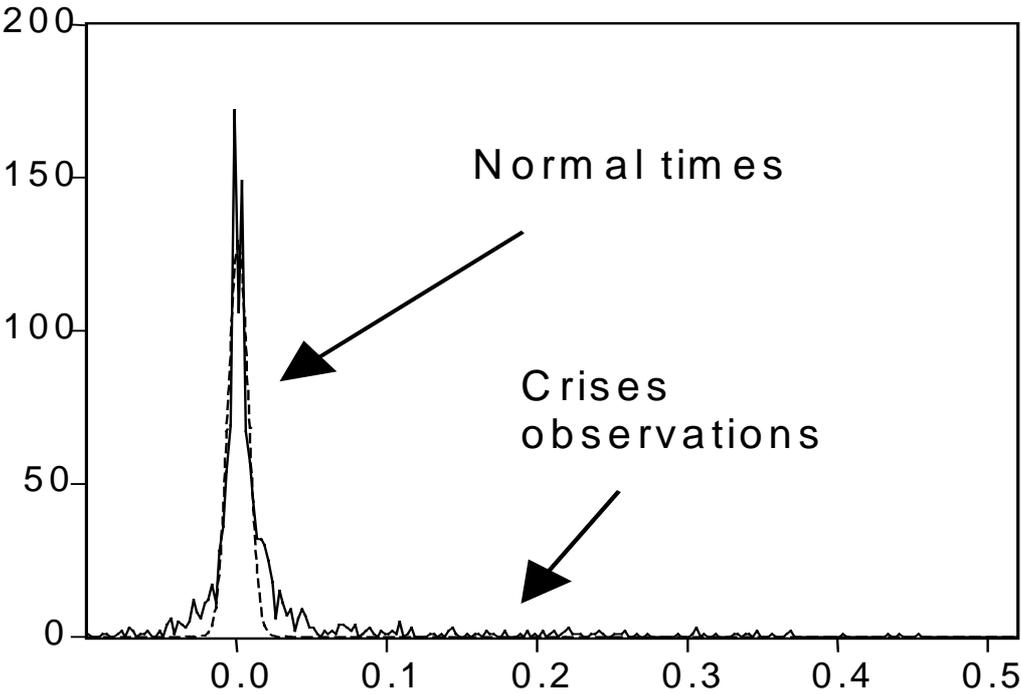


Figure 1: Summed distribution of exchange-rate returns for all countries (solid line), fitted histogram (dashed line).
Note: X-axis: Foreign exchange-rate returns. Y-axis: Number of entries.

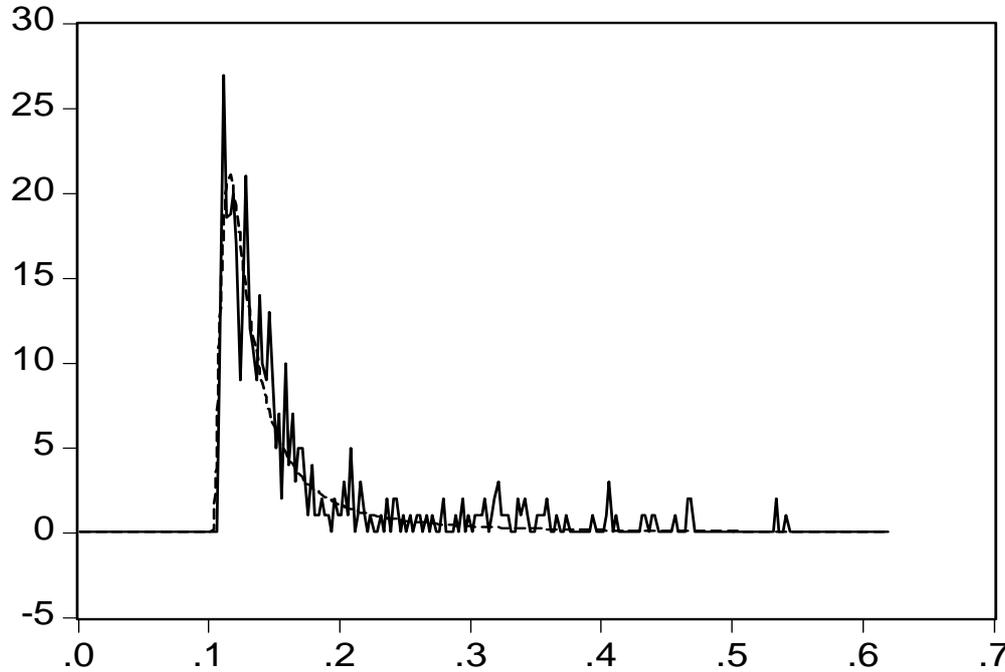


Figure 2: The exchange-rate return series (solid line) after subtracting the normal distribution along with a plot of the function we use for the parameterisation (dashed line).
Note: X-axis: Exchange-rate depreciation. Y-axis: Number of entries.

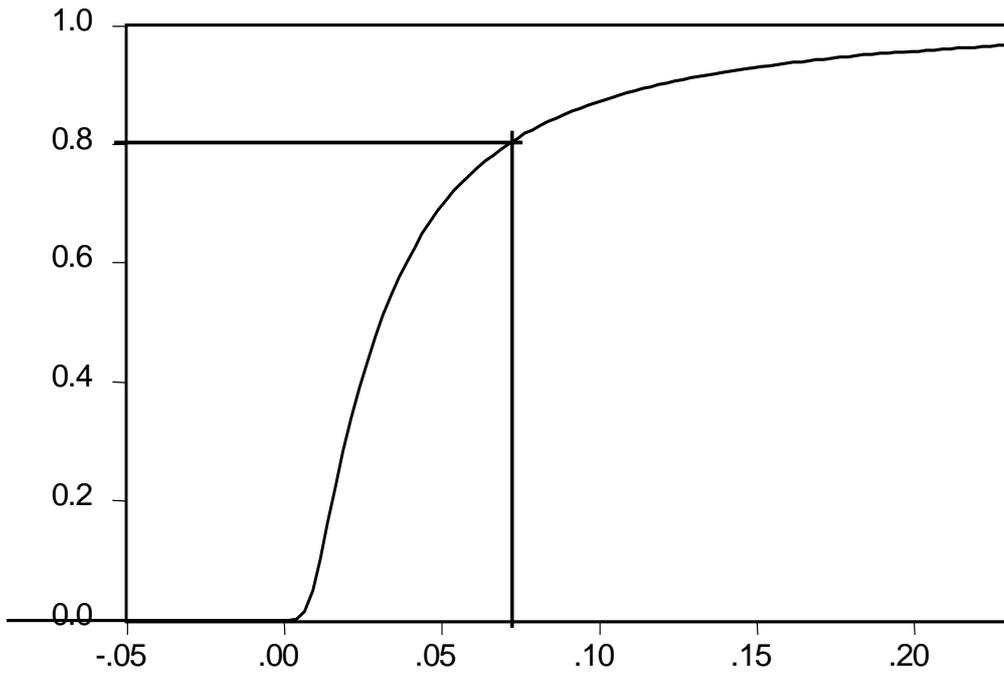


Figure 3: A crisis stance of 0.80 corresponds to an exchange-rate depreciation of 7.5%.
Note: X-axis: Crisis variable. Y-axis: Change in exchange rate, interest rate or a high level of the latter.

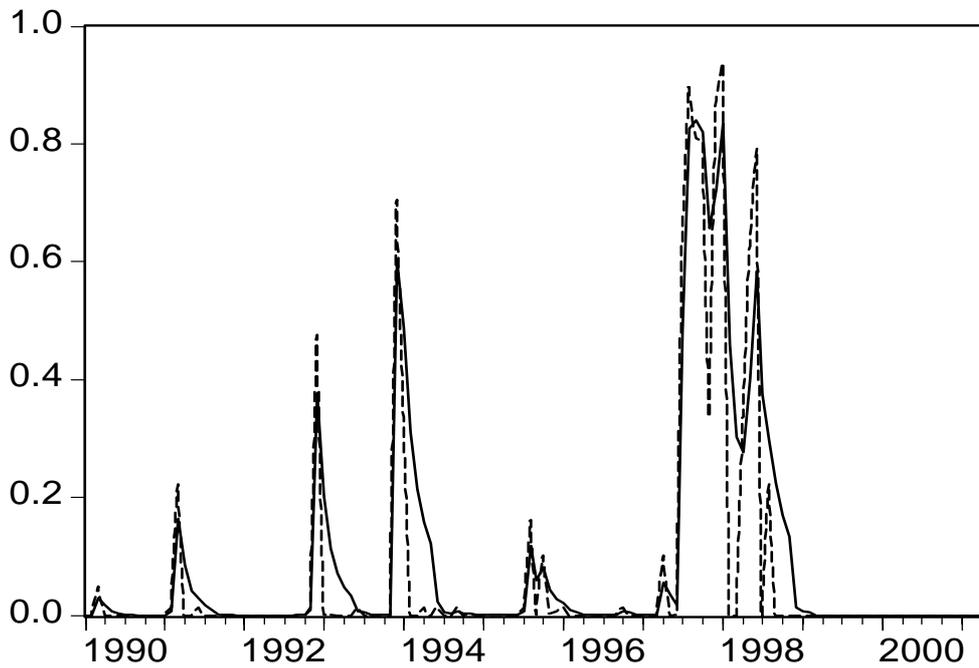


Figure 4: The crisis variable before (dashed line) and after (solid) smoothing.

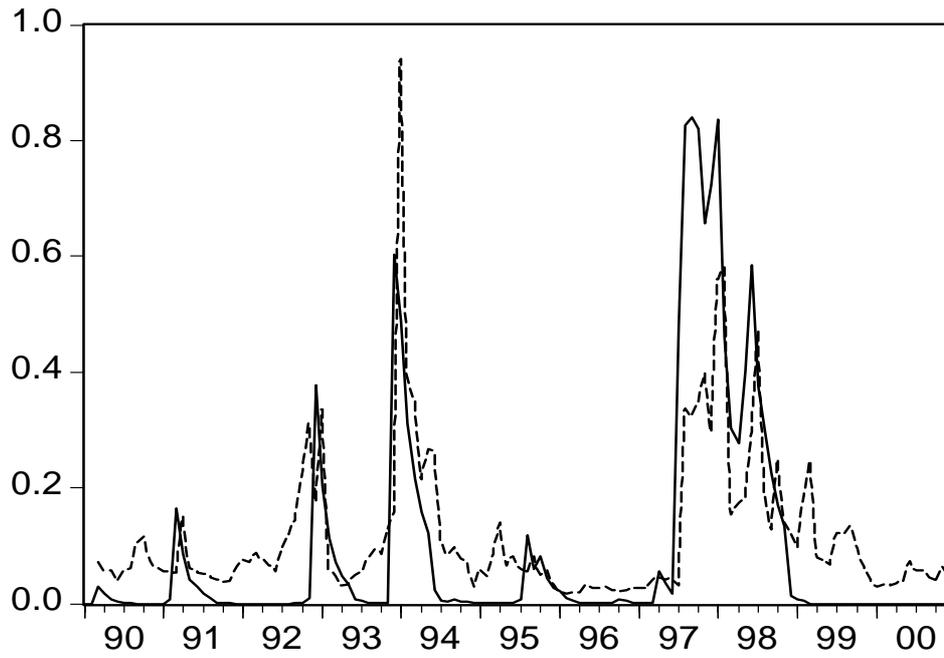


Figure 5: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Indonesia 1990:1-2000:12.

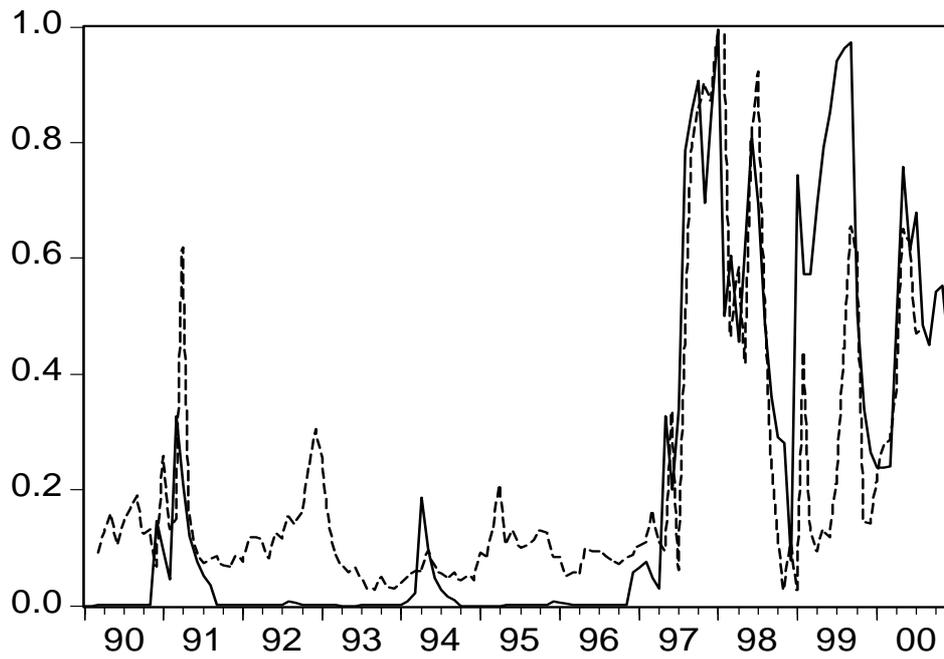


Figure 6: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Korea 1990:1-2000:12.

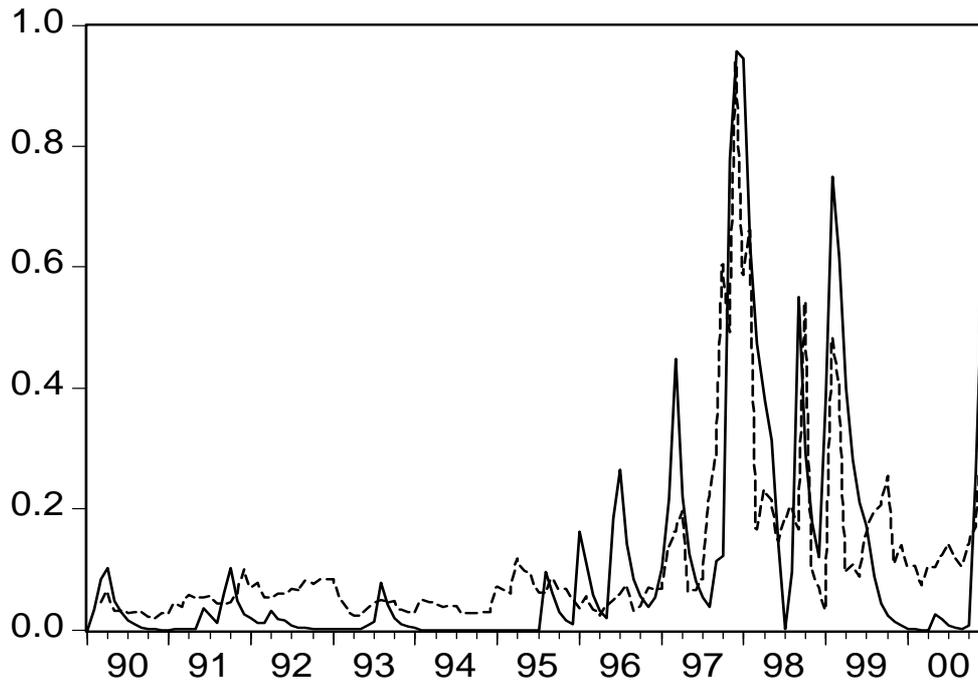


Figure 7: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Malaysia 1990:1-2000:12.

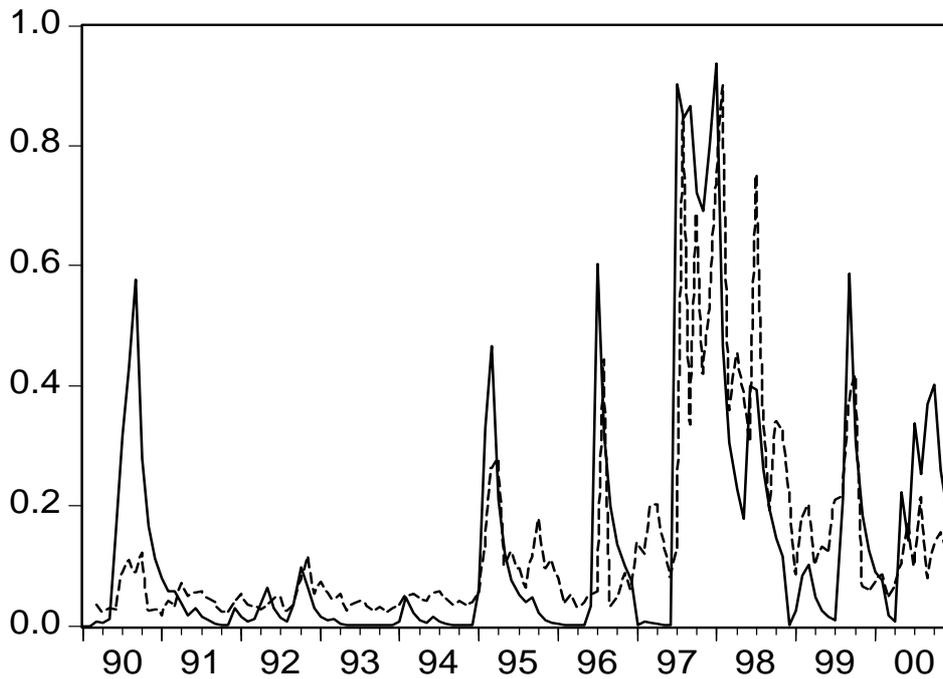


Figure 8: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Philippines 1990:1-2000:12.

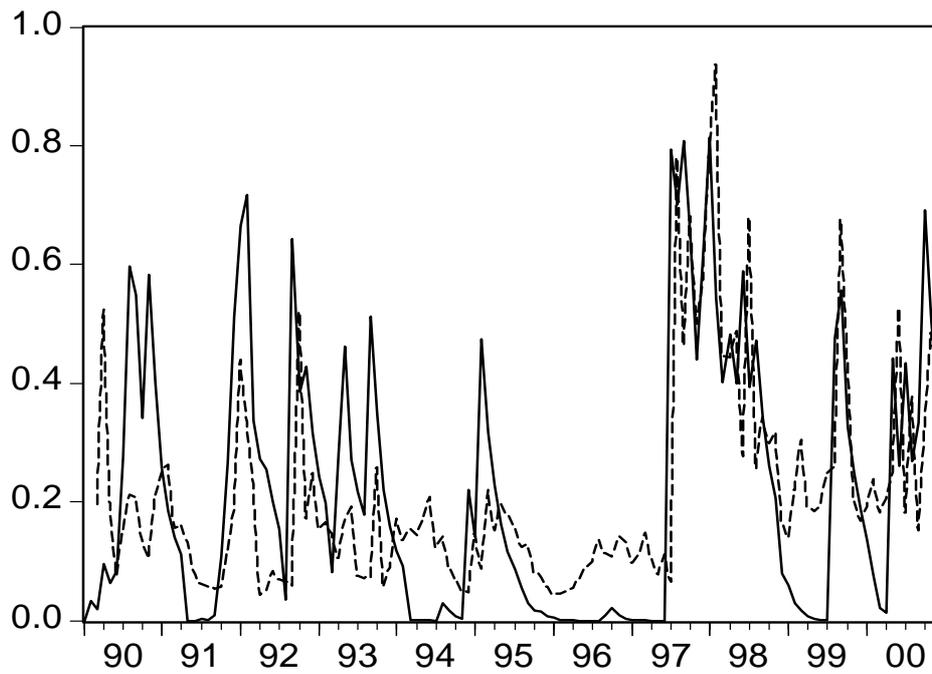


Figure 9: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Thailand 1990:1-2000:12.

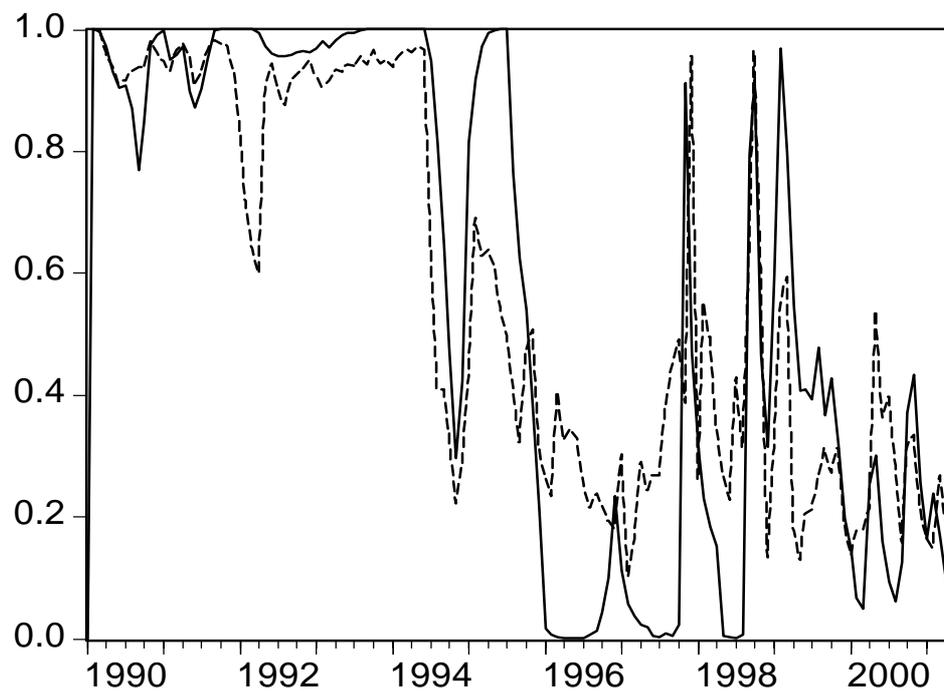


Figure 10: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Brazil 1990:1-2000:12.

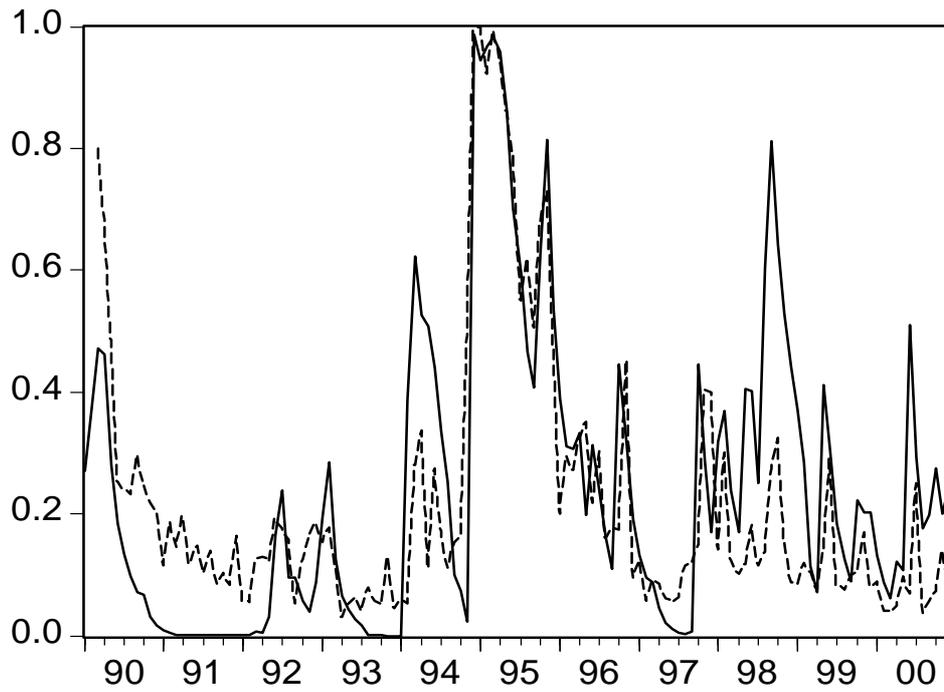


Figure 11: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Mexico 1990:1-2000:12.

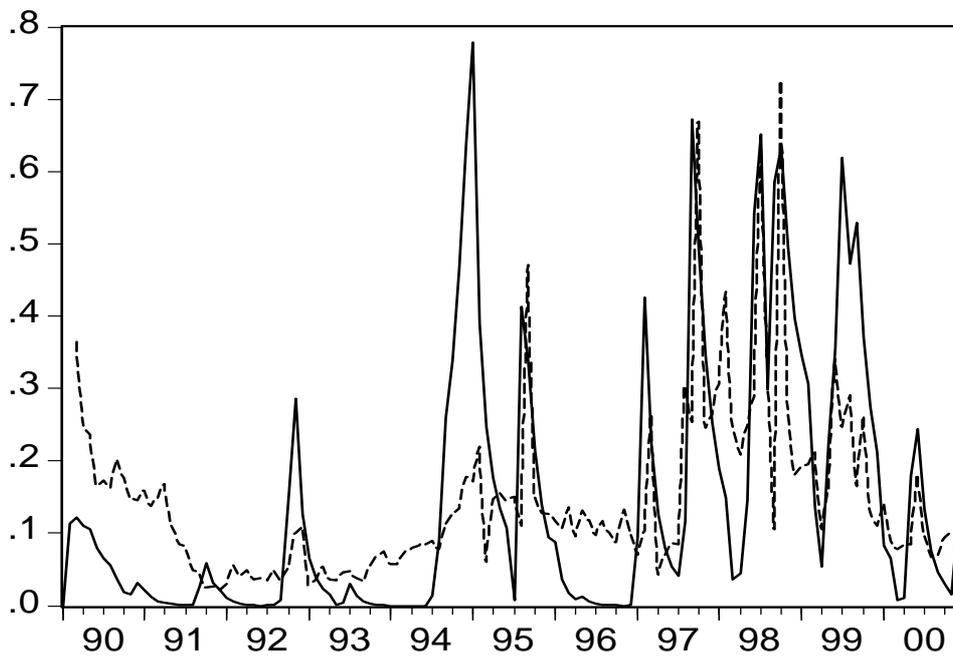


Figure 12: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Colombia 1990:1-2000:12.

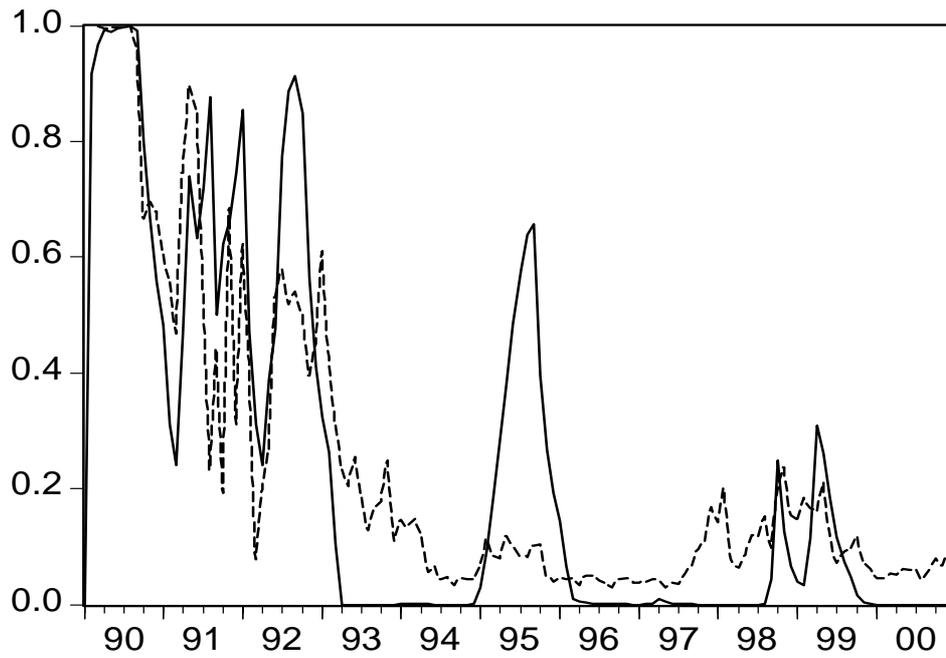


Figure 13: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for Peru 1990:1-2000:12.

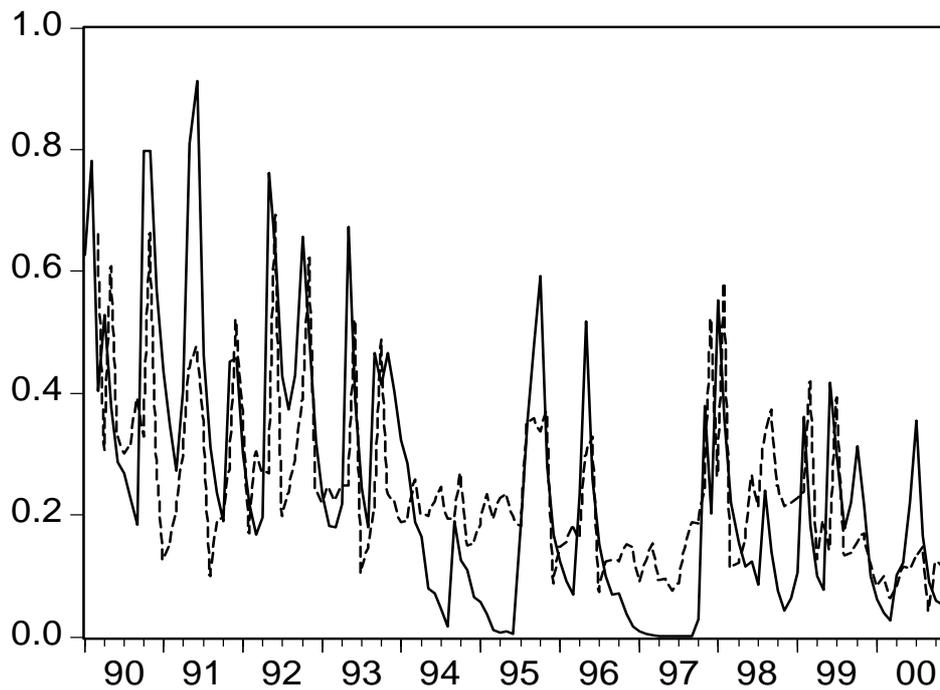


Figure 14: The estimated crisis definition (solid line) and the model estimates (dashed) plotted for the Chile 1990:1-2000:12.

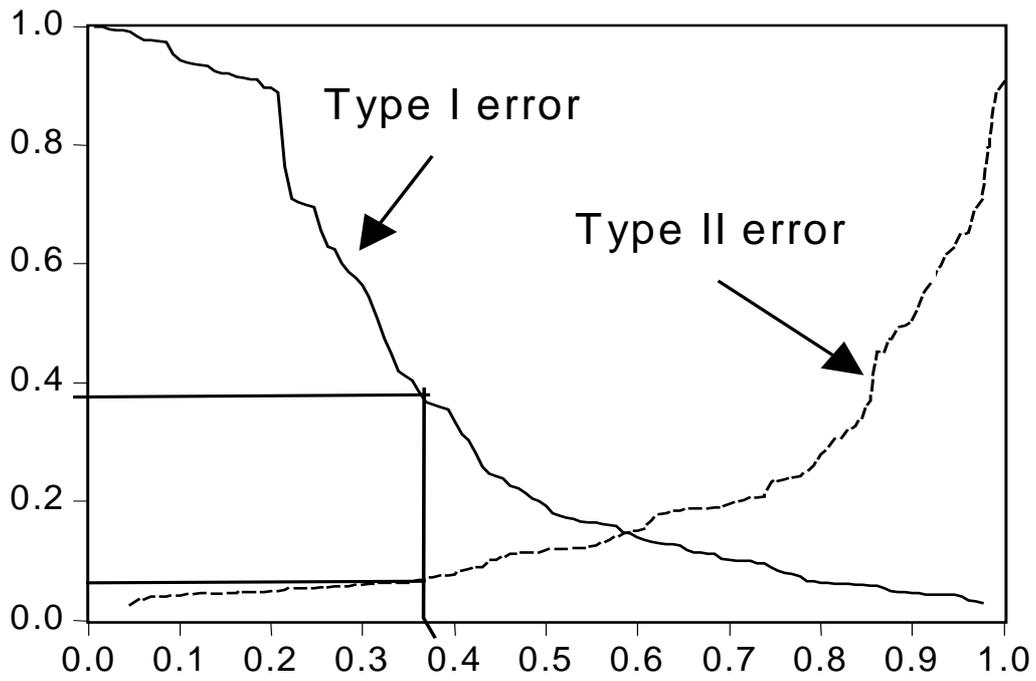


Figure 15: Type I (solid line) and Type II errors (dashed) showing the probability of a 10% currency depreciation or a 20% real interest-rate increase within 1 month.

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Printed by: HST Offsetdruck GmbH, Dieburg.

Print: ISSN 1615-956X / Elektr.: 1615-9683 / Internet: ISSN 1616-0428